Engel and Baumol: How much can they explain the rise of service employment in the United States?

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Engel and Baumol: How much can they explain the rise of service employment in the United States?*

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Abstract

High income elasticity of demand for services and low income elasticity of demand for food (Engel's law), and relatively slow productivity growth in the service sectors (Baumol's disease) have been viewed as key drivers of rising share of service sector employment in the United States during the twentieth century. How much of the rising share of services can be explained by these two forces? A calibrated model of structural change shows that jointly Engel's law and Baumol's disease could explain about two thirds of the reallocation of labor into services.

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1 Introduction

As is well-known, over the last two hundred years, the sectoral composition of employment has changed dramatically in the United States. Figure 1 shows the employment shares of agriculture, manufacturing and services since 1800. Agriculture, which accounted for more than 70 percent of employment in 1800 generated only about 2 percent of employment by 2000. Manufacturing share of employment rose secularly from 1800 to a peak of about 30 percent in the 1960s, and has been declining since. The share of service sector employment, by contrast, has been rising unabated, and by 2000 accounted for about 80 percent of total private sector employment.

How can we explain these trends? According to Griliches (1992, pp. 1–3):

> There are at least two, possibly complementary, explanations of [the rising share of services in employment]. The first is slower technical change in services, resulting from their intrinsically more labor intensive nature [Baumol's disease], and a potentially higher income elasticity of the demand for them [Engel's law].

From a conceptual standpoint, the potential significance of each of these mechanisms in explaining the rise of service sector employment share has long been recognized. For instance, Kindleberger (1958, cited in Gershuny and Miles 1983, p. 27) credits Fourastié (1952) for an early account of economic development based on the combination of differential productivity growth rates across agriculture, industry and services, and Engel's law. More recently, a *theoretical* literature has examined the conditions under which differential income elasticity of demand (Kongsamut et al., 2001) and differential productivity growth rates across sectors (Ngai and Pissarides, 2007) lead to both structural change and an aggregate balanced growth path.[1]

Yet, from an empirical standpoint, little is known about whether and by how much these two complementary factors can account for the rising share of services in employment in the United States.[2] This paper considers a quantitative model of structural change appropriate for the United States, which incorporates both the Engel's law and Baumol's disease.[3] The results shows that that jointly Engel's law

[1]However, these models do not consider the combined treatment of these drivers of structural change. Acemoglu and Guerrieri (2008) study aggregate balanced economic growth with changing industrial composition when there is differential rates of capital deepening across industries. However, they explicitly write that their "model does not attempt to account for [those] structural changes" (p. 469, footnote 4) associated with the changing shares of agriculture, manufacturing and services in employment.

[2]Earlier accounts of the rising service economy include Fuchs (1968), Gershuny (1978), Gershuny and Miles (1983). Not all of these authors have embraced the high income elasticity of demand for services as an explanation. In fact, services have been the most contentious industry for the competing theories of structural change. Baumol et al. (1989) argue that slow productivity growth in services accounts for the rise of the service employment in the United States. Schettkat and Yoncarini (2006) present an excellent, balanced overview of the demand and supply side determinants of the rising share of services in employment. "Service economy" is sometimes defined with reference to the *occupational* structure of employment. This paper, instead, focuses on the *industrial* structure of employment.

[3]The quantitative framework is related to Echevarria (1997), who uses simulations to establish that structural change models are broadly consistent with *cross-national* patterns documented in Syrquin (1988). This paper contributes to the line of research initiated by Echevarria (1997) by providing a detailed calibration appropriate for the United States. Caselli and Coleman (2001) use simulations to examine south-north income convergence in the United States, and Dennis and İşcan (2007) use simulations to examine agricultural out-migration in the United States. These papers primarily focus on the decline in the employment share of agriculture, and thus do not account for the significantly different patterns of manufacturing and service sector shares in employment.

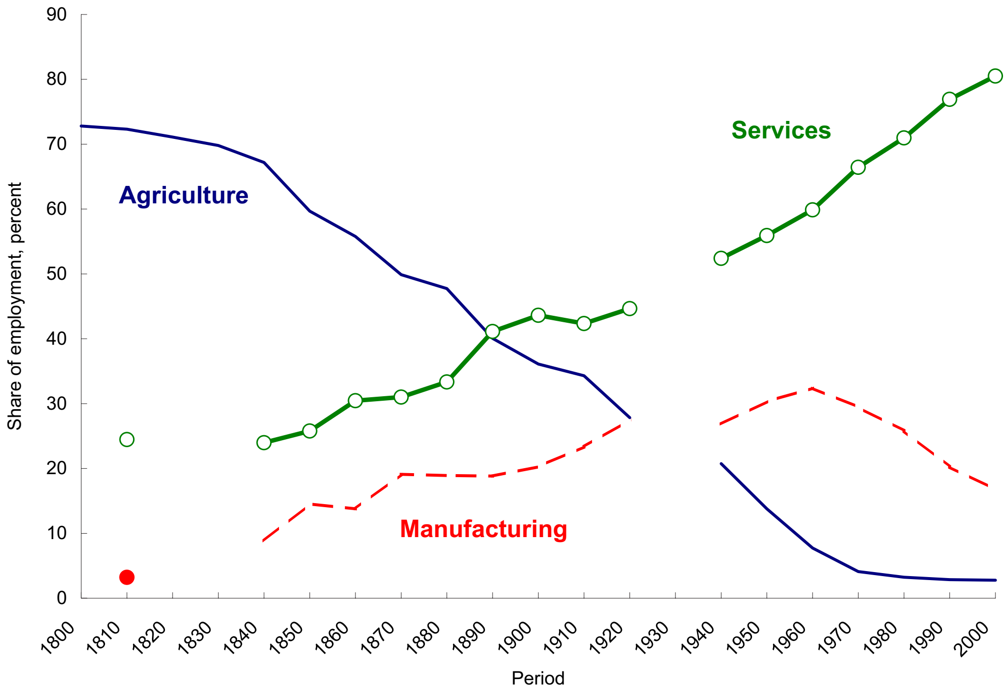

Figure 1: Employment shares by industry, U.S. 1800–2000

Notes: This figure plots the employment shares of agriculture, manufacturing and services. There is no census-based industrial employment data available for 1930, and there is no manufacturing employment estimates for 1800, 1820, and 1830. From 1800 to 1900, the denominator is total employment and from 1910 to 2000 the denominator is total employment in agriculture, manufacturing and services, excluding public administration and government.
Sources: From 1800 to 1900, employment share of agriculture is based on Weiss series in Carter et al. (2006, series Ba829 and Ba830), manufacturing is based on Lebergott series in Carter et al. (2006, series Ba814 and Ba821, and services is computed by the author as a residual. From 1910 to 1990, data based on Sobek (2001, Table 4). For 2000, data from U.S. Census Bureau, Statistical Abstract of the United States, 2001, Table no. 596.

and Baumol's disease could explain about two thirds of the actual reallocation of labor into services.

To account for the Engel's law, in the quantitative analysis I follow the lead of Kongsamut et al. (2001) and consider non-homothetic preferences that result in low income elasticity of demand for food produced by agriculture, and high income elasticity of demand for services. So, as income per capita rises, service-producing sectors face relatively higher demand compared to agriculture and manufacturing, and thus end up employing a relatively higher share of total labor force. Although, strictly speaking, Engel's law refers to low income elasticity of demand for food, in this paper I use it to refer to structural change driven by nonlinear income effects that influence *demand* for services, as well as demand for food. Figure 2 presents suggestive evidence for these trends.

The quantitative analysis also allows for differential productivity growth rates across sectors. In this

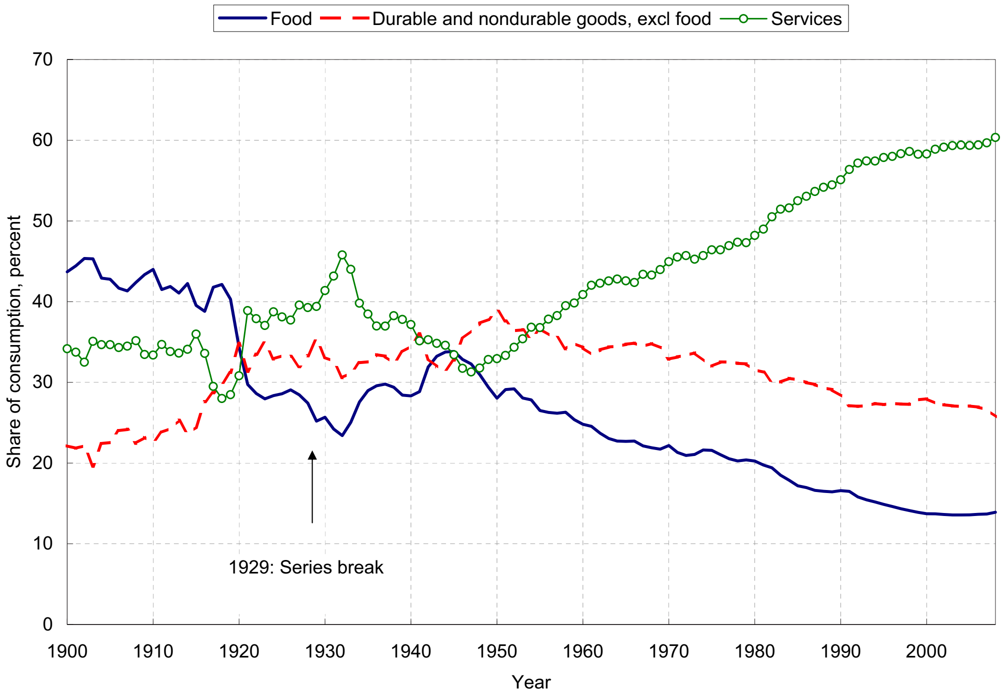

Figure 2: Expenditure shares of food, goods (non-food), and services in the United States, 1900–2008

Sources: From 1900 to 1928, Lebergott (1996, Tables A1 and A8. From 1929 to 2008, Bureau of Economic Analysis, Personal Consumption Expenditures by Major Type of Product, Table 2.3.5.

case, as long as the goods produced by different sectors are gross complements, the sector with a relatively higher productivity growth sheds labor. All else being equal, higher-productivity growth sectors increase their output faster that the rest. However, due to gross complementarity, labor and capital shift to slower-productivity growth sectors, so that output in these sectors can increase in tandem with those of the higher-productivity growth sectors. Although, strictly speaking, Baumol's (1967) disease refers to low productivity growth in the service sector, in this paper I use it refer to structural change driven by differential productivity growth effects that influence the *supply* of all sectors. (See, e.g., Nordhaus (2008) on different interpretations of Baumol's disease.)

Part of the difficulty in ascertaining the contribution Baumol's disease to the rising share of services in employment is due to the paucity of data on the service sector. There are significant measurement issues associated with service sector output, value added and productivity (e.g., Triplett and Bosworth, 2004). Thus, Section 2 reviews the available evidence on the productivity growth rates by industry. The evidence suggests that since WWII productivity growth in agriculture has surpassed the productivity growth in the rest of the economy, and service sector productivity has been the laggard. However, the evidence also indicates significant industry specific accelerations and decelerations of productivity growth rates, which are highly relevant for a quantitative assessment of complementary drivers of structural change.

Part of the difficulty in ascertaining the contribution of Engel's law, on the other hand, to the rising share of services in employment is due to the uncertainties surrounding the preference parameters governing the income elasticity of demand for services. While there are econometric estimates of income elasticity of demand for food and other consumption items, these estimates have varied across time and across studies. Thus, in the quantitative analysis in Section 4, I consider a range of parameter values that are consistent with many different configurations of low income elasticity of demand for food and high income elasticity of demand for services. These parameter configurations form the basis of my findings concerning how much of actual change in share of service employment in the United States *could* a unified model with Engel's law and Baumol's disease explain.

The rest of the paper is organized as follows. Section 3 presents the structural change model that I use to organize the data. Section 4 uses sector-specific productivity estimates and calibrated parameters to quantify the combined contributions of Engel and Baumol effects to the rise of service sector employment. Since this combined contribution is about two thirds of the rise in service share of employment, Section 5 considers several complementary demand- and supply-side explanations. Section 6 concludes. A data appendix describes the main data sources, and a technical appendix contains the derivations omitted from the text.

2 Productivity growth by industry

Baumol's disease explanation for the rising share of employment in services hinges on two premises: differential productivity growth rate across sectors, and low elasticity of substitution between services and other consumption goods. Thus, in this section, I review the empirical evidence on productivity growth by industry in the United States.[4]

U.S. Department of Agriculture, Economic Research Services publishes multi-factor productivity estimates for the farm sector, and their estimates cover the period since 1948. I use these estimates to construct agricultural productivity growth rates. Bureau of Labor Statistics (BLS) publishes multi-factor productivity estimates for the private non-farm business sector dating back to 1948.[5]

Baumol's (1967) original conjecture about the role of differential productivity growth rates as the driving force of structural change is motivated by slow productivity growth in the service sector. There is, however, little long-term data on total factor productivity that distinguishes between services and manufacturing within the private non-farm business sector. BLS publishes estimates of manufacturing multi-factor productivity, but these series start in 1987.[6] BLS does not publish corresponding estimates

[4]See Pasinetti (1981), and Schettkat and Yoncarini (2006) on Engel's law in the context of structural change.

[5]I should note that for the period 1948–2006, average TFP growth rate is 1.26 percent in the non-farm sector, and 1.50 percent for the farm sector, with average annual relative TFP growth of 0.24 percent in favor of the farm sector.

[6]Jorgenson, Gollop and Fraumeni (1987) develop their own database for measuring total factor productivity at the sector level. However, their estimates (i) cannot be easily aggregated to broader industry groups, and (ii) cannot be easily

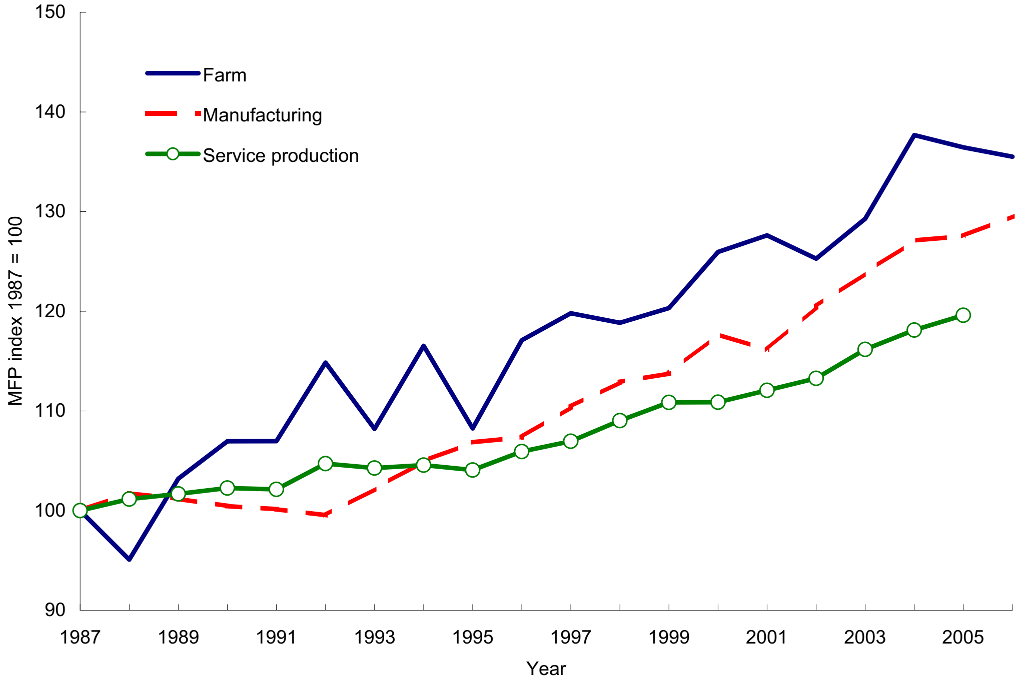

Figure 3: Farm, private non-farm business and service producing sectors TFP in the United States, 1987–2005

Sources: Bosworth and Triplett (2007) for services, U.S. Department of Commerce, Bureau of Economic Analysis for the manufacturing sector (NAICS 31–33), and U.S. Department of Agriculture, Economic Research Services for the farm sector. Notes: The following are the average total factor productivity growth rates for the farm $\hat{g}_a$, manufacturing $\hat{g}_m$, and services $\hat{g}_s$ from OLS coefficients on a linear time trend with Newey-West heteroscedasticity and AR(1) consistent standard errors in parentheses:

1987–2006: $\hat{g}_a = 0.0173(0.0071)$, $\hat{g}_m = 0.0135(0.0038)$, $\hat{g}_s = 0.0099(0.0021)$.

of productivity for service-producing sectors.

In a series of recent studies Barry Bosworth and Jack Triplett have examined the productivity in the service sector in the United States by taking advantage of a newly developed database at the Bureau of Economic Analysis.[7] Figure 3 presents Bosworth and Triplett's service sector multi-factor productivity estimates, alongside with those for farm sector and manufacturing, from 1987 until 2006. Over this period the farm sector had the highest productivity growth, followed by manufacturing, and then services. There is thus considerable empirical evidence for differential productivity growth rates.

compared with other estimates given that re-classification of an industry in manufacturing rather than in services can have substantial impact on productivity estimates; see, e.g., Bosworth and Triplett (2007).

[7] Triplett and Bosworth (2001, 2003, 2004) report the first set of findings of their project. Bosworth and Triplett (2007) update these estimates.

Table 1: Multifactor productivity growth estimates by industry

		Productivity growth rate, %		
Author	Period	Farm	Manufacturing	Services
Kendrick (1961)	1900–1948	0.88	1.94	–
ERS	1948–2006	1.50	–	–
Gullickson and Harper (1999)	1949–1996	–	1.2	–
BLS	1987–2006	–	1.35	–
Triplett and Bosworth (2003)	1977–1995	–	–	0.10
Bosworth and Triplett (2007)	1987–2006	–	–	0.99

Notes: This table reports the annualized growth rate of multifactor productivity by industry in percent. See Appendix A for detailed data sources. ERS is Economic Research Services, and BLS is Bureau of Labor Statistics.

The data are too short to be definitive about productivity growth accelerations or decelerations (structural breaks), and reversals of relative productivity growth rates. However, there is a noticeable increase in the productivity growth rate in the service producing sectors since 1995 (Bosworth and Triplett, 2007). Time will tell whether the increase in service sector productivity growth can be sustained, and will eventually surpass the growth rate in the rest of the economy.

How about the long-term evidence? Here there are several independent estimates that we can combine to have a general idea about trends—although the data limitations are daunting for services, coverage is good for farm and manufacturing (see Table 1). Fuchs (1968, pp. 75–76) estimates that during the period from 1929 to 1965 multi-factor productivity growth rate in the service sector lagged behind that of manufacturing by about 0.5 percentage points on average.[8] For the period from 1949 to 1996, Gullickson and Harper (1999, Table 3) estimate the average productivity growth rate in the manufacturing industry at 1.2 percent per year. Based on limited data and extrapolations Triplett and Bosworth (2003) provide estimates of multi-factor productivity growth rate in the service sector between 1977 and 1995. Their estimates suggest that multi-factor productivity growth rate in services during this period has been at best anemic (about 0.1 percent per year or less). Of course, there was a slowdown in manufacturing multi-factor productivity growth rate during much of this period. Gullickson and Harper's (1999) manufacturing multi-factor productivity growth estimates indicate -0.4 percent for the period 1973–1979, and 1.0 percent for the period 1979–1990. By all accounts, then, it is safe to conclude that at least during the postwar period the productivity growth rate in the service-producing sectors has been on average below that of those in manufacturing and the farm sectors.[9]

[8]Fuchs (1968) refers to "industry," which includes manufacturing, mining and construction. He arrives at this estimate by decomposing the relative rise in the employment share of services into four components: relative (to industry) decrease in the number of hours worked, relative increase in labor quality in industry, relative increase in capital–labor ratio in industry, and relative increase in TFP in industry (the residual).

[9]There are estimates of multi-factor productivity growth rate in individual service industries that start earlier (e.g., Gordon 2004, pp. 172–217), but it is not known whether these sectors are representative of the broader service industry.

3 A three-sector model

To organize the data relevant for structural change in the United States in a parsimonious way, I consider a three sector model of agriculture, manufacturing and services. This section describes the economic environment in the model (production, demand and resource constraints), determines both intra- and intertemporal equilibrium, and discusses the asymptotic properties of the aggregate capital stock, and consumption. I draw on the existing literature to model Engel's law and Baumol's disease effects. The specification of non-homothetic preferences responsible for Engel's law effects follows Kongsamut et al. (2001), and the specification of logarithmic instantaneous utility function when there are sectoral productivity growth differentials responsible for Baumol's disease follows Ngai and Pissarides (2007). Since the main features of these models are well-known, the presentation here focuses on the key implications of a model that combines these two effects.

3.1 The environment

In the model, time is continuous.[10] The labor force is constant and normalized to one—extending the analysis to non-constant labor force is straightforward, and the quantitative analysis in Section 4 allows for changes in the labor force. There are three consumption goods produced by three sectors, agriculture, manufacturing and services, indexed by $i = a, m, s$, respectively. The m-sector good can be either consumed or converted into capital stock in any of the sectors, whereas the outputs of a and s sectors are nondurable.

Production.—At time t, output in each sector is given by

$$Y_{it} = A_{it} F(K_{it}, L_{it}), \tag{1}$$

where, for each sector $i = a, m, s$, Y_i is output, K_i is capital stock, A_i is total factor productivity, and L_i is labor input. With an eye toward calibration, I consider Cobb-Douglas production functions $F(K_i, L_i) = K_i^{\alpha} L_i^{1-\alpha}$, with $0 < \alpha < 1$ (see, e.g., Gomme and Rupert, 2007).

Growth rates of sectoral total factor productivity levels are exogenous, and possibly different across sectors:

$$\frac{\dot{A}_{it}}{A_{it}} = g_{it}(1 - \alpha), \tag{2}$$

where, here and elsewhere, for any variable X, we let $\mathrm{d}X_t/\mathrm{d}t \equiv \dot{X}_t$. Also, in the above expression, g_i should be thought of as the growth rate of labor augmenting technological progress.

Feasibility.—Sectors a and s produce nondurable consumption goods, whereas the m-sector good can be either consumed or converted into capital stock in any of the sectors. The transformation of the

[10]The continuous time analysis facilitates the exposition of the model, as well as the comparison of the model with existing theoretical models. The calibration of the model later in the paper, however, relies on the discreet time counterpart of the basic environment.

m-sector good into capital stock is linear. Thus, we have:

$$C_{it} = A_{it}F(K_{it}, L_{it}), \quad i = a, s, \tag{3}$$

$$C_{mt} + \dot{K}_t + \delta K_t = A_{mt}F(K_{mt}, L_{mt}), \tag{4}$$

where, for each sector $i = a, m, s$, C_i is aggregate consumption, $0 < \delta < 1$ is the depreciation rate, and $K = \sum_{i=a,m,s} K_i$. Feasibility of production also requires $\sum_{i=a,m,s} L_i = 1$.

Allocative efficiency.—There is perfect factor mobility across sectors. Thus, production efficiency implies the equality of marginal rates of transformation across sectors. This production efficiency condition determines capital-labor ratios

$$\frac{K_{it}}{L_{it}} = k_{it} = \frac{K_t}{\sum_{i=a,m,s} L_{it}} = K_t. \tag{5}$$

Moreover, competitive product markets imply equality of marginal value product of labor across sectors. This unique wage rate determines relative prices

$$\frac{P_{it}}{P_{mt}} = \frac{A_{mt}}{A_{it}}, \tag{6}$$

where P_{it} is the ith good's price.

Consumption.—There is an additively separable lifetime utility function with logarithmic instantaneous utility, which describes consumption behavior:

$$\int_0^{\infty} e^{-\rho t} \log(C_t)\, \mathrm{d}t. \tag{7}$$

Logarithmic preferences are special, but as Ngai and Pissarides (2007) show, in the absence of Engel effects, and when long-run productivity growth rates are different across sectors, aggregate balanced growth occurs only when the elasticity of intertemporal substitution is unitary.

The composite consumption good is

$$C_t = \left[\sum_{i=a,m,s} \eta_i^{1/\nu} \; (C_{it} + \gamma_i)^{(\nu-1)/\nu} \right]^{\nu/(\nu-1)}, \quad \text{with} \sum_{i=a,m,s} \eta_i = 1. \tag{8}$$

In equation (8) $\nu > 0$ is the elasticity of substitution across consumption goods, η_i is the relative weight of each good, and $\gamma_i \in (-\overline{\gamma}, \overline{\gamma})$, with $\overline{\gamma} < \infty$ is a fixed subsistence or natural endowment parameter. For goods with low income elasticity of income, such as food $\gamma_i < 0$, and with high income elasticity, $\gamma_i > 0$. Following Kongsamut et al. (2001), I set the subsistence parameter for manufacturing to zero, $\gamma_m = 0$. C_i is the *consumption* of the ith good. I denote consumption of each good net of subsistence by $\overline{C}_i = C_i + \gamma_i$, or *net consumption*. Finally, define *(net) consumption expenditures* for the ith good as the value of (net) consumption based on market prices.[11]

[11] In what follows, I only consider those non-trivial situations in which available resources can always meet the minimum subsistence requirements in all sectors. Also, I leave out the formal definition of competitive equilibrium in this problem.

3.2 Equilibrium allocations

In this section, I describe the equilibrium allocations of consumption and employment in agriculture, manufacturing and services. Appendix B presents the derivations in detail.

Intratemporal consumption choices.—The representative household maximizes lifetime utility subject to feasibility constraints. The first-stage of utility maximization allocates total expenditures across any two consumption goods by setting the ratio of their marginal utilities to the ratio of their prices:

$$\left[\left(\frac{\eta_i}{\eta_m}\right)\left(\frac{\overline{C}_{mt}}{\overline{C}_{it}}\right)\right]^{1/\nu} = \frac{P_{it}}{P_{mt}}. \tag{9}$$

The above expression relates ratios of *net* consumption to relative prices. However, from an empirical standpoint, it is more informative to think about the share of consumption expenditures. To this end, I first define total "net consumption expenditures" as

$$\overline{C}_t = \frac{\sum_{i=a,s,m} P_{it}\overline{C}_{it}}{P_{mt}}. \tag{10}$$

Note that net consumption expenditure, $\overline{C}$, is measured in terms of the m-good, which is the numeraire. However, $\overline{C}$ is indeed identical to the conventional measure of consumption expenditures

$$\overline{C} = P \times C, \tag{11}$$

where P is the consumption *expenditure*-based price index in terms of the m-good

$$\begin{aligned} P_t &= \left[\sum_{i=a,s,m} \eta_i \left(\frac{P_{it}}{P_{mt}}\right)^{1-\nu}\right]^{1/(1-\nu)} \\ &= \left[\sum_{i=a,s,m} \eta_i \left(\frac{A_{mt}}{A_{it}}\right)^{1-\nu}\right]^{1/(1-\nu)}. \end{aligned} \tag{12}$$

Intratemporal allocation of labor.—To determine the share of labor in each sector, let $Y = A_m F(K, 1)$. Then,

$$L_i = \left(\frac{\overline{x}_i}{\overline{\overline{X}}}\right)\left(\frac{\overline{C}}{Y}\right) - \left(\frac{A_m}{A_i}\right)\left(\frac{\gamma_i}{Y}\right), \qquad \text{for } i = a, s, \tag{13}$$

$$L_m = \left(\frac{\overline{x}_i}{\overline{\overline{X}}}\right)\left(\frac{\overline{C}}{Y}\right) + \left(1 - \frac{\overline{C}}{Y}\right), \tag{14}$$

where

$$\overline{x}_{it} = \frac{P_{it}\overline{C}_{it}}{P_{mt}\overline{C}_{mt}} = \left(\frac{\eta_i}{\eta_m}\right)\left(\frac{A_{mt}}{A_{it}}\right)^{1-\nu},$$

and $\overline{X} = \sum_{i=a,m,s} \overline{x}_i$. Equation (13) highlights the effects over time of both the Engel's law and Baumol's disease on the employment shares by sector. When $\gamma_i = 0$ for all $i = a, s$ (no Engel effects), the second term in this expression drops out and changes in the share of employment over time are solely driven by differential productivity growth rate across sectors (i.e., Baumol effects only). Also, the second term in equation (14) captures the fact that sector m produces capital goods which are used in production in all sectors (i.e., capital accumulation effect).

Intertemporal allocations.—The second stage of the utility maximization problem allocates resources over time. The next set of expressions show (i) how aggregate capital accumulation is related to aggregate consumption expenditures, and (ii) how aggregate consumption expenditures change over time. So, I define the following transformed variables in effective labor units:

$$\bar{c} = \frac{\overline{C}}{A_m^{1/(1-\alpha)}}, \qquad k = \frac{K}{A_m^{1/(1-\alpha)}}, \qquad a_i = \frac{A_i}{A_m^{-\alpha/(1-\alpha)}}.$$

With these transformed variables optimal consumption and capital accumulation equations can be stated as

$$\dot{\bar{c}} = \bar{c}\left[\alpha k^{\alpha-1} - (\delta + \rho + g_m)\right] \tag{15}$$

$$\dot{k} = k^{\alpha} - \bar{c} - (\delta + g_m)k + \sum_{i=a,m,s} \frac{\gamma_i}{a_i}. \tag{16}$$

Discussion.— Equations (15) and (16) collapse to expressions familiar from the one-sector Ramsey optimal growth model when the economy meets the following two conditions: (i) when there are no Engel effects ($\gamma_i = 0 \ \forall i = a, m, s$), and (ii) when there are no Baumol effects ($g_m = g_i$ for $i \neq 1$). Otherwise, this three-sector model with either Engel or Baumol effects generates structural change.[12]

Moreover, in general, this three-sector model does not exhibit a steady state. In particular, in the presence of both Engel and Baumol effects, the values of $\bar{c}$ and k do not converge to a steady-state value, and, at the aggregate, the net consumption–income ratio is never constant. However, as the economy grows, the forces that tend to prevent the economy from attaining a constant net consumption-income ratio in the short run become progressively weaker. Thus, in the long run, the consumption–income ratio asymptotically *approaches* to a constant value. More importantly for this analysis, the shares of employment in agriculture, manufacturing and services converge towards constant values. I consider and solve a parameterized version of such a three-sector model in the next section.

3.3 A parameterized solution of the model

To gain insights regarding the dynamics of the baseline three-sector model, in this section, I numerically solve the model and report the emerging employment shares by industry.[13] In principle, this simulation exercise can allow for transition dynamics in capital stock per effective worker, k: that is, it is possible

[12] There is structural change even if the productivity-adjusted subsistence terms sum to zero, $\left(\sum_{i=1}^{m}(\gamma_i/a_i) = 0\right)$ (see Kongsamut et al., 2001). This, however, is a knife-edge condition, and is not essential for the quantitative analysis in the next section.

[13] I use a forward-iteration algorithm to numerically solve this model. See, e.g., Heer and Maußner (2005) on this approach.

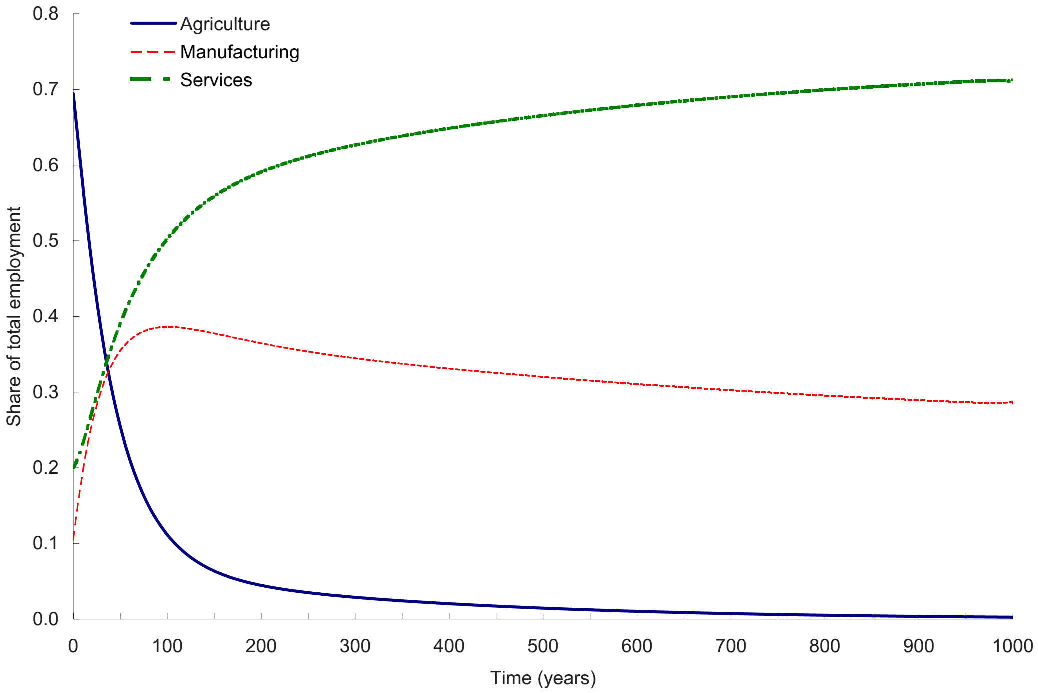

Figure 4: Employment shares in the parameterized version of the baseline model

Notes: This figure plots the shares of agriculture, manufacturing and services in total employment along the transition to the asymptotic balanced growth path based on a simulation of the baseline multi-sector model. The parameter values are: $\alpha = 0.33$, $\nu = 0.5$, $\delta = 0.05$, $\rho = 0.02$, $\gamma_a = -400$, $\gamma_m = 0$, $\gamma_s = 250$, $\eta_a = 0.10$, $\eta_m = 0.15$, $\eta_s = 0.75$, $A_a(0) = 400$, $A_m(0) = 250$, and $A_s(0) = 400$, $g_a = 0.026$, $g_m = 0.020$, and $g_s = 0.015$.

to start the simulations with k below its (asymptotic) steady-state value, and let it approach to its asymptotic limit through capital deepening. However, the broader tendencies I examine in this paper concerning the changing shares of employment have taken place over sufficiently long periods that I ignore those major events that displace k far away from its asymptotic steady-state value.[14] Suppose, for instance, the asymptotic steady-state value of k is the initial condition, and γ_a is negative, as food is a necessity (Engel's law);[15] γ_m is equal to zero, as share of manufacturing in employment does not have a strong "trend" in the U.S. data; and γ_s is positive as income elasticity of services tends to be greater than one.[16] The specific parameter values of this illustrative calibration are listed in the caption to Figure 4.

Figure 4 illustrates the sectoral employment shares pertaining to a numerically solved, parameterized

[14] See, e.g., Alvarez-Quadrado (2008) who uses a second world war-related destruction of capital stock to examine economic growth outside the balanced growth path.

[15] For instance, in the International Food Consumption Patterns Database compiled by the U.S. Department of Agriculture, the income elasticity of food in the United States is about 0.1, which corresponds to $\gamma_a < 0$.

[16] For instance, expenditures on health care fall into this category; see, e.g., Hall and Jones (2007).

version of the baseline model. The solution path corresponds to $1,000$ annual observations. The figure shows employment shares as they approach to their respective asymptotic steady-state values. These simulation results exhibit two remarkable features. First, economically significant reallocation of labor across industries can be a long-lasting process. Within the first hundred years, the share of agriculture in employment declines from 70 percent to just over 11 percent, and that of services rises from 20 to 50 percent. Even after two hundred years of (modern) economic growth, this economy exhibits substantial reallocation of labor from agriculture and into services: the share of manufacturing in employment declines from 36 percent to 28 percent, and that of services increases from about 60 percent to 71 percent over time.

The second remarkable aspect of the simulation results is that sectoral employment shares can exhibit non-monotonic behavior over time. In this example, the share of employment accounted by the manufacturing sector increases in the first hundred years of structural change, and it subsequently decreases. This hump-shaped behavior of employment share of manufacturing reflect the time-varying, relative influences of Engel and Baumol effects. Initially, income per capita is low, and, since food is a necessity, agriculture accounts for a large fraction of total employment. During the first stage of structural change, as income per capita rises, labor reallocates from agriculture into manufacturing (and services), with very little change in consumption expenditures on food (see Figure 5). The demand for food increases very slowly at early stages of development, but the productivity growth rate in agriculture exceeds that of manufacturing (and services), so its relative price declines. These two forces culminate in a flat personal consumption expenditure profile ("Engel curve"). At this relatively early stage, both manufacturing and services increase their employment shares. Due to the Engel effect, both the demand for non-food goods and demand services rise. Although relative productivity growth in the manufacturing exceeds that of services, the Engel effect dominates the Baumol effect in the context of manufacturing share of employment. In fact, initially the Engel curves are steeper for non-food goods than for services.

In the second stage of structural change, as income per capita rises, labor begins to reallocate from manufacturing to services, while the reallocation of labor from agriculture continues. The decline in the share of employment in manufacturing is due to two forces. First, the Engel effect operating on non-food good items looses its strength, and manifests itself primarily on services, which have high income elasticity (see Figure 5). Second, manufacturing productivity growth rate is higher than that of services, so manufacturing sheds labor. At this stage, therefore, the concomitant rise in the share of employment in services is due to the fact that both Engel and Baumol effects reinforce each other.

Overall, the parameterization of the model in this section suggests that the model *can* accommodate, at least qualitatively, several salient features of the data: (i) secularly declining employment share of agriculture and secularly rising employment share of services; (ii) hump-shape in the employment share of manufacturing (see Figure 1); and (iii) rather complex dynamics in the expenditure shares of manufacturing and services, whereby initially expenditure share of services is higher than that of (non-food) goods, subsequently falls about equal to that of goods, and then rises again (see Figure 2). However, this

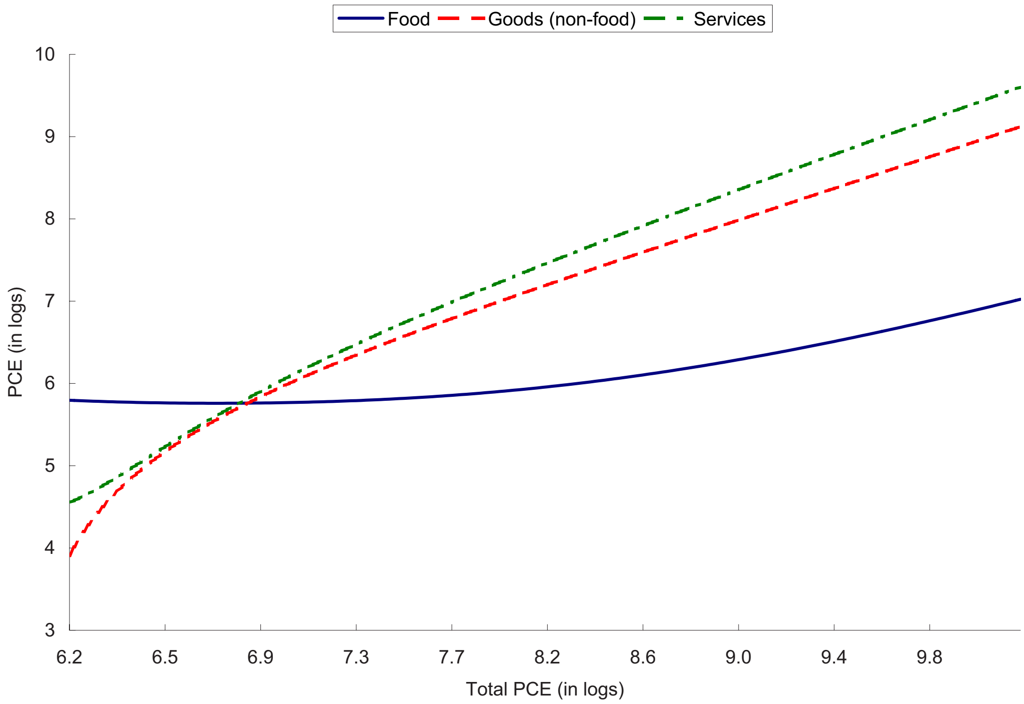

Figure 5: Engel curves in a parameterized version of the baseline model

Notes: This figure plots changes in log personal consumption expenditures (PCE) on food, goods (non-food) and services associated with changes in total PCEs based a simulation of the baseline multi-sector model with both Engel and Baumol effects. The reported expenditure figures are based on the first 200 observations in the simulated data. The parameter values are: $\alpha = 0.33$, $\nu = 0.5$, $\delta = 0.05$, $\rho = 0.02$, $\gamma_a = -400$, $\gamma_m = 0$, $\gamma_s = 250$, $\eta_a = 0.10$, $\eta_m = 0.15$, $\eta_s = 0.75$, $A_a(0) = 400$, $A_m(0) = 250$, and $A_s(0) = 400$, $g_a = 0.026$, $g_m = 0.020$, and $g_s = 0.015$. The initial capital stock per worker is equal to its asymptotic steady-state value.

qualitative "match" critically depends on specific parameter choices. Using a more carefully calibrated version of the baseline model, the next section examines whether and by how much the Engel and Baumol effects are jointly capable of explaining structural change in the United States.

4 Accounting for the rising employment share of services

There are several complex dimensions of the U.S. structural change (Figures 1 and 2). In this paper, I focus the quantitative model in matching a single dimension of structural change: the share of employment by industry from 1910 to 2000 (which are based on a consistent set of estimates from censuses).[17] The

[17] Nordhaus (2008, p. 14), argues that, in the context of Baumol's disease, studying employment shares is "the most interesting question from a social perspective."

general strategy I adopt here is to solve the model, and compare the model-generated data on employment share by industry with the actual data. To solve the model I need to assign values to parameters. When there are uncertainties surrounding the parameter values, I consider alternative parameterizations. To compare these alternative model-generated data, I need a measure. I discuss these two issues next.

4.1 Parameters

To solve the three-sector model, I need parameters from both the demand and the production side of the model economy. I use several complementary procedures to specify the values of these parameters.[18]

Parameters available from the literature.—In the literature on macroeconomic calibration there is reasonable agreement on the following parameter values: the time discount rate $\rho = 0.06$, the depreciation rate $\delta = 0.065$, and the elasticity of output with respect to capital $\alpha = 0.283$. See, e.g., Gomme and Rupert (2007, Table 4). I choose unitary elasticity of intertemporal substitution, because it ensures asymptotic aggregate balanced growth path, and is within the range of available estimates.

Parameters calibrated from the data.—In the model the η terms measure the weight of each good in aggregate consumption, and are proportional to expenditure shares; see equation (9). I thus calibrate these parameters using the shares of expenditures on food, non-food goods and services in total personal consumption expenditures at the end of the sample period available to me (Figure 2). Since in NIPA food includes food consumed outside home and non-food goods include retail, both of which have a large service component, I adjust the long-run share of expenditures on food to $\eta_a = 10$ percent (from about 13 percent at the end of the sample) and on non-food other than services to $\eta_m = 20$ percent (from about 25 percent). In Section 4.4, I discuss the sensitivity of the results to changes in these parameters.

One important aspect of the quantitative analysis is the treatment of labor augmenting technological progress. I use the estimates of multi-factor productivity growth rates by industry as data and back-out the implied rates of labor augmenting technological progress by industry. Furthermore, I use these estimates in solving the model. So, I do not appeal to a constant growth rate of productivity during the sample period. (See Appendix A for details.) However, in order to solve the model and tie down the asymptotic steady-state values of consumption and capital stock per effective worker, I have to assign the anticipated (future) growth rates of labor augmenting technological progress by industry. Here, I consider two scenarios: First, I assume that 1987–2005 averages are the best forecasts of productivity growth rates (2005 is the last year for which I have MFP data on service-producing sectors: see Figure 3). Second, I use a single productivity growth rate, under the assumption that industry growth rates will converge to an exogenous constant in the future. In this case, I use the average multi-factor productivity growth in the private non-farm business sector from 1987 to 2005 as the unique productivity growth rate in all three sectors—1.05 per cent per annum.

The calibration also allows for the growth rate of employment. To maintain consistency with the employment share data, I only include the employment in agriculture, manufacturing, and services in

[18] In several respects, this strategy is similar to the one pursued by Hall and Jones (2007).

total employment. As in the case of productivity, I use the average annual growth rate of employment per decade (see Appendix A).

Parameters calibrated to match the data.—There are remaining parameters on both the demand and supply sides of the model that are difficult to identify either from the existing literature or from the data. I calibrate these parameters in the following way.

On the demand side, the parameters that determine the sensitivity of consumption expenditures to income γ_a and γ_s are difficult to estimate (recall that throughout $\gamma_m = 0$). So, I pursue the following approach. I set $\gamma_s = 0.25$, and vary γ_a over the range $[-.85, -0.10]$, which corresponds to a wide variation in the γ_a/C_a ratio as implied by the solution of the model. Also on the demand side, I consider a range of values for the elasticity of substitution across goods ν, when the goods are gross complements $\nu < 1$.

On the supply side, I need to set the initial levels of technology $A_a(0), A_m(0)$ and $A_s(0)$. Since the model allows for differential productivity growth rates at the sector level, I uniformly set the initial levels of technology equal to one, and let the differences in the level of technology emerge as a consequence of differential productivity growth. In general, these initializations should be viewed relative to the endowment and subsistence terms, and I examine a range of these later parameters in the analysis below.

To summarize, the uncertainty about parameter values emerge in three contexts: future productivity growth rates, the elasticity of substitution across goods ν, and the subsistence parameters. Table 2 shows the parameter values taken from the literature and the data, and the data ranges I consider in the simulations (base case parameter values are discussed below). The next section discusses the method I employ to compare the alternative parameterizations of the model.

4.2 Root mean squared error criterion

Given that there are several parameters that cannot be specified by appealing to data or existing literature, I use a root mean squared error (RMSE) criterion to discriminate across different parameterizations of the model. Specifically, for each set of parameter values, I solve the model numerically. Then, I calculate the RMSE corresponding to that parameterization, where the error is the difference between the simulated data and the actual data on each of the three employment shares: L_a, L_m and L_s. (There are 10 such errors for each employment share.) I label the parameterized model with the lowest RMSE as the "base-case parameterization."[19]

4.3 Simulation results

Table 2 reports the parameter values for the model with the lowest RMSE within the range of parameters considered—the base case parameter values. Note that the sectoral productivity growth rates in the first 100 years of the simulations are based on the estimates reported in Section 2 (see also Appendix A). For those parameters that are calibrated to match the data, the RMSE criteria selects the calibrated model

[19] I do not conduct a fine grid search that would identify the parameters which deliver the lowest RMSE, and instead identify the parameter ranges that are promising to account for the rise of the share employment in services.

Table 2: Parameter values for the simulation of the three-sector model

Description	Mnemonic	Base case	Min.	Max.
Time discount rate	ρ	0.06		
Depreciation rate	δ	0.065		
Share of capital in production	α	0.283		
Elasticity of substitution across goods	ν	0.1	0.1	0.9
Weight of each good in aggregate consumption				
Agriculture	η_a	0.10	0.10	0.10
Manufacturing	η_m	0.20	0.15	0.20
Services	η_s	0.70	0.70	0.75
Subsistence terms				
Agriculture	γ_a	−0.25	−0.85	−0.10
Manufacturing	γ_m	0		
Services	γ_s	0.25		
Initial total factor productivity levels				
Agriculture	A_a	1		
Manufacturing	A_m	1		
Services	A_s	1		
Future growth rate of total factor productivity				
Agriculture	$g_a/(1-\alpha)$	0.0173	0.0105	0.0173
Manufacturing	$g_m/(1-\alpha)$	0.0135	0.0105	0.0135
Services	$g_s/(1-\alpha)$	0.0099	0.0099	0.0105

Notes: "Min." and "Max." are, respectively, minimum and maximum values of the parameters considered in the simulations. Time discount rate, depreciation rate and the share of capital in income are from Gomme and Rubert (2007). Weight of each consumption good in aggregate consumption is based on personal consumption expenditure shares in National Income and Product Accounts (NIPA) published by the U.S. Department of Commerce, Bureau of Economic Analysis (http://www.bea.gov); see Appendix A. Base case future growth rates of labor augmenting technological progress are based on total factor productivity growth rates estimated using U.S. data from 1987–2005; see Figure 3 and Appendix A. Alternative future productivity growth rates are based on the private non-farm business sector productivity growth rate estimated using U.S. data from 1987–2005.

with differential (as opposed to uniform) long-term sectoral productivity growth rates, low elasticity of substitution across goods $\nu = 0.1$, as apposed to higher values, and subsistence parameter of $\gamma_a = -0.25$, which is in the mid-range of parameters considered.[20]

Figure 6 shows the share of employment by industry in actual data (marked by symbols) and based on simulated data (marked by lines) using the base-case parameter values.[21] The model-based simulated employment shares are generally in agreement with the broader trends observed in the actual data: they exhibit secular downward trend for agriculture, and upward trend for services, with a slight hump-

[20] The main discrepancy between the two alternative calibrations in terms of the future sectoral productivity growth rates emerges towards the end of the sample period: relative to the base-case specification, the uniform future productivity growth scenario dictates a higher share of employment in manufacturing and lower share of employment in services, partly because the uniform scenario imparts a lower productivity growth rate for manufacturing, which increases employment share of this sector at the expense of services. The RMSE results for alternative calibrations are not reported, but are available from the author upon request.

[21] I report the simulated data by the census year (e.g., 1910), starting from 1900 although the RMSE cover 1910–2000, excluding 1930 for which the census data are not yet available.

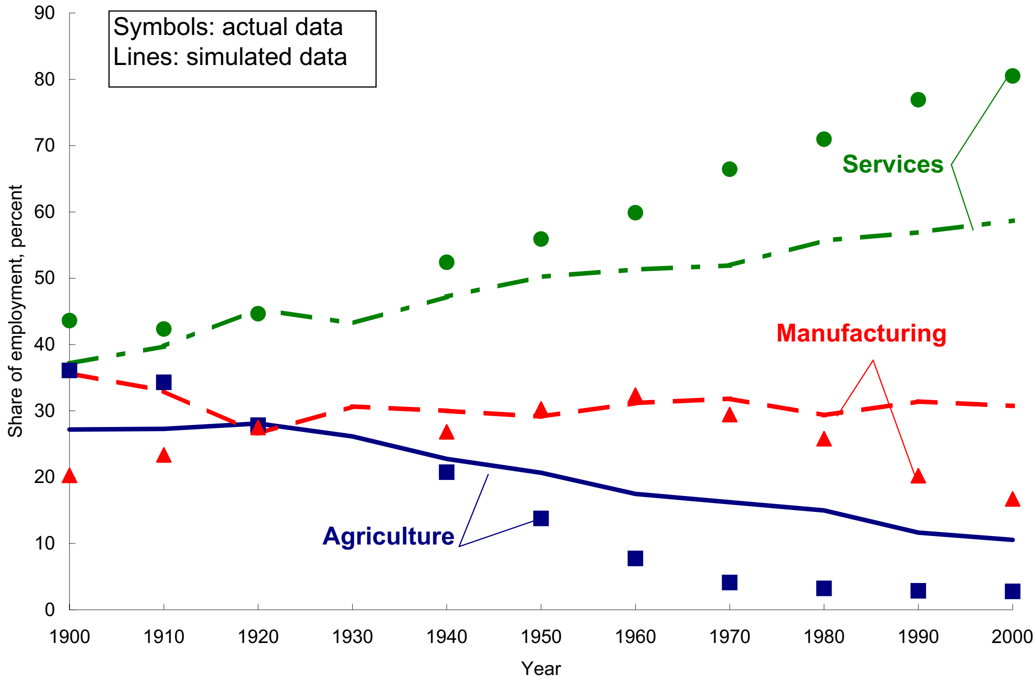

Figure 6: Employment shares by industry, U.S. 1900–2000

Notes: This figure plots the employment shares of agriculture, manufacturing and services. There is no census based industrial employment data available for 1930. For the actual data, from 1910 to 2000 the denominator is total employment in agriculture, manufacturing and services, excluding public administration and government. Simulated data are based on numerical calibration of the model described in the text with parameter values given in table 2. The simulation horizon is 1,000 annual observations.

Sources: See figure 1 for the actual data.

shape for manufacturing. However, there are two dimensions which are unsatisfactory: compared to the calibrated series, over the second half of the twentieth century (i) the rise in the share of services in employment is significantly more pronounced in the data; and (ii) the decline in the share of agriculture in employment is more marked in the data. The data also exhibit a relatively sharp decline in the share of manufacturing in employment over the last three decades of the twentieth century, whereas the calibrated series are rather flat.[22]

There is another dimension of the simulated model that is worth mentioning. While the subsistence and endowment terms γ_a, γ_s are not immediately intuitive, the ratios γ_a/C_a and γ_s/C_s are informative

[22]In the calibrated model, employment and consumption shares move in tandem. Therefore, while the quantitative model has the aforementioned shortcomings in matching the shares of employment by industry, it performs better in matching the expenditure shares reported in Figure 2. This suggests that the demand side of the model has more realistic features than the supply side, an issue that is left for future research.

about the significance of subsistence and endowment effects. These ratios as implied by the solution of the model for the *initial* period of the base-case simulation are as follows: $\gamma_a/C_a = -70.4\%$ and $\gamma_s/C_s = 51.3\%$. These ratios suggests that at the turn of the twentieth century (1910), the fraction of the food consumption accounted by subsistence needs was above 70 percent, and non-market consumption of services was about half the total market consumption of services.

One of the advantages of the quantitative approach pursued in this paper is that it provides a partial assessment of the relative contributions of Engel and Baumol effects to the base-case model. In principle, one could achieve this assessment by turning off each of these channels one at a time. However, these two effects are not additive, so these relative contributions should be viewed as suggestive. In particular, I consider two scenarios. In one scenario preferences are homothetic and sectoral productivity growth rates are different across sectors—the scenario with Baumol effects only. In the other scenario preferences are non-homothetic and sectoral productivity growth rates are identical—the scenario with Engel effects only. In each of these cases, the remaining model parameters are equal to those in the base case.[23]

Figure 7 demonstrates the results of this exercise for the share of employment in services. In the figure, the solid squares are actual data. The dashed line with solid circles show the model-base results for the corresponding census years based on parameter values in Table 2 (Engel and Baumol effects), and the remaining two lines show the results with Engel effects only and Baumol effects only. In particular, the scenario with "Baumol effect only" has homothetic preferences, and thereby sets the endowment and subsistence terms to zero ($\gamma_i = 0$). As I have discussed above, the sectoral productivity growth rates have been different over time, and the simulations assume that they will remain different in the future—as in the base case. The scenario with "Engel effect only" sets the total factor productivity growth rate equal to 0.0105 for the entire simulation, including calibrated analog of the sample period from 1900 to 2000.

The simulation results show that the calibrated model with Baumol effects only imparts a significantly higher share of employment in services in the first half of the twentieth century, and does a poor job in accounting for the upward trend in the employment share of services during the same period. For the same period, the calibrated model with Engel effects only is considerably more successful in matching the share of employment in services. However, the Engel effects impart a much slower pace of increase in the share of employment in services after about 1940. While still lower than the observed pace, the combination of Engel and Baumol effects are more successful in accounting for the increase in the employment share of services, which quantitatively demonstrates the increasingly significant contribution of the Baumol effect to structural change in the United States.

Table 3 shows the percentage changes in the share of services in employment from 1900 to 2000, for both the actual data and calibrated models. The results highlight that the contribution of the Engel effect to the rising share of services in employment is significantly larger in the first half of the twentieth century, and overall this effect accounts for about half of the growth rate share of service employment.

[23] I do not investigate how much of actual change could each effect explain. Such a question would lead to an (over)explanation of structural change through Baumol effects by appealing to empirically unsubstantiated productivity growth rates.

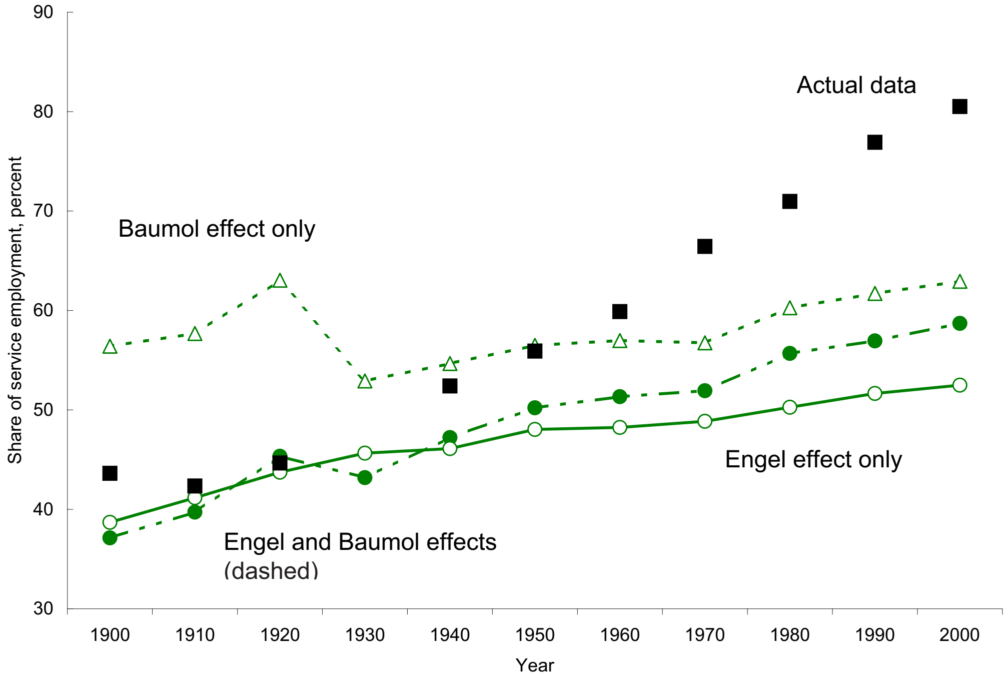

Figure 7: Employment share of services, U.S. 1900–2000

Notes: This figure plots the employment share of services using actual data and three calibrated models. There is no census based industrial employment data available for 1930. For the actual data, from 1910 to 2000 the denominator is total employment in agriculture, manufacturing and services, excluding public administration and government. The simulated data with Engel and Baumol effects are based on numerical calibration of the model described in the text with parameter values given in table 2. The scenario with "Baumol effect only" sets the endowment and subsistence terms to zero ($\gamma_i = 0$). The scenario with "Engel effect only" sets the total factor productivity growth rate equal to 0.0105 for the entire simulation, including calibrated analog of the sample period from 1900 to 2000. The simulation horizon is $1,000$ annual observations for each calibrated series.
Sources: See figure 1 for the actual data, and figure 6 for the simulated series with "Engel and Baumol effects."

The Baumol effect, by contrast, is significantly larger in the second half of the twentieth century, and over this period it accounts for about one sixth of the growth rate share of service employment. Overall, the base case accounts for about two thirds of the growth rate of share of services in employment. While this exercise underscores the merits of a unified approach to structural change, it is important to point out that the results still rest on parameter choices that are difficult to identify with precision, and productivity growth estimates are at best "approximate" in the first half of the twentieth century.

Table 3: Growth rate of share of services in employment, actual data and calibrated models

Period	Data	Base case model	Baumol effect only	Engel effect only	Alternative η's
1900–1910	−0.30	0.68	0.22	0.62	0.61
1910–1920	0.53	1.33	0.89	0.61	1.25
1920–1930	–	−0.48	−1.74	0.43	−0.59
1930–1940	0.80	0.90	0.33	0.10	0.83
1940–1950	0.65	0.62	0.33	0.41	0.57
1950–1960	0.69	0.22	0.09	0.04	0.19
1960–1970	1.04	0.12	−0.04	0.13	0.09
1970–1980	0.66	0.70	0.60	0.29	0.68
1980–1990	0.81	0.22	0.24	0.27	0.20
1990–2000	0.46	0.30	0.20	0.16	0.27
1900–2000	0.61	0.46	0.11	0.31	0.41

Notes: Average annual growth rates computed using the formula $(L_{s,t+T}/L_{s,t})^{1/T} - 1$, and are in percent. There is no census based employment share data for 1930, so for data 1940 is the average annual growth rate from 1920 to 1940. The parameter values for the base case are in Table 2. The scenario with "Baumol effect only" has homothetic preferences, and thereby sets the endowment and subsistence terms to zero ($\gamma_i = 0$). The scenario with "Engel effect only" sets the total factor productivity growth rate equal to 0.0105 for the entire simulation, including calibrated analog of the sample period from 1900 to 2000. The alternative values for η's are: $\eta_a = 0.1$, $\eta_m = 0.15$, and $\eta_s = 0.75$. The data source for 1900 is different from the rest of the observations.

4.4 Sensitivity to η's

How sensitive are the results to alternative calibrations of the relative weights of the final consumption categories in composite consumption (the η terms)? In the simulations, I calibrated these parameters based on the shares of expenditures on food, non-food goods and services in total personal consumption expenditures at the end of the sample period (about 2008). Over the last 100 years, these shares have changed and more specifically, the share of services in total consumption expenditures increased significantly. It is also likely that the consumption share of services will continue to increase.

From equation (13) it is easy to see the impact of this likely increase in the consumption share of services on employment shares, which depend on the η_i/η_m ratio. A higher value of η_s relative to η_m would lead to a shift in the simulated values of L_s relative to the baseline calibration of the model, bringing the *level* of simulated series closer to the actual data. However, in terms of accounting for the percentage change in the share of services in employment, such an alternative does not necessarily perform better relative to the baseline model (despite having a lower RMSE), and the last column of Table 3 presents one such example. Therefore, while imputing a higher value to η_s relative to η_m would be a quantitatively promising route, for now, there is insufficient empirical justification to pursue it.

5 Complementary explanations

The theoretical framework used in this paper has so far maintained as close conceptual connections to Engel and Baumol effects as possible, and explored their quantitative implications for the changes in the service sector employment in the United States. Even a unified Engel and Baumol approach at its best shot leaves a considerable component of the rising share of service employment unaccounted for. So, it is natural to ask whether there are *complementary* demand- and supply-side explanations that may help improve our understanding. In this section, I present several mechanisms that are potentially worthwhile pursuing.

5.1 The demand side

Alternative non-homothetic utility functions.—The driver of the high income elasticity of demand for services in Section 3 is non-homothetic preferences. In the baseline model these preferences are represented by a Stone-Geary utility function, which attributes non-homotheticity of preferences to subsistence or endowment effects. However, Stone-Geary utility functions have a drawback: they allow for negative optimal consumption levels at low levels of income.

I also considered an alternative non-homothetic preference specification, in which income elasticity of demand for each good captured by a different curvature parameter:

$$C = \sum_{i=a,m,s} \frac{C_i^{1-\nu_i}}{1-\nu_i}, \quad \text{with } \nu_i > 0. \tag{17}$$

This specification avoids the possibility of negative consumption, and, more importantly, relative to the baseline model, it can potentially deliver a faster relocation of labor out of agriculture into services in a calibrated twentieth century model of the United States.[24] However, it has its own drawback: with distinct curvature parameters, ν_i's, the sector with the lowest ν ends up employing practically the entire labor force in finite time. For this reason and for comparability with the existing literature (e.g., Kongsamut et al. 2001), the analysis in this paper has relied on a Stone-Geary sub-utility function.

Hierarchy of wants.—Suppose consumption goods can be ranked in terms of their priority on a "shopping list" of wants as in Matsuyama (2002), Foellmi and Zweimüller (2008), and Buera and Kaboski (2007). Consumption of low priority goods can only occur once high priority wants are met. These are yet another form of non-homothetic preferences, and provide complementary ways to model the demand side of an economy. At the same time, hierarchy of wants models are conceptually more suitable for empirical analysis with many industries (and certainly with more than three sectors), and do require researchers to take a position on the ranking of *commodities* but not necessarily of *sectors* (Pasinetti

[24] In fact, a calibrated model with the sub-utility function in equation (17) with $\nu_a > \nu_m > \nu_s$ delivers interesting nonlinear dynamics for the shares of employment by industry—even in the absence of sectoral productivity growth differentials: a secular decline in agriculture, a secular rise in services, and a hump-shaped behavior in manufacturing. Details are available from the author upon request.

1981, p. 75). However, the desirability of alternative formulations of non-homothetic preferences remains an open issue.

5.2 The supply side

Productivity data.—Productivity literature emphasizes that the estimates of service sector productivity data often rely on assumptions about unobserved prices and quantities (e.g., Triplett and Bosworth, 2004). It is quite possible that future research would significantly revise the "best-case" productivity estimates I have used in this study. With such data revisions, and even without any major demand- or supply-side modifications, it is quite possible that the unified model could explain more of the actual structural change in the United States.

Intermediate inputs.—Intermediate inputs can be handled in the present framework in a variety of ways. Here I use the setup examined by Ngai and Pissarides (2007, Section IV). In their setup, a separate industry combines output originating from all final-goods producing sectors in the economy to form a single "intermediate" input. In turn, this intermediate input is used, together with capital and labor, in the production process in all other sectors. While modeling intermediate inputs in this fashion is rather unusual, the setup is tractable, which is why I consider it here.

Specifically, assume that sectors a and s produce nondurable goods and services that can be either consumed or used in the production of the intermediate good. The m-sector good can be either consumed, used in the production of the intermediate good, or converted into capital stock in any of the sectors. The intermediate goods sector transforms inputs from all three sectors into an intermediate input T using a Cobb-Douglas production function:

$$T = H_a^{\phi_a} H_m^{\phi_m} H_s^{\phi_s}, \quad \text{with } \phi_a + \phi_m + \phi_s = 1, \tag{18}$$

where H_i, for $i = a, m, s$ is the goods and services originating from sector i and that are used in the production of the unique intermediate input.

All sectors use this intermediate good. The sectoral resource constraints are:

$$C_{at} + H_{at} = A_{it} K_{at}^{\alpha} L_{at}^{1-\alpha-\beta} T_{at}^{\beta}, \tag{19}$$

$$C_{mt} + H_{mt} + \dot{K}_t + \delta K_t = A_{mt} K_{mt}^{\alpha} L_{mt}^{1-\alpha-\beta} T_{mt}^{\beta}, \tag{20}$$

$$C_{st} + H_{st} = A_{st} K_{st}^{\alpha} L_{st}^{1-\alpha-\beta} T_{st}^{\beta}, \tag{21}$$

where T_i is intermediate goods purchased by sector i with $T = \sum_i T_i$, and $1-\alpha-\beta > 0$. The demand-side of the model is identical to that of the baseline model.

These lead to the modification of the employment shares by industry given in equations (13) and (14) as:[25]

$$L_i = \left(\frac{\overline{x}_i}{\overline{\overline{X}}}\right)\left(\frac{\overline{C}}{Y}\right) - \left(\frac{A_m}{A_i}\right)\left(\frac{\gamma_i}{Y}\right) + \phi_i\beta, \qquad \text{for } i = a, s, \tag{22}$$

$$L_m = \left[\left(\frac{\overline{x}_i}{\overline{\overline{X}}}\right)\left(\frac{\overline{C}}{Y}\right) + \phi_m\beta\right] + \left(1 - \beta - \frac{\overline{C}}{Y}\right). \tag{23}$$

These expressions modify the equilibrium employment shares through two novel channels: (i) relative shares of sectoral outputs in the production of the intermediate goods (the ϕ terms), and (ii) relative share of intermediate inputs in the production of final goods (the β term). For instance, the combination of high ϕ_s, whereby services are essential for the production of the intermediate good, and high β, whereby the intermediate good is essential for final goods production, would lead to a higher share of services in employment. However, these novel channels have a level effect on the share of services in employment and no growth effect, which is the principle shortcoming of the baseline model relative to the data in the second half of the twentieth century.

Overall, therefore, while this is a promising step towards modeling intermediate goods in a tractable way, it falls short of accounting for changes in the employment shares by industry as a stand-alone mechanism.

Consumption categories and industries.—In this paper I have followed the common modeling assumption and associated a consumption expenditure category with a particular industry. This conveniently leads to linking productivity estimates from production (value added) accounts to corresponding consumption expenditure categories (final demand) using broadly defined sector groupings. In reality, however, the association of a particular consumption item with an industry is not straightforward. For instance, personal consumption expenditures on food in the expenditure side of the national income accounts in particular instances (e.g., pasta) include agricultural goods originating from the farm sector, food products originating from the manufacturing sector, and transportation and retail of such agricultural and manufacturing goods originating from the service sector.[26] Modifying the analysis by adjusting the weights in the composite consumption good (η terms), as I have outlined in Section 4.4, only partially addresses this issue, because it does not distinguish between, say, intermediate and final farm goods.

Also, within industries there may be sufficient heterogeneity to warrant a differential analysis of sectors. For instance, industry productivity estimates used here do not distinguish between business services and services for final consumption. However, there may be systematic differences between these two service industries. This, together with demand-side factors, would lead to industries within broader sectoral definitions growing at different rates during structural change. For instance, using U.S. manufacturing value added data at the four digit level, Krüger (2005) finds that the distribution of the shares of valued added have been stable over the period 1958–1996, despite the fact that intra-distributional mobility is

[25] Ngai and Pissarides (2007) drive similar expressions in the absence of Engel effects. Briefly, the extended setup uses two additional intratemporal efficiency conditions: optimal choice of H_i's in the production of intermediate goods, and optimal allocation of C_i versus H_i. Derivations are available from the author upon request.

[26] Triplett and Bosworth (2001, Table 4) provide estimates of final demand accounted by each sector's production.

remarkably high. And, Nordhaus (2008) finds that within manufacturing industries there was a *positive* relationship between productivity growth and employment from 1948 to 2001. However, the implication of such within-sector heterogeneity for aggregate variables during structural change remains a largely unexplored issue.

Home production.—The baseline model has no home production sector. Does this omission matter for the analysis in this paper? This possibility is based on two premises. First, home- and market-produced services are gross substitutes. Second, the productivity growth rate in market production of services exceeds that of market production of services. These two premises deliver the differential sectoral productivity effect that arises in the context of structural change, whereby the sector with relatively low productivity growth sheds labor because households allocate their resources towards the sector with higher productivity growth and the one that produces a close substitute.[27]

Beyond its first-order implications for the leisure-labor tradeoff, in order for the declining prevalence of home-produced services to have an economically significant impact on the overall share of services in employment, a model would require strong income effects on market labor supply. Such an income effect would not only pull hours worked out of home-production, but would also increase total hours worked in the economy, with a larger fraction of this additional market-hours worked being absorbed by the market-service sector—as long as services have a high income elasticity of demand. However, in the United States, average market hours have actually declined in the first half of the twentieth century (Vandenbroucke, 2009, Figure 1), and had no visible trend in the second half (Richardson, 2008, Figure 1). For this reason, I conjecture that it is unlikely that changing composition of service consumption between home and market production has been a significant contributor to the rise in the share of service employment.

6 Concluding remarks

This paper asked a quantitatively motivated question: how much of actual change in share of service employment *could* a unified model of structural change explain? The paper quantified both the joint and relative strengths of Engel and Baumol effects to the rising share of employment in services in the United States. The main conclusion is an inclusive message: both of these factors have been significant, and their relative strengths have varied over time. Nevertheless, there remains considerable gaps between the calibrated model and the actual data. The paper has also identified several directions for future research, and pointed to the supply side of the economy as requiring the most urgent attention.

[27] Recent literature on the trends over time in the allocation of hours between labor and leisure has emphasized the distinction between market and home production in the broader context of structural change—but *not* as a driver of structural change; see, e.g., Freeman and Schettkat (2001), Ngai and Pissarides (2008), and Rogerson (2008). This literature attributes part of the increase in leisure in the twentieth century (at least in the United States) to the reallocation of labor from home production to market production of services.

Appendix

A Data

A.1 Share of employment by industry

- From 1800 to 1900, employment share of agriculture is based on Weiss series in Carter et al. (2006, series Ba829 and Ba830), manufacturing is based on Lebergott series in Carter et al. (2006, series Ba814 and Ba821), and services is computed by the author as a residual. There is no manufacturing employment estimates for 1800, 1820, and 1830. Employment shares are relative to total employment.
- From 1910 to 1990, data based on Sobek (2001, Table 4). There is no census based industrial employment data available for 1930. Employment shares are relative to total employment in agriculture, manufacturing and services, excluding public administration and government.
- For 2000, data from U.S. Census Bureau, Statistical Abstract of the United States, 2001, Table no. 596. Employment shares are relative to total employment in agriculture, manufacturing and services, excluding public administration and government.

A.2 Share of consumption expenditures by consumption category

- From 1900 to 1928, Lebergott (1996, Tables A1 and A8).
- From 1929 to 2008, Bureau of Economic Analysis (http://www.bea.gov), Personal Consumption Expenditures by Major Type of Product, Table 2.3.5.

A.3 Productivity growth estimates by industry, 1900–2005

To construct time-series on multi-factor productivity (MFP) growth rates for the three sectors (agriculture, manufacturing, and services), I rely on various sources. The methodologies for calculating MFP vary across these sources. Some sources do not estimate the MFP in the service-producing sector separately. Taken together these strongly suggest that the estimates I use in this study have significant comparability issues and margins of errors. The estimates are superior after 1987, but post-1987 data are too short to provide a meaningful quantitative assessment of the ongoing rise of employment in services relative to other sectors. With these qualifications in mind, I follow the following strategy for the industry level total factor productivity growth rates. (The data are available at http://myweb.dal.ca/tiscan/research/.)

Farm:

- From 1899 to 1948, Kendrick (1961, Table B–I). Kendrick's estimates are available on an annual basis, however, for the purposes of consistency with the manufacturing and services productivity growth rates, I compute the annualized average productivity growth rates for the episodes 1899–1909, 1909–1919, 1919–1929, 1929–1937 and 1937–1948 using the formula

$$(\mathrm{TFP}_{t+n}/\mathrm{TFP}_t)^{(1/n)} - 1. \tag{A.1}$$

- From 1948 to 2005, U.S. Department of Agriculture, Economic Research Services, http://www.ers.usda.gov/Data/AgProductivity/.

Manufacturing:

- From 1899 to 1948, Kendrick (1961, Table D–I). Kendrick's estimates are only available for 1899, 1909, 1919, 1929, 1937 and 1948. For each of these periods (e.g., 1900–1909), I compute the annualized average productivity growth rates using the formula (A.1).
- From 1948 to 1987, Gullickson and Harper (1999, Table 3), who report annualized average growth rates for 1949–1973, 1973–1979, and 1979–1990.
- From 1987 to 2005, U.S. Department of Commerce, Bureau of Labor Statistics, MFP in Manufacturing Sector (NAICS 31-33), http://www.bls.gov/mfp/.

Services:

- From 1900 to 1977, manufacturing TFP growth rate minus 0.5 percent per year, based on Fuchs (1968, pp. 75–76).
- From 1977 to 1987, 0.1 percent per year, based on Triplett and Bosworth (2003).
- From 1987 to 2005, Bosworth and Triplett (2007).

Private non-farm business sector:

- From 1899 to 1948, Kendrick (1961, Table A-XXIII, Private Domestic Nonfarm Economy) Kendrick's estimates are available on an annual basis, however, for the purposes of consistency with the manufacturing and services productivity growth rates, I compute the annualized average productivity growth rates as in the case of farm sector.
- From 1987 to 2005, U.S. Department of Commerce, Bureau of Labor Statistics, MFP in Private Non-Farm Business Sector (Excluding Government Enterprises), http://www.bls.gov/mfp/.

A.4 Growth rate of employment, 1900–2000

Since the model does not have a government sector, in the calibration, I consider total employment in farm, manufacturing and services as the appropriate population. I use annualized average productivity growth rates based on the estimates from decennial censuses.

- From 1900 to 1910, Weiss series on total employment in Carter et al. (2006, series Ba829), and Sobek (2001, Table 4, excluding government and industry unknown).
- From 1910 to 1990, Sobek (2001, Table 4, excluding government and industry unknown).
- From 1990 to 2000, U.S. Census Bureau, Statistical Abstract of the United States: 2001, Table no. 596.

I also use the 1990–2000 average growth rate as the long-run growth rate of employment.

B Derivations

In this appendix, I formally derive the relationships stated in the text (the baseline model) without proof or derivation. I also draw parallels between the measure of net consumption expenditures as defined in (10), which includes subsistence terms, and consumption expenditures that are commonly reported in the national income and product accounts. In the presentation below, I index the industries by $i = 1, \ldots, m$, reserving the last industry for "manufacturing."

Net consumption expenditures.—Using equations (6) and (9) define, respectively, "relative net consumption expenditures" and "net consumption expenditures"

$$\overline{x}_{it} = \frac{P_{it}\overline{C}_{it}}{P_{mt}\overline{C}_{mt}} = \left(\frac{\eta_i}{\eta_m}\right)\left(\frac{A_{mt}}{A_{it}}\right)^{1-\nu}, \tag{B.1}$$

$$\overline{C}_t = \frac{\sum_{i=1}^{m} P_{it}\overline{C}_{it}}{P_{mt}}. \tag{B.2}$$

Note that net consumption expenditure, $\overline{C}$, is measured in terms of the m-good, and lemma 1 below shows that it is in fact identical to the conventional measure of consumption expenditures measured in terms of a consumption-based price index.

To see this, denote the sum of the relative expenditure terms by $\overline{X}_t = \sum_{i=1}^{m} \overline{x}_{it}$, whereby

$$\overline{X}_t = \sum_{i=1}^{m}\left(\frac{\eta_i}{\eta_m}\right)\left(\frac{A_{mt}}{A_{it}}\right)^{1-\nu}. \tag{B.3}$$

Note that $\overline{C}_t = \overline{X}_t\overline{C}_{mt}$.

Consumption-based price index.—Define the consumption *expenditure*-based price index in terms of the m-good

$$\begin{aligned} P_t &= \left[\sum_{i=1}^{m}\eta_i\left(\frac{P_{it}}{P_{mt}}\right)^{1-\nu}\right]^{1/(1-\nu)} \\ &= \left[\sum_{i=1}^{m}\eta_i\left(\frac{A_{mt}}{A_{it}}\right)^{1-\nu}\right]^{1/(1-\nu)} \end{aligned} \tag{B.4}$$

The following result formally shows that $\overline{C}$ is equal to consumption expenditures in terms of the m-good. (In what follows I drop time indexes to economize on notation.)

Lemma 1 *$P \times C = \overline{C}$.*

Proof. Using equation (9), we have

$$\overline{C}_i = \left(\frac{\eta_i}{\eta_m}\right)\left(\frac{A_i}{A_m}\right)^{\nu}\overline{C}_m. \tag{B.5}$$

Substitute this expression in equation (8) and use $\overline{C}_m = \overline{C}/\overline{X}$, to obtain

$$C = \left[\sum_{i=1}^{m}\eta_i\left(\frac{A_m}{A_i}\right)^{1-\nu}\right]^{\nu/(\nu-1)}\frac{\overline{C}}{\eta_m\overline{X}}. \tag{B.6}$$

Using (B.4), the term in square brackets is $P^{1-\nu}$, which in turn is equal to $\eta_m\overline{X}$. Hence, the result. ■

The next result shows the share of labor in sectors $i = 1, \ldots, m-1$.

Lemma 2 *Let* $Y = A_m F(K, 1)$. *Then, for* $i \neq m$

$$L_i = \left(\frac{\overline{x}_i}{\overline{\overline{X}}}\right)\left(\frac{\overline{C}}{Y}\right) - \left(\frac{A_m}{A_i}\right)\left(\frac{\gamma_i}{Y}\right). \tag{B.7}$$

Proof. Use equations (3) and (6) to obtain

$$\frac{P_i C_i}{P_m} = L_i Y. \tag{B.8}$$

Adding $P_i \gamma_i / P_m$ to both sides of this expression gives

$$\left(\frac{P_i \overline{C}_i}{P_m \overline{C}_m}\right)\overline{C}_m = L_i Y + \frac{P_i \gamma_i}{P_m}. \tag{B.9}$$

Re-arranging the terms, using $\overline{C} = \overline{\overline{X}}\overline{C}_m$, and the definition of $\overline{x}_i$ gives the desired result. ■

The next key result shows how aggregate capital accumulation, $\dot{K}$ is related to aggregate consumption expenditures, $\overline{C}$.

Lemma 3

$$\dot{K} = A_m K^\alpha - \overline{C} - \delta K + \sum_{i=1}^{m}\left(\frac{A_m}{A_i}\right)\gamma_i.$$

Proof. Rewrite equation (4) using equation (5) and the definition of $\overline{C}_m$

$$\dot{K} = A_m K^\alpha \left(1 - \sum_{i \neq m} L_i\right) - \left(\overline{C}_m + \gamma_m\right) - \delta K. \tag{B.10}$$

Use Lemma 2 in the above expression to substitute out L_i terms:

$$\begin{aligned}
\dot{K} &= A_m K^\alpha - \overline{C}\sum_{i=1}^{m-1}\frac{\overline{x}_i}{\overline{\overline{X}}} - \overline{C}_m - \delta K + \sum_{i=1}^{m}\gamma_i \frac{A_m}{A_i} \\
&= A_m K^\alpha - \overline{C}\sum_{i=1}^{m-1}\frac{\overline{x}_i}{\overline{\overline{X}}} - \frac{\overline{C}}{\overline{\overline{X}}} - \delta K + \sum_{i=1}^{m}\gamma_i \frac{A_m}{A_i} \\
&= A_m K^\alpha - \overline{C}\left[\sum_{i=1}^{m-1}\frac{\overline{x}_i}{\overline{\overline{X}}} + \frac{1}{\overline{\overline{X}}}\right] - \delta K + \sum_{i=1}^{m}\gamma_i \frac{A_m}{A_i}.
\end{aligned} \tag{B.11}$$

Using $\overline{\overline{X}} = 1 + \sum_{i=1}^{m-1}\overline{x}_i$ in the last line, gives the desired result. ■

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