How much can Engel's law and Baumol's disease 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 services in 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. The share of manufacturing in employment rose secularly from 1800 to a peak of about 30 percent in the 1960s, and has been declining since. The share of services in employment, by contrast, has been rising unabated, and by 2000 the service sector 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 rising share of services in employment 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) can 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 show that jointly Engel's law and Baumol's disease could explain about two thirds of the actual reallocation of labor into services.

[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 rising share of services in 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 of structural change documented in Syrquin (1988). This paper contributes to the line of research initiated by Echevarria (1997) by providing a detailed calibration appropriate for the

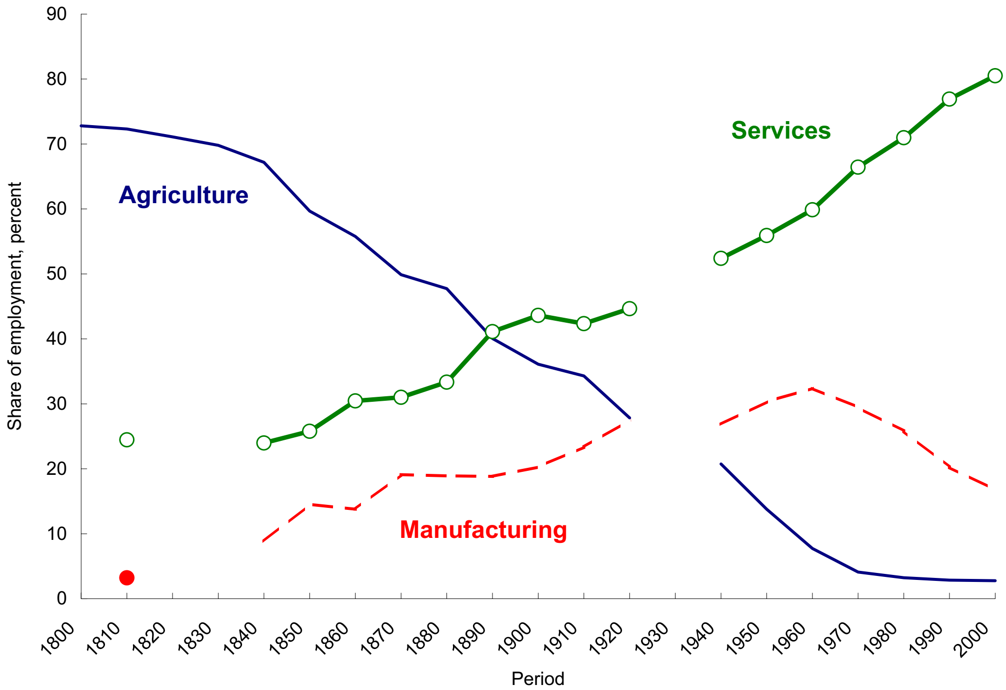

Figure 1: Employment shares by sector in the United States, 1800–2000

Notes: This figure plots the employment shares of agriculture, manufacturing and services. There is no census-based sectoral 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, the share of agriculture in agriculture is based on Weiss series in Carter et al. (2006, series Ba829 and Ba830), the share of manufacturing is based on Lebergott series in Carter et al. (2006, series Ba814 and Ba821, and the share of services is computed by the author as a residual. From 1910 to 1990, the data are based on Sobek (2001, Table 4). For 2000, the data are from the U.S. Census Bureau (2001, Table 596).

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. (See

United States. Caselli and Coleman (2001) use simulations to examine income convergence between the north and south 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.

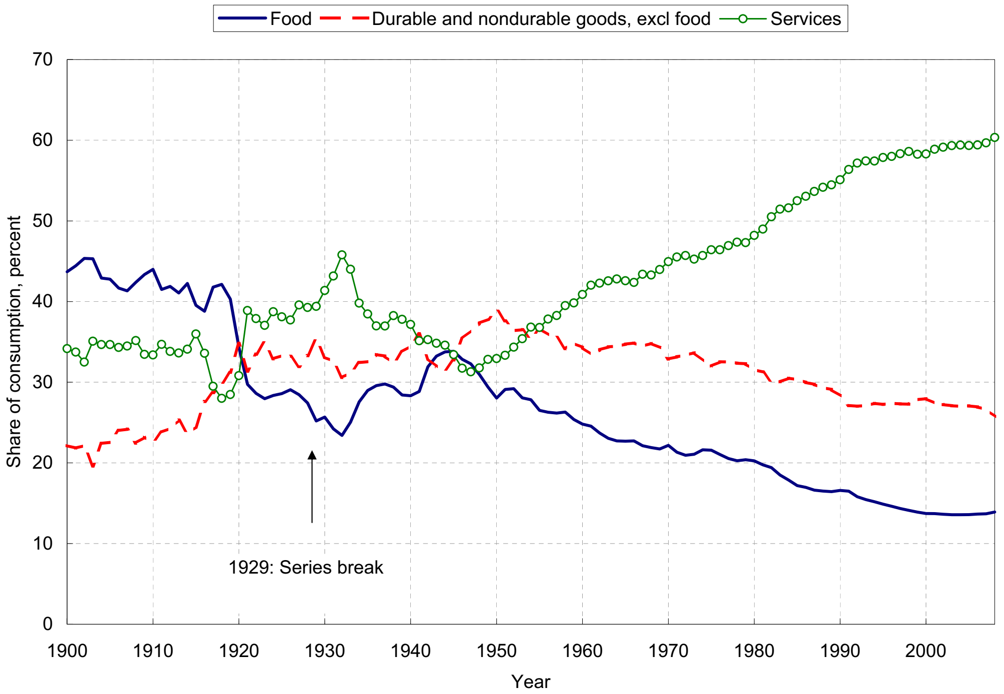

Figure 2: Expenditure shares of food, goods (non-food), and services in the United States, 1900–2008

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.

also Chai and Moneta, 2010). Figure 2 presents suggestive evidence for these trends.[4]

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

[4]The evidence in Figure 2 is only suggestive because the rising share of services in consumption expenditures may be driven by a rise in the relative price of services, which the data suggest has been the case. However, a careful discussion of this topic by Schettkat and Yoncarini (2006) concludes that the service component of the personal consumption expenditures has risen faster than food and non-food commodity components in *real* terms.

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 productivity growth by sector. The evidence suggests that since the late 1940s productivity growth in agriculture has surpassed the productivity growth in the rest of the economy, and the service sector has been the laggard. However, the evidence also indicates significant sector-specific accelerations and decelerations of productivity growth, 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 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 the rising share of services in employment in the United States *could* be explained by a unified model with Engel's law and Baumol's disease.

The rest of the paper is organized as follows. Section 3 presents the structural change model that I use to organize the data. Section 2 reviews the available evidence on sectoral productivity growth. 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 those derivations that are omitted from the text.

2 Productivity growth by sector

Baumol's disease as an explanation for the rising share of services in employment hinges on two premises: differential productivity growth across sectors, and low elasticity of substitution between services and other consumption goods. In this section, I review the empirical evidence on productivity growth by sector in the United States.[5]

The U.S. Department of Agriculture, Economic Research Service 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. The Bureau of Labor Statistics (BLS) publishes multi-factor productivity growth estimates for the private non-farm business sector dating back to 1948.[6]

Baumol's (1967) original conjecture about the role of differential productivity growth as the driving

[5] See Pasinetti (1981), and Schettkat and Yoncarini (2006) on Engel's law in the context of structural change. See Dennis and İşcan (2009) for productivity growth in the U.S. agriculture and non-agriculture in the nineteenth and twentieth

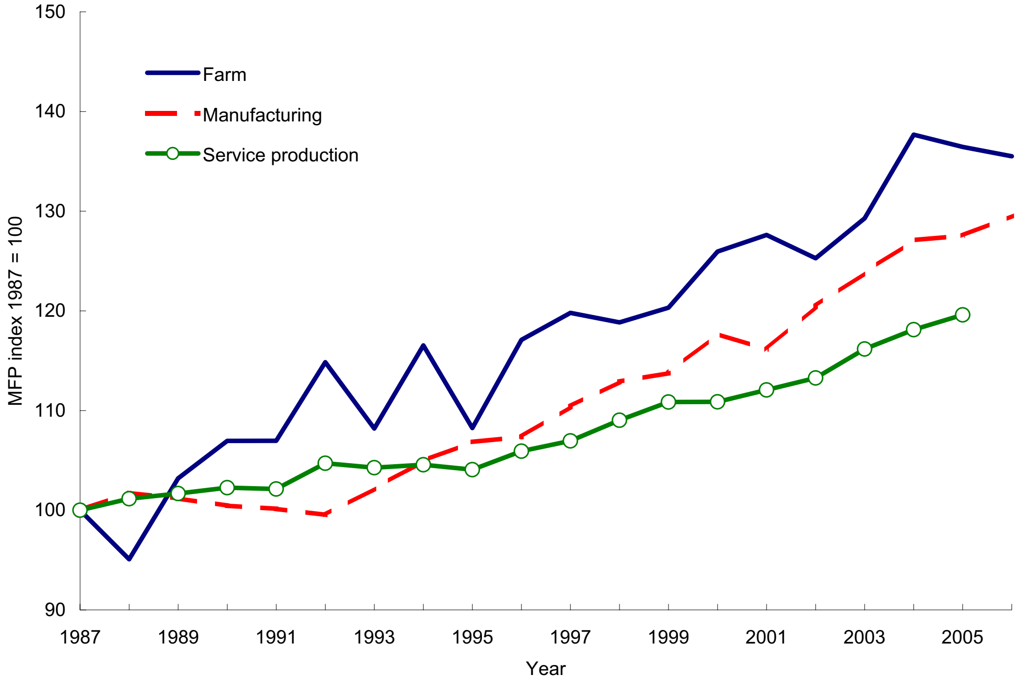

Figure 3: Farm, private non-farm business and service producing sectors TFP in the United States, 1987–2005

Notes: The following are the average growth rates of total factor productivity 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:

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

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 Service for the farm sector.

force of structural change is motivated by slow productivity growth in the service sector. Unfortunately, there is 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.[7] BLS does not publish corresponding estimates of productivity for service-producing sectors.

centuries.

[6] For the period from 1948 to 2006, average growth rate of non-farm TFP is 1.26 percent, and farm TFP is 1.50 percent, with average annual relative TFP growth rate of 0.24 percent in favor of the farm sector.

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

Table 1: Multifactor productivity growth by sector

		Productivity growth, %		
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 rates of multifactor productivity by sector in percent. See Appendix A for detailed data sources. ERS is the Economic Research Service, and BLS is the Bureau of Labor Statistics.

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.[8] 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. According to these data, there is considerable empirical evidence for differential productivity growth across sectors.

Bosworth and Triplett's (2007) estimates are too short to be definitive about productivity growth accelerations or decelerations (structural breaks), and reversals of relative productivity growth. However, there is a noticeable increase in the growth rate of productivity 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 productivity growth 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 growth rate of multi-factor productivity in the service sector lagged behind that of manufacturing by about 0.5 percentage points on average.[9] For the period from 1949 to 1996, Gullickson and Harper (1999, Table 3) estimate the average growth rate of productivity in the manufacturing sector at 1.2 percent per year. Based on limited data and extrapolations Triplett and Bosworth (2003) provide estimates of multi-factor productivity growth in the service sector between 1977 and 1995. Their estimates

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

[9]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).

suggest that multi-factor productivity growth in services during this period has been at best anemic (about 0.1 percent per year or less). Of course, there was also a slowdown in manufacturing multi-factor productivity growth during much of this period. Gullickson and Harper's (1999) manufacturing multi-factor productivity growth estimates indicate an annual growth rate of −0.4 percent for the period from 1973 to 1979, and 1.0 percent for the period from 1979 to 1990. By all accounts, then, it is safe to conclude that at least during the postwar period the growth rate of productivity in the service-producing sectors has been on average below that of those in agriculture and manufacturing.[10]

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 allocations. I draw on the existing literature to model Engel and Baumol effects. The specification of non-homothetic preferences responsible for Engel's law 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.[11] 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 with $F(K_i, L_i) = K_i^{\alpha} L_i^{1-\alpha}$, and $0 < \alpha < 1$ (see, e.g., Gomme and Rupert, 2007).

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

[11] 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 this environment.

Growth rates of sectoral total factor productivity 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, let $\mathrm{d}X_t/\mathrm{d}t \equiv \dot{X}_t$. In equation (2), 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 to be used in any of the sectors. The transformation of the 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 $K \leq \sum_{i=a,m,s} K_i$. Feasibility of production also requires $\sum_{i=a,m,s} L_i \leq 1$.

Allocative efficiency.—There is perfect factor mobility across sectors. Thus, full employment of resources and production efficiency implies the equality of marginal rates of transformation across sectors. These determine the 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 price of i-sector good.

Consumption.—There is an additively separable lifetime utility function with logarithmic instantaneous utility, which depends on aggregate consumption C, and exponential discounting at a constant rate $\rho > 0$:

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

Logarithmic preferences are special, but as Ngai and Pissarides (2007) show, in the absence of Engel effects, and when growth rates of long-run productivity 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 i-sector 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 i-sector good as the value of (net) consumption based on market prices.[12]

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 the 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-sector good, which is the numeraire. At the same time, $\overline{C}_t$ is identical to the conventional measure of consumption expenditures

$$\overline{C}_t = P_t \times C_t, \tag{11}$$

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

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

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

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

$$L_{it} = \left(\frac{\overline{x}_{it}}{\overline{X}_t}\right)\left(\frac{\overline{C}_t}{Y_t}\right) - \left(\frac{A_{mt}}{A_{it}}\right)\left(\frac{\gamma_i}{Y_t}\right), \qquad \text{for } i = a, s, \tag{13}$$

$$L_{mt} = \left(\frac{\overline{x}_{it}}{\overline{X}_t}\right)\left(\frac{\overline{C}_t}{Y_t}\right) + \left(1 - \frac{\overline{C}_t}{Y_t}\right), \tag{14}$$

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 $i = a, m, s$ (no Engel effects), the second term in this expression drops out and changes over time in the shares of sectoral employment are solely driven by differential productivity growth across sectors (i.e., Baumol effects only). Also, the second term in equation (14) captures the fact that the m-sector produces capital goods, which are used in production in all sectors (i.e., the capital-accumulation effect).

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

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

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

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

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

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: (1) when there are no Engel effects ($\gamma_i = 0\ \forall i = a, m, s$), and (2) when there are no Baumol effects ($g_m = g_i$ for $i = a, s$). Otherwise, this three-sector model with either Engel or Baumol effects generates structural change.[13]

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 $\overline{c}$ 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

[13] 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.

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 employment shares of agriculture, manufacturing and services converge toward constant values. In the next section, I consider and solve a parameterized version of this three-sector model.

3.3 A parameterized solution of the model

To gain insights regarding the dynamics of the three-sector model above, in this section, I numerically solve the model and report the emerging sectoral employment shares.[14] In principle, this simulation exercise can allow for transition dynamics in capital stock per effective worker, k: that is, it is possible 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.

Specifically, 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 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 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.[17] Initially, income per capita is low, and, since food is a necessity,

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

[15] For instance, in the International Food Consumption Patterns Database compiled by the U.S. Department of Agriculture (2009), 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).

[17] Of course, this particular hump shape must be interpreted in the context of this numerical example—the Engel effect contributes to the hump shape but is not necessary.

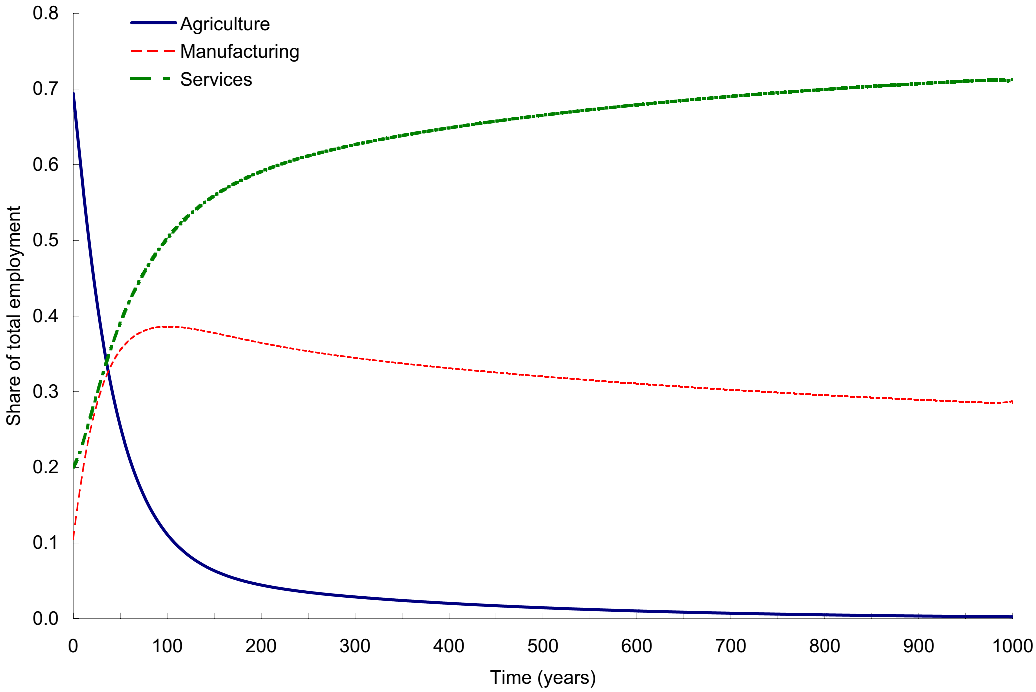

Figure 4: Employment shares in the parameterized version of the model

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

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, and, since productivity growth in agriculture exceeds that of in manufacturing (and services), the relative price of food declines. These two forces culminate in a flat personal consumption expenditure profile for food. 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 for services rise. Although productivity growth in manufacturing exceeds that of in services, the Engel effect dominates the Baumol effect in the context of the share of manufacturing in employment. In fact, initially the expenditure curves are steeper for non-food goods than for services, so the budget share of non-food goods rises.

In the second stage of structural change, as income per capita rises, labor begins to reallocate from

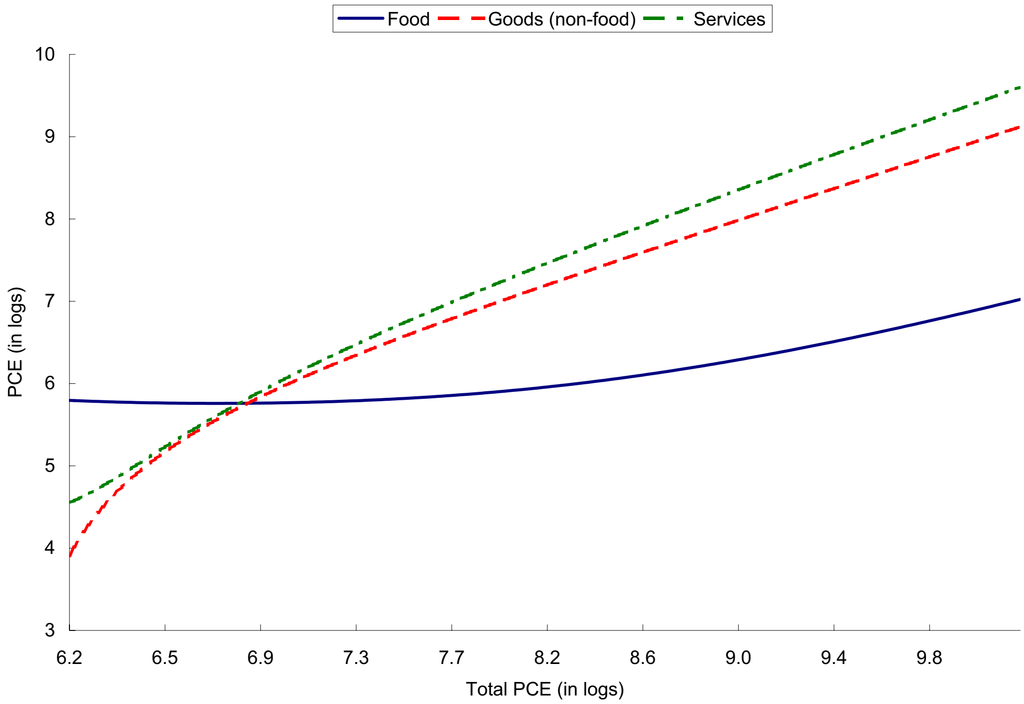

Figure 5: Engel curves in a parameterized version of the model

Notes: This figure plots the log personal consumption expenditures (PCE) on food, goods (non-food) and services associated with total PCEs in logs based a simulation of the 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: $\alpha = 0.33$, $\nu = 0.5$, $\delta = 0.05$, $\rho = 0.02$, $\gamma_a = -400$, $\gamma_m = 0$, $\gamma_s = 250$, $\eta_a = 0.10$, $\eta_m = 0.15$, $\eta_s = 0.75$, $A_a(0) = 400$, $A_m(0) = 250$, $A_s(0) = 400$, $g_a = 0.026$, $g_m = 0.020$, and $g_s = 0.015$. The initial capital stock per worker is equal to its asymptotic steady-state value.

manufacturing to services, while the reallocation of labor from agriculture continues. The decline in the share of manufacturing in employment 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 is higher than services productivity growth, so manufacturing sheds labor. At this stage, therefore, the concomitant rise in the share of services in employment is due to the fact that both Engel and Baumol effects reinforce each other.

Overall, this parameterized version of the model suggests that Engel and Baumol effects *can* accommodate, at least qualitatively, several salient features of the data: (1) secularly declining employment share of agriculture and secularly rising share of services in employment; (2) hump-shape in the share of manufacturing in employment (see Figure 1); and (3) rather complex dynamics in the shares of manufacturing and services in consumption expenditures, 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 qualitative "match" critically depends on specific parameter choices. Using a more carefully calibrated version of the model, the next section examines whether and by how much Engel and Baumol effects are jointly capable of explaining the rising employment share of services 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 on 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).[18] The general strategy I adopt here is to solve the model, and compare the model-generated data on employment shares by sector 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 side and the production side of the model economy. I use several complementary procedures to specify the values of these parameters.

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).

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.[19]

One important aspect of the quantitative analysis is the treatment of labor augmenting technology.

[18] 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."

[19] Along the sample path, η terms interact with Engel and Baumol effects in delivering the model-based consumption expenditure and employment shares, and the influence of η's on these shares varies quantitatively over the sample path. In the model, these shares asymptotically converge to constant values, which also depend on attendant *assumptions* about growth rates of sectoral long-run productivity. Thus, the η values in the text are consistent with the assumption that the U.S. economy is "close" to these constant shares at the end of the sample period.

I use the existing estimates of multi-factor productivity growth by sector as data, back-out the implied growth rates of labor augmenting technology by sector, and 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 technology by sector. Here, I consider two scenarios: First, I assume that 1987–2005 averages are the best forecasts of productivity growth (2005 is the last year for which I have MFP data on service-producing sectors: see Figure 3). Second, I use a single growth rate of productivity for the three sectors, under the assumption that sectoral productivity growth 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 growth rate of productivity—1.05 percent per year.

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 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 and γ_s/C_s ratios 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 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, an uncertainty about parameter values emerges in three contexts: growth rates of future productivity, 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.

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				
Agriculture	A_a	1		
Manufacturing	A_m	1		
Services	A_s	1		
Growth rate of future 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. The time discount rate, depreciation rate and the share of capital in income are from Gomme and Rubert (2007). The 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. The base-case growth rates of future labor augmenting technology are based on the growth rates of total factor productivity from 1987 to 2005; see Figure 3 and Appendix A. Alternative growth rates of future productivity are based on the growth rate of private non-farm business sector productivity from 1987 to 2005.

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."[20]

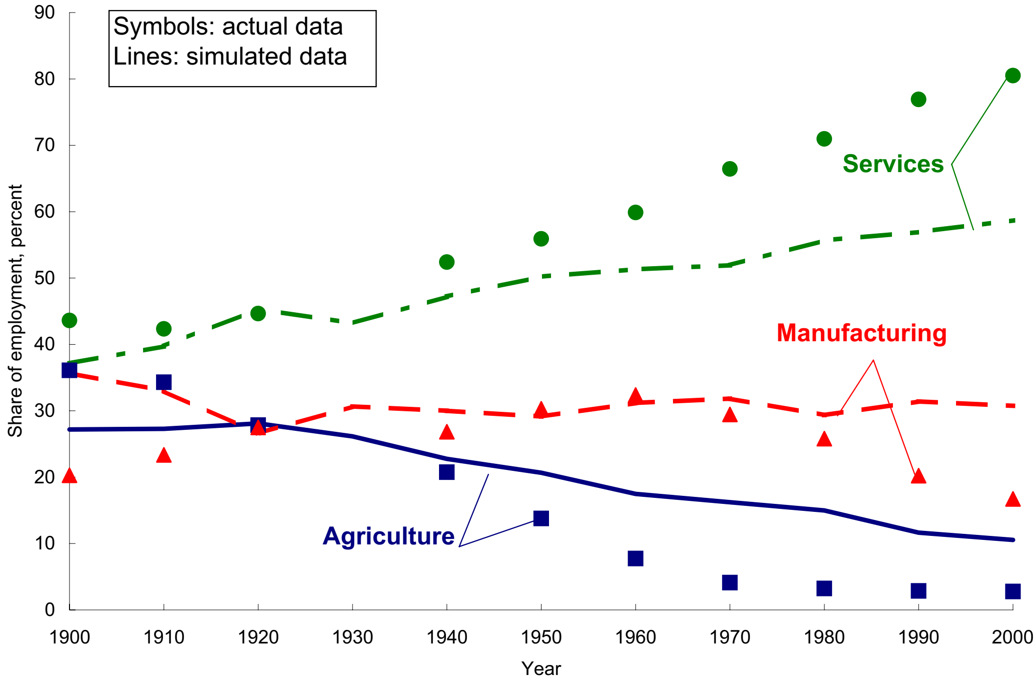

Figure 6: Employment shares by sector in the United States, 1900–2000

Notes: This figure plots the shares of agriculture, manufacturing and services in employment. There is no census-based sectoral 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 1000 annual observations.
Sources: See Figure 1 for the actual data.

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. Recall that the growth rates of sectoral productivity 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 with differential (as opposed to uniform) future 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.[21]

[20] I do not conduct a "fine" grid search, since the objective here is to identify those parameter ranges that are promising to account for the rising share of services in employment.

[21] The main discrepancy between the two alternative calibrations in terms of the future sectoral productivity growth emerges toward the end of the sample period: relative to the base-case specification, the uniform future-productivity-

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.[22] 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-shape for manufacturing. However, there are two dimensions which are unsatisfactory: compared to the calibrated series, over the second half of the twentieth century (1) the rise in the share of services in employment is significantly more pronounced in the data; and (2) 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.

One important dimension of the class of models I consider here is the tight relationship that exists between employment shares and consumption shares (see, e.g, Kongsamut et al., 2001). In practice, there are important empirical issues in mapping consumption expenditures that are reported in the national income and product accounts to their counterparts in these models. These issues include proper accounting of intermediate inputs and consumption categories. So, a careful matching of consumption expenditures with model-based expenditures would require significantly more detailed data.[23]

Also, there are two dimensions of the simulated model that are worth mentioning. First, while the subsistence and endowment terms γ_a and γ_s are not immediately intuitive, the ratios γ_a/C_a and γ_s/C_s are informative about the significance of subsistence and endowment effects. For the *initial* period of the base-case calibration, the corresponding ratios implied by the solution of the model are as follows: $\gamma_a/C_a = -70.4$ percent and $\gamma_s/C_s = 51.3$ percent. 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 consumption of non-market services was about half the consumption of market services.[24]

Another dimension of the simulated model is the personal consumption expenditures implied by the base-case calibration. Figure 7 shows the expenditures on each commodity group associated with total personal consumption expenditure (PCE) implied by the model. Consistent with the Engel curves estimated in the microeconometric literature (e.g., Blundell, Browning, and Crawford, 2003, Figures 2

growth scenario dictates a higher share of manufacturing in employment and lower share of services, partly because the uniform productivity-growth scenario imparts a relatively lower productivity growth to manufacturing, which increases the employment share of this sector at the expense of services.

[22] 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.

[23] Thus, since there are significant conceptual differences in final consumption expenditure data as reported in national income and product accounts and consumption expenditures implied by these models, this paper does not motivate γ parameters by directly matching actual and model-based expenditure data.

[24] Orshansky (1965, pp. 6–8) presents evidence on subsistence food consumption in the United States for 1960. She defines "subsistence consumption" as the lowest-cost food plan that can provide all of the recommended nutrients, vitamins, and caloric intake. She calculates the cost of such a subsistence bundle as $240 per capita per year for a 4-person family, at a time when the share of income spent on food was 25 percent for an urban family of four, and the per capita income of such a family was $1,854. (Oshansky's share and income estimates are based on a BLS consumer expenditure survey.) Based on this estimate of $(\gamma_a/C_a)_{1960} \approx .5$, it is possible to back out the initial ratio for the beginning of our period. Assuming that from 1910 to 1960 consumption expenditures on food in constant prices increased at a compounded rate of about 0.8 percent, the subsistence–consumption ratio should have *shrunk* at the same rate. This gives $(\gamma_a/C_a)_{1910} \approx .65$, which is close to the initial subsistence–consumption ratio selected by the RMSE criteria.

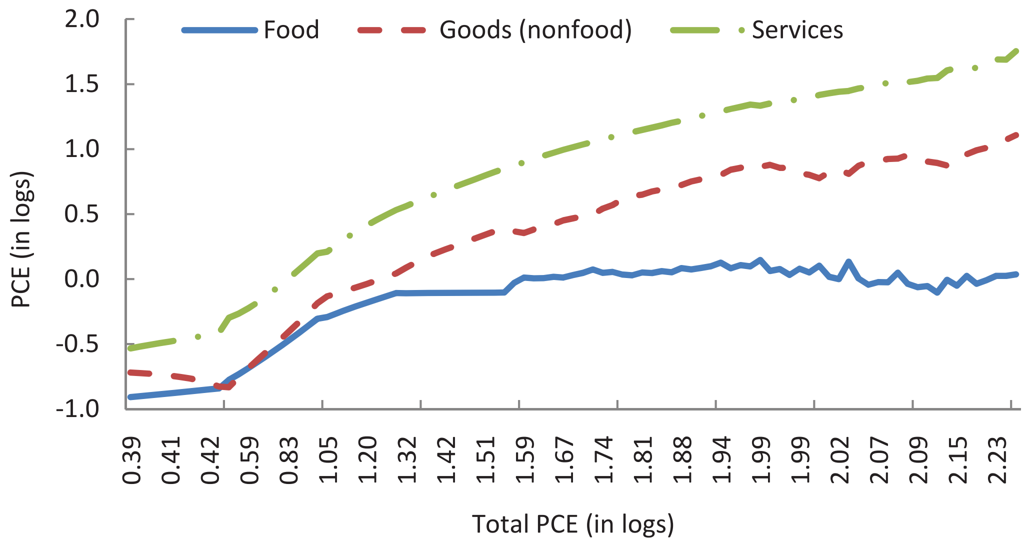

Figure 7: Engel curves in the base-case model

Notes: This figure shows the log personal consumption expenditure (PCE) on food, goods (non-food) and services corresponding to total PCE based on the base-case calibration of the model with both Engel and Baumol effects. The reported expenditure data are the model-based equivalents of the per capita U.S. data from 1910 to 2000. See Table 2 for the base-case parameters.

and 3), the implied expenditure shares are nonlinear in total expenditures, PCE on food rises with income but the expenditure share of food falls, and the expenditure share of services rises throughout the period.

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 differ across sectors—the scenario with Baumol effects only. In the other scenario preferences are non-homothetic and growth rates of productivity are identical across sectors—the scenario with Engel effects only. In each of these cases, the remaining model parameters are equal to those in the base case.

Figure 8 demonstrates the results of this exercise for the share of services in employment. In the figure, the solid squares are actual data. The dashed line with solid circles show the model-based 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 discussed above, growth rates of productivity have been significantly different across sectors, 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 growth rate of total factor

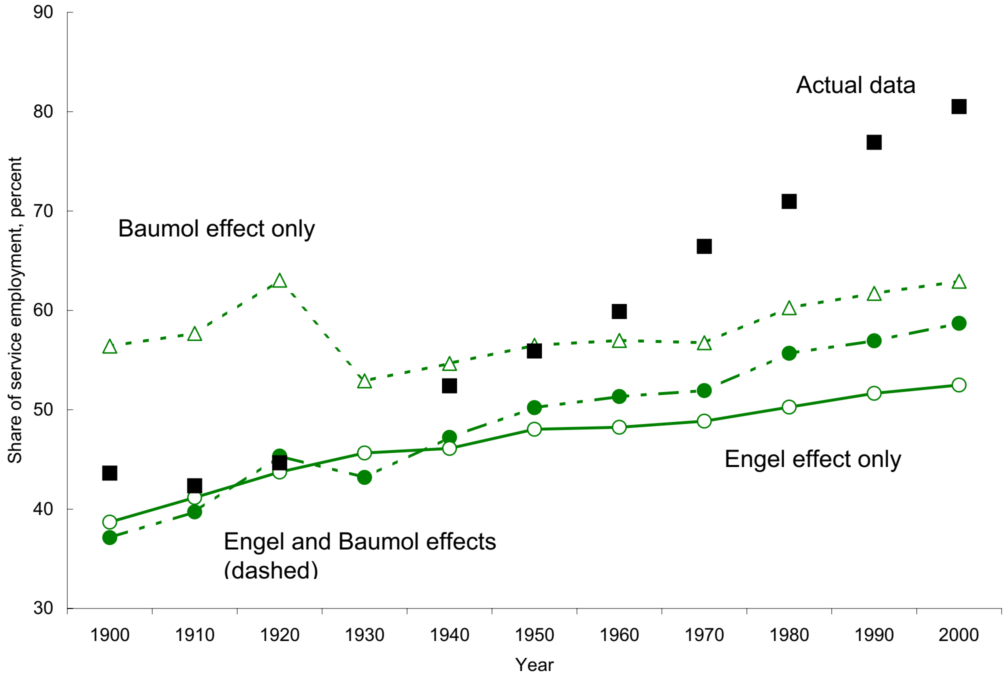

Figure 8: Employment share of services in the United States, 1900–2000

Notes: This figure plots the share of services in employment using actual data and three calibrated models. There is no census-based sectoral 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 the base-case parameters 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 growth rate of total factor productivity equal to 0.0105 for the entire simulation, including calibrated analog of the sample period from 1900 to 2000. The simulation horizon is 1000 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."

productivity equal to 0.0105 for the entire simulation, including the calibrated analog of the sample period from 1900 to 2000.

The simulation results show that, relative to the data, the calibrated model with Baumol effects only imparts a significantly higher share of services in employment 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 services in employment. However, the Engel effect imparts a much slower pace of increase in the share of services in employment after about 1940, whereas the Baumol effect contributes increasingly more. While still lower than the observed pace, the combination of Engel and Baumol effects is more successful in accounting for the increase in the employment share of services

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 data for 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 growth rate of total factor productivity 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.

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 of the share of services in employment. 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 of the share of services in 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 on productivity growth estimates in the first half of the twentieth century that are less comprehensive.

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 share of services in consumption expenditures will continue to increase.

From equation (13) it is easy to see the impact of this likely increase in the share of services in consumption expenditures on employment shares, which in turn 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 base-case calibration, 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 base-case calibration (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 have also considered an alternative non-homothetic preference specification, in which income elasticity of demand for each good is 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.[25] However, it has its own drawback:

[25] In fact, a calibrated model with the sub-utility function in equation (17) with $\nu_a > \nu_m > \nu_s$ delivers interesting nonlinear

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, 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 available productivity growth 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:

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

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.

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 is identical to that of the model in Section 3.

These lead to the modification of the employment shares by sector given in equations (13) and (14) as:[26]

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

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

These expressions modify the equilibrium employment shares through two novel channels: (1) relative shares of sectoral outputs in the production of the intermediate goods (the ϕ terms), and (2) 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 growth 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 example, personal consumption expenditures on food in the expenditure side of the national income accounts in many 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

[26]Ngai and Pissarides (2007) drive similar expressions in the absence of Engel effects. 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.

and manufacturing goods originating from the service sector.[27] 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 industrial valued added have been stable over the period 1958–1996, despite the fact that intra-distributional mobility is 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 growth rate of productivity in market production of services exceeds that of in non-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 toward the sector with higher productivity growth and the one that produces a close substitute.[28]

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 services in employment.

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

[28] Recent literature on the trends over time in the allocation of hours between market and non-market 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, which is part of non-market hours, in the twentieth century (at least in the United States) to the reallocation of labor from home production to market production of services.

6 Concluding remarks

This paper asked a quantitatively motivated question: how much *could* a unified model of structural change with Engel and Baumol effects explain the rising share of services in employment in the United States? The paper quantified both the joint and relative strengths of Engel and Baumol effects in accounting for the rising share of services in employment 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, considerable gaps between the calibrated model and the actual data remain. 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.

Appendix

A Data

A.1 Share of employment by sector

- From 1800 to 1900, the share of agriculture in employment is based on Weiss series in Carter et al. (2006, series Ba829 and Ba830), the share of manufacturing is based on Lebergott series in Carter et al. (2006, series Ba814 and Ba821), and the share of 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 are 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 are from the 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 sector, 1900–2005

To construct time-series on multi-factor productivity (MFP) growth 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 to construct the series on total factor productivity growth by sector. (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 productivity data on manufacturing and services, 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 Service, 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 growth rates of productivity using equation (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 productivity data on manufacturing and services, I compute the annualized average growth rates of productivity in the case of the 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 growth rates of productivity 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, the U.S. Census Bureau (2001, Table 596).

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

B Derivations

In this appendix, I formally derive the relationships stated in the text without proof or derivation. I also draw parallels between the measure of net consumption expenditures as defined in equation (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 the net consumption expenditure, $\overline{C}$, is measured in terms of the m-sector 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 the time index 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 shares of employment in sectors $i = 1, \ldots, m-1$.

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

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

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

The final 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:

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

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

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