Essays on Structural Transformation

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Dedication

To my family.

Abstract

The three chapters of this dissertation investigate major topics on structural transformation - reallocation of production across broad sectors of the economy. The first chapter investigates how substitutable are the demand for goods in the U.S. and its relationship to income elasticity. The second chapter studies the relationship between the reallocation of production and energy use in the United States. Lastly, the third chapter analyzes the structural transformation process of the Brazilian economy from 1950-2010.

In Chapter 1, I study the importance of changes in income and relative prices for the consumption demand between agriculture, manufacturing and services goods in the U.S.. I use an (indirect) utility representation that takes the commonly used Stone-Geary preferences as special case and is able to generate persistent income effects. I find that a fairly low value of the substitution parameter, but sustained income effects.

In Chapter 2, I study the role of structural transformation - from goods towards services - and of the increase in energy-saving productivity in the decline of carbon intensity (carbon emission per output) in the U.S. from 1950 to 2015. Because services require relatively less energy for production, shifts toward this sector decreases the necessary energy for production and, as consequence, less carbon per unit produced. Energy-saving productivity, on the other hand, reduces the necessary energy input for each unit of production. I use a multi-sector model to quantify the effects of energy-saving productivity in the economy. I find that in the absence of energy-saving productivity growth, aggregate consumption would be 6.2% lower than observed in 2015 and labor share in the goods sector 6.1% higher. In addition, I find that energy-saving productivity growth is responsible for 71.5% of the decline in carbon intensity (carbon emission per output) and structural transformation is of minor importance. I also use the model to evaluate the effects of implementing a per unit energy tax equal to the social cost of carbon provided by the Energy Information Agency. The tax decreases aggregate consumption by 3.5% and it increases the labor share in the goods sector by 1.61%.

Finally, Chapter 3, jointly with Daniela Costa, examines the labor reallocation across agriculture, manufacturing and services, and their impacts on aggregate labor productivity in Brazil from 1950 to 2010. We use a multisector model that features nonhomothetic preferences and constant elasticity of substitution to decompose the drivers of the labor reallocation. For the entire 1950-2010 period, the income effect accounts for most of the reallocation of labor away from agriculture towards manufacturing and services. On the other hand, if we focus only in the 1980-2010 sub-period, the relative price change is now the main driver of the reallocation of labor, even though income effect is still quantitatively important. In addition, we explore two important aspects of the Brazilian economy: the fast growth of manufacturing productivity from 1950 to 1980 and its subsequent sluggish behavior, and the decline of services labor productivity after 1980. We find that the fast growth of manufacturing productivity between 1950 and 1980 is responsible for 15% of the aggregate productivity level in 1980. We also find that if services labor productivity had stayed constant at its 1980 level, aggregate labor productivity in 2010 would be 28% higher than observed.

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Chapter 1

A Perspective on Preferences and Structural Transformation

1.1 Introduction

Structural transformation is defined as the reallocation of production across three broad sectors - agriculture, manufacturing and services - that accompanies the process of economic growth. As the economies grow, the value-added share of the agricultural sector declines, the services sector share increases steadly and the manufacturing share first increases and then decreases following a hump-shape pattern[1]. These structural transformation facts and patterns are also observed for other economic variables such as employment shares, consumption shares or expenditure shares. The economic literature has focused on explanations based on supply and demand drivers to better understand the process of structural transformation. The supply side explanation is based on unequal productivity growth across the sectors. The demand side is characterized by the importance of relative price and income effects on household demand.

For the U.S. economy, there are two additional facts in the postwar period: (i) the price of services increases relative to manufacturing and agriculture, and the price of manufacturing increases relative to agriculture; (ii) the consumption of services increases relative to the consumption manufacturing and agriculture, and the consumption of manufacturing increases relative to agriculture through most of the time. So, for example, we observe an increase in the relative consumption of services concomitant with the increase of its relative price. These facts are not rationalized by consumers with homothetic preferences for which the increase of the relative price of a good is associated with the decrease of its relative demand[2].

The structural transformation literature has commonly relied on the Stone-Geary (SG) preferences where nonhomothetic demand arises from subsistence consumption requirements and consumption endowments[3]. Past studies relying on the SG preferences, such as Buera and Kaboski (2008), Herrendorf, Rogerson and Valentinyi (2013) or Moro, Moslehi and Tanaka (2017), have found fairly low substitution parameter value implying that the utility function takes a Leontief specification. The low substitution is consequence of vanishing nonhomothetic effects that asymptotically converges to an homothetic preference, as income grows. This result is, for some authors, viewed as unappealing. For example, Buera and Kaboski (2009) consider the Leontief estimate with an "implausibly low elasticity of substitution".

In this paper, I ask if an extension of the SG preferences that generates persistent income

[1] During the postwar period, the U.S. manufacturing production is already in the declining phase.

[2] Unless consumers preferences are represented by a Leontief utility function. In which case an increase in price does not affect the relative demand of different goods.

[3] These consumption endowments are usually interpreted as home production. See Rogerson (2008).

effects exhibits different properties. More specifically, I examine if this utility function takes a Leontief specification once sustained income effects are present. I use an (indirect) utility representation which nests the SG preferences as special case and is able to produce nonhomothetic sectoral demand for all levels of income. Throughout this paper, I refer to them as Generalized Stone-Geary (GSG). Lewbel (1989) introduced a class of (indirect) utility representations for which the GSG is a special case and Alder, Boppart and Muller (2018) have used them in the context of structural transformation. In the estimation of the GSG, I also find a fairly low substitution parameter value. However, differently from the SG specification, the GSG utility exhibits sustained income effects and it does not converge to an homothetic representation. To examine these income effects further, I look upon the income elasticities behavior of both utility specifications. I find that: (i) the income elasticity of the agriculture sector grows much faster with the GSG specification than with the SG; (ii) the manufacturing income elasticity grows in the SG specification while it declines in the GSG; (iii) the income elasticity of services declines for both specifications, but while it converges to zero in the SG specification, it converges to a positive value in the GSG. I also evaluate the implications of each utility representation for the evolution of the expenditure shares of the U.S. economy. The GSG forecasted consumption shares in 2050 are 0.7%, 6.3% and 93% for agriculture, manufacturing and services, respectively. The SG shares are 0.1%, 10.8% and 88.9%.

In addition to the papers already cited, a closely related paper is Comin et al (2015). The authors use the Implicit Nonhomothetic Constant Elasticity of Substitution (CES) preference that displays constant relative income elasticities and persistent nonhomothetic demand. They estimate a substitution parameter statistically different from zero and, as consequence, the preference does not have a Leontief specification. Because the nonhomothetic CES does not impose declining income effects as the SG does, both income and price effects help account for the increase in expenditure shares in services and the estimation does not select a Leontief demand system.

An outline of the paper follows. In the next section, I describe the data. In section (1.3), I describe the model and discuss the preferences. In section (1.4), I discuss the estimation results, the fit to the data and the income elasticity that results from the model. In section (1.5), I compare the future behavior of expenditure shares. Section (1.6) concludes.

1.2 Data and Facts

In this section, I discuss the stylized facts of the structural transformation process in the U.S. from 1947 to 2010. Usually value-added data come from production side of the national income and products accounts and so contain both consumption and investment. In this paper, I will use the consumption data in value-added terms for agriculture, manufacturing and services provided by Herrendorf, Rogerson and Valentinyi (2013)[4]. This focus on value-added data is motivated by the common assumption that production functions in multi-sector models are usually value-added production functions. Consistency requires that consumption derived of utility representations are also in value-aded terms. To illustrate the importance of consumption in value-added form, consider the example of a cotton shirt[5]. With the value-added interpretation, a cotton shirt represents consumption of all three commodities: raw cotton from agriculture, processing from manufacturing, and retail from the services sectors.

Figure (1.1) shows the evolution of consumption shares, price indices and consumption quantities for each sector. Figure(1.1a) displays the consumption shares in value-added. They follow the usual structural transformation patterns observed for value-added and employment shares in the postwar period for the U.S.: a declining share of agriculture and of manufacturing, and an increase in the share of consumption of services. The share of agriculture declined from 9.2% to 1.2% and the share of manufacturing from 27.4% to 14.3%. The share of services increased steadly from 63.4% to 84.5%.[6].

Figure (1.1b) diplays the evolution of prices since 1947 and their unequal growth throughout the period. The price of services has grown more than the price of manufacturing and the price of manufacturing more than the price of agriculture. The price of services increased at about the same pace as the manufacturing price until the early 1980s, but the growth rate of services price is much higher than manufacturing price since then. From 1947 to 1980, the price of services had increased 3.89-fold and the price of manufacturing 3.53-fold. By 2010, the price of services increased 10-fold and the price of manufacturing about 6-fold. The price of agriculture increased only slightly since the initial period and is roughly constant since mid 1970s.

Finally, Figure (1.1c) shows the increase of the quantity consumed since 1947. The

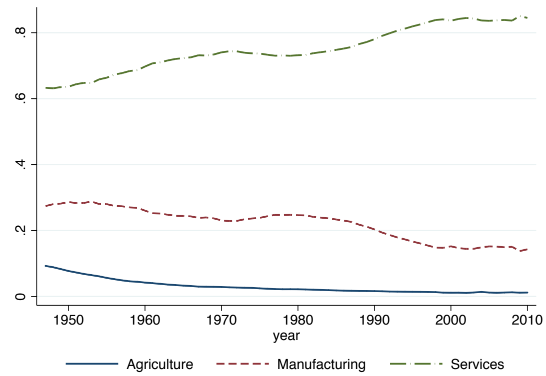
[4]See Herrendorf, Rogerson and Valentinyi (2013) for a thorough discussion of the methodology to construct the data.

[5]This example is from Herrendorf, Rogerson and Valentinyi (2013).

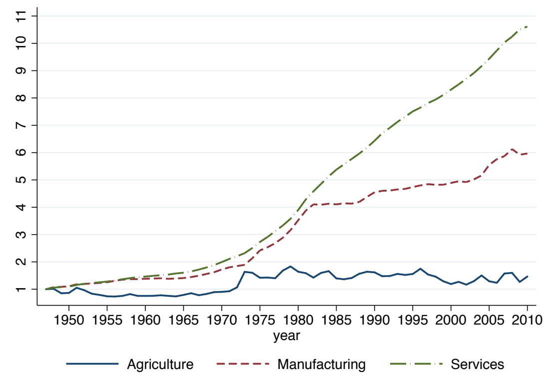
[6]The behavior of consumption in value-added follows the same pattern as production in value-added. Agricultural and manufacturing production declined from 8.1% to 1% and from 31.6% to 16.9%, respectively. Value-Added production of services increased from 60.3% to 82.1%. See Appendix for a comparison between production and consumption value-added data.

Figure 1.1: Data Facts

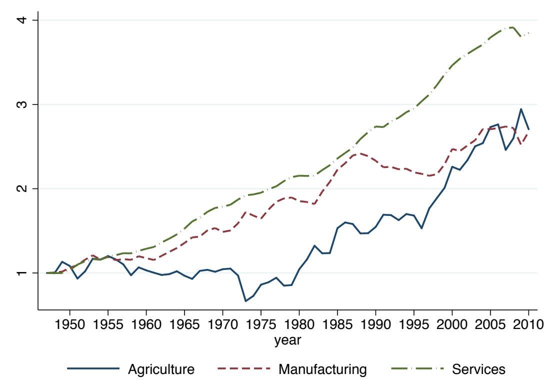
(a) Consumption Shares



(b) Price Indices



(c) Quantity Indices



Note: Graph (a) shows the nominal expenditure share in each sector. Graph (b) shows the sectoral price indices normalized for 1947. Graph (c) shows the sectoral consumption quantity indices normalized for 1947.

quantity consumed of services has grown more than manufacturing and agriculture. The quantity consumed of manufacturing has grown more than agriculture for most of the period, and is only slightly lower in the last few years of the period.

Observing the data, notice that the consumption of services relative to manufacturing and agriculture increased at the same time that the relative price of services with respect to manufacturing and agriculture increased. That is, relative consumption of services increased concomitant with an increase in relative prices. This fact is inconsistent with an homothetic utility specification which would have relative prices and relative quantities consumed moving in opposite directions. Therefore, to fit the data, it is necessary that income growth generates an increase in the demand of services relative to manufacturing and agriculture. An analogous argument is necessary to explain the demand of manufacturing goods relative to agriculture.

1.3 Model

I consider a representative household that demands three different goods: agriculture (a), manufacturing (m) and services (s). Household takes the prices of the goods, p_i, $i \in \{a, m, s\}$, and income as given, and chooses how much of each good to consume. The household only makes intratemporal consumption choices. The preferences are represented by the indirect utility function firstly presented in Lewbel(1989)[7][8]:

$$v(e, P) = h\left(\frac{e}{\mathbf{B}} - \mathbf{A}\right) - \mathbf{D} \tag{1.1}$$

The indirect utility v is specified over the vector of prices $P = (p_a, p_m, p_s)$ where the indices a, m and s refer to the three sectors of agriculture, manufacturing and services, and household expenditure level is e. Let h be some increasing and differentiable function. Let $\mathbf{B}$ be any twice differentiable, homogeneous of degree one function of prices. Also, let $\mathbf{A}$ and $\mathbf{D}$ be any twice differentiable, homogeneous of degree zero functions of prices.

Let e be the total expenditure on consumption observed in the period, then household budget constraint is:

$$\sum_{i \in \{a,m,s\}} p_i c_i = e \tag{1.2}$$

Applying Roy's identity[9] gives the marshallian demand for good i, c_i, from 1.1 equal to:

$$c_i = \mathbf{A}_i \mathbf{B} + (\mathbf{B}_i/\mathbf{B})\, e + \mathbf{D}_i [v_e(e, P)]^{-1} \tag{1.3}$$

where $\mathbf{A}_i$, $\mathbf{B}_i$ and $\mathbf{D}_i$ denote the derivatives with respect to price p_i and $v_e(e, P)$ denotes the derivative with respect to expenditure e. Lewbel (1989) shows that this is the most general form of an utility-derived demand represented by an additive system that has three parts. The first part, $\mathbf{A}_i\mathbf{B}$, depends solely on prices and is independent of expenditure. The second, $(\mathbf{B}_i/\mathbf{B})\, e$, is linear on the expenditure level. The third part, $\mathbf{D}_i[v_e(e, P)]^{-1}$, is nonlinear on expenditure. Since h (implicitly in $v_e(e, P)$) can be any function[10], this allows for a variety of different Engel's curves.

Following Alder, Boppart and Muller (2018), I will focus on the case where h is a power function. The preferences throughout the paper takes the form:

$$v(e, P) = \frac{1}{\epsilon}\left(\frac{e}{\mathbf{B}} - \mathbf{A}\right)^{\epsilon} - \frac{1}{\epsilon} - \mathbf{D} \tag{1.4}$$

[7] Also used in the context of structural transformation by Alder, Boppart and Muller (2018).

[8] Throughout the paper, bold letters will represent functions of price vector. For example, $\mathbf{A} : P \to \mathbb{R}$.

[9] Roy's Identity gives $c_i = -\frac{\partial v/\partial p_i}{\partial v/\partial e}$.

[10] Notice that $v_e(e, P) = h_e(.)(1/\mathbf{B})$.

with $\epsilon \neq 0$. Let ω_i be expenditure share on good i:

$$\omega_i = \frac{p_i c_i}{e} = \mathbf{A}_i \, p_i \left(\frac{\mathbf{B}}{e}\right) + \frac{\mathbf{B}_i \, p_i}{\mathbf{B}} + \mathbf{D}_i \, p_i \left(\frac{e}{\mathbf{B}} - \mathbf{A}\right)^{1-\epsilon} \left(\frac{\mathbf{B}}{e}\right) \tag{1.5}$$

The second term of the right hand side of (1.5), $(\mathbf{B}_i p_i)/\mathbf{B}$, is independent of expenditure e and it represents the homothetic part of the Engel's curve[11]. The other terms depend on expenditure e, generating the nonhomothetic behavior of the consumption demand.

1.3.1 Functional Forms

In this section, I discuss the functional forms of $\mathbf{A}, \mathbf{B}$ and $\mathbf{D}$. I consider functional forms for which the Stone-Geary utility, commonly used in the structural transformation literature, is a special case. Let function $\mathbf{B}$ be of the CES form:

$$\mathbf{B} = \left[\sum_{i \in \{a,m,s\}} \phi_i p_i^{1-\sigma}\right]^{\frac{1}{1-\sigma}} \tag{1.6}$$

with $\sum_{i \in \{a,m,s\}} \phi_i = 1$ and $\phi_i \geq 0$, and $\sigma \geq 0$. As $\sigma \to 1$, the price function $\mathbf{B}$ approaches the Cobb-Douglas functional form. Functions $\mathbf{A}$ and $\mathbf{D}$ only needs to be of degree zero. Throughout the paper I will assume:

$$\mathbf{A} = \mathbf{B}^{-1} \sum_{i \in \{a,m,s\}} p_i \bar{c}_i \tag{1.7}$$

with $\bar{c}_s \leq 0$, $\bar{c}_m = 0$ and $\bar{c}_a \geq 0$, and $c_a \geq \bar{c}_a$. The functional form of $\mathbf{D}$ is:

$$\mathbf{D} = \bar{D} \sum_{i \in \{m,s\}} \nu_i \ln\left(\frac{p_i}{p_a}\right) \tag{1.8}$$

where $\bar{D}$ is a parameter and $\sum_{i \in \{a,m,s\}} \nu_i = 1$. The standard Stone-Geary preferences [12] used in the economic literature such as Herrendorf, Rogerson and Valentinyi (2013, 2014) is just the case when $\bar{D} = 0$.

[11] If relative prices are constant, it doesn't affect the expenditure share on good i.

[12] The Stone-Geary direct utility function is given by:

$$u(c) = \begin{cases} \frac{1}{\epsilon}\left(\left[\sum_{i \in \{a,m,s\}} \phi_i^{\frac{1}{\sigma}} (c_i - \bar{c}_i)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}\right)^{\epsilon} - \frac{1}{\epsilon}, & \epsilon \in (-\infty, 0) \cup (0, 1) \\ \ln\left(\left[\sum_{i \in \{a,m,s\}} \phi_i^{\frac{1}{\sigma}} (c_i - \bar{c}_i)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}\right), & \epsilon \to 0 \end{cases}$$

1.4 Quantitative Results

In this section, I discuss the estimation procedure and the quantitative results of the model. I estimate the parameters using the prices and the consumption expenditure observed in the data. Then, I compare the results obtained from the model with the data and discuss their properties.

1.4.1 Estimation

To estimate the demand system, I follow closely previous work in the literature such as Deaton (1986), Herrendor, Rogerson and Valentinyi (2013) and Moro, Moslehi and Tanaka (2017). More specifically, I estimate the parameters of the model using the demand system (1.5) applying the iterated feasible generalized nonlinear least square estimation method[13]. For the parameters with constraints such as $\sigma \geq 0$, $\sum_{i\in\{a,m,s\}} \phi_i = 1$, $\phi_i \geq 0$, I transform them into unconstrained parameters as:

$$\sigma = e^{b_0}, \quad \phi_a = \frac{1}{1+e^{b_1}+e^{b2}}, \quad \phi_m = \frac{e^{b_1}}{1+e^{b_1}+e^{b2}}, \quad \phi_s = \frac{e^{b_2}}{1+e^{b_1}+e^{b2}} \tag{1.9}$$

where $b_0, b_1, b_2 \in (-\infty, +\infty)$. I estimate the model in terms of the unconstrained parameters, then I calculate the point estimates and standard errors of the constrained parameters $\sigma, \phi_a, \phi_m, \phi_s$. Table (I) shows the results for the Generalize Stone-Geary and Stone-Geary specifications[14].

The GSG specification fits the data better than the SG. The AIC values reported in Table (I) decrease (i.e. more negative) from -875.36 to -923.58. The RMSE for both sectors is also lower for the GSG. Since the SG specification is a special case of the GSG, the additional terms increase the explanatory power of the model, as it would be expected. After all, $\bar{D}\nu_i = 0$ is always a feasible value.

The estimated value of the substitution parameter σ is close to zero for both specifications[15]. As mentioned in the Introduction, the low value of σ is also found in other studies in the literature such as Buera and Kaboski (2009), Herrendorf, Rogerson and Valentinyi (2013) and Moro, Moslehi and Tanaka (2017). This result implies that for both specifications, the utility function takes a Leontief form (in the absence of nonhomothetic effects). Therefore, even including persistent nonhomothetic effects, the substitution between goods is fairly low.

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[13] Since the sum of expenditure shares sum one, I only need to estimate for manufacturing and services expenditure shares. In addition, this estimator is implemented using the Stata command *nlsur*.

[14] Recall that the Stone-Geary specification assumes $\bar{D} = 0$.

[15] The estimated values are $\sigma = 4.83e-8$ for the SG and $\sigma = 0.0000167$ for the GSG. The estimation value of the Stone-Geary specification is the same as Herrendorf *et al.* (2013).

Table I: Estimated Parameter Values

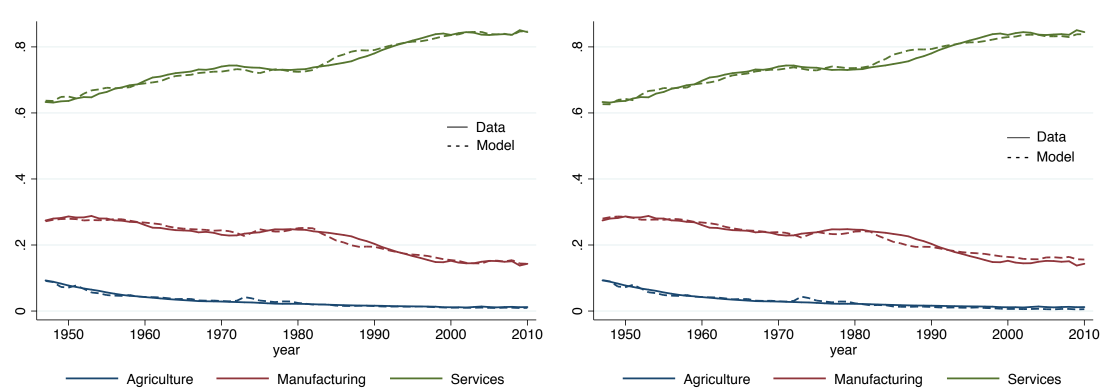
	SG	GSG
σ	0.000	0.000
	(0.000)	(0.000)
$\bar{c}_a$	138.87	150.19
	(3.370)	(16.03)
$\bar{c}_s$	-4268.06	-322.17
	(439.93)	(14.492)
ϕ_a	0.001	0.000
	(0.000)	(0.000)
ϕ_m	0.146	0.247
	(0.003)	(0.003)
ϕ_s	0.853	0.753
	(0.003)	(0.003)
ϵ		-0.262
		(0.007)
$\bar{D}\nu_m$		-0.006
		(0.000)
$\bar{D}\nu_s$		0.005
		(0.000)
AIC	-875.36	-923.58
$\mathrm{RMSE_m}$	0.011	0.009
$\mathrm{RMSE_s}$	0.011	0.010

Note: Robust standard errors are in parentheses. SG stands for Stone-Geary and GSG for Generalized Stone-Geary. AIC is Akaike Information Criteria. $\mathrm{RMSE_i}$ is the root mean squared for sector i expenditure share equation (1.5).

Figure 1.2: Consumption Shares: Data and Model

(a) Generalized Stone-Geary

(b) Stone-Geary



The subsistence parameter $\bar{c}_a$ has similar values in both estimations and they are not statistically different[16]. For both estimations, the consumption of agricultural good is higher than the subsistence level, $c_a > \bar{c}_a$, in every period. This suggests that the subsistence parameter $\bar{c}_a$ is able to generate income effects strong enough to match the data of the agricultural consumption share. On the other hand, the value of the endowment parameter $\bar{c}_s$ changes considerably from the SG to the GSG. The value increases (i.e. less negative) from -4268.06 in the SG specification to -322.71 in the GSG. It suggests that persistent income effects is an essential property of demand necessary to match the consumption expenditure data.

Figure (1.2) plots the consumption shares implied by both specifications. It confirms the good fit of both models to the data as previously suggested by the RMSE statistics. As additional summary statistic for the performance of the models, I compute the average absolute deviation over time between the consumption expenditure shares in the data and in the model:

$$\Omega_i = \frac{1}{T}\sum_{t=1947}^{2010} \text{abs}(\omega_{i,t}^{d} - \omega_{i,t}^{m}) \tag{1.10}$$

where $i \in \{a, m, s\}$, $T = 64$ is the number of years, d stands for data and m for model. The average asolute deviation in percentage points between model and data for agriculture expenditure is 0.3% for the GSG specification and 0.4% for the SG. For manufacturing expenditure is 0.7% for the GSG and 0.9% for the SG. For services is 0.8% for the GSG and 0.9% for the SG. This confirms the good fit of both specifications and the improvement of the GSG specification compared to the SG.

1.4.2 Income Elasticity

In this section I use the model to calculate the elasticity of the consumption share with respect to expenditure (income) for both specifications. The income elasticity is given by:

$$\xi_i = \frac{\partial \omega_i/\omega_i}{\partial e/e} = -\mathbf{A}_i p_i \left(\frac{\mathbf{B}}{e}\right)\frac{1}{\omega_i} + \mathbf{D}_i p_i \left(\mathbf{A}\left(\frac{\mathbf{B}}{e}\right) - \epsilon\right)\frac{1}{\omega_i}\left(\frac{e}{\mathbf{B}} - \mathbf{A}\right)^{-\epsilon} \tag{1.11}$$

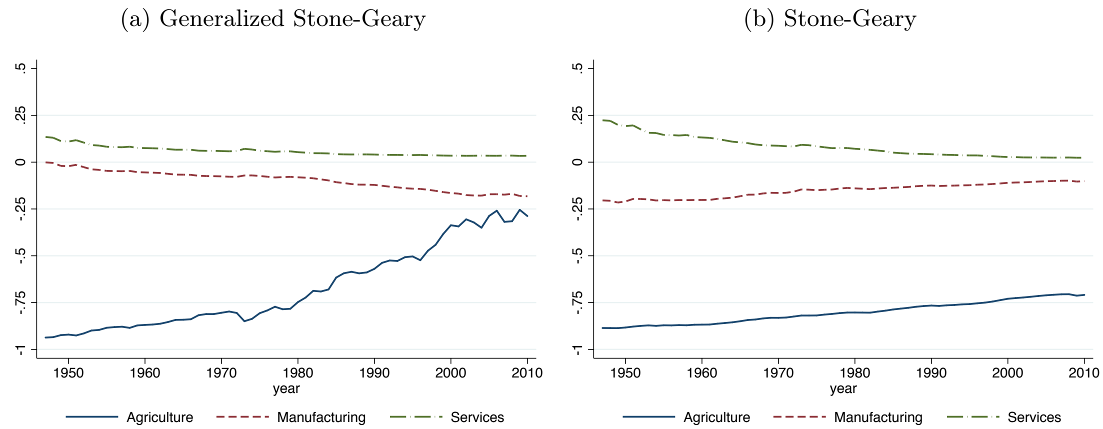
When the elasticity ξ_i is positive, the expenditure share on good i increases with income, corresponding to a luxury good. When the elasticity ξ_i is negative, the expenditure share allocated for the consumption of good i decreases with income, corresponding to a necessity good. Recall that for the SG specification, $\mathbf{D}_i = 0$, and its income elasticity equals the first term of equation (1.11).

Figure (1.3) plots the income elasticity ξ_i for both specifications[17]. The income elasticity

[16] The value estimated for the GSG specification is less than one standard deviation of the SG

[17] The income elasticity of consumption gives similar results found in this section. See Apendix (A.2) for

Figure 1.3: Income Elasticity



Note: The income elasticity is ξ_i. The elasticity for the Stone-Geary specification is monotone and becomes weaker over time, converging towards zero.

for services, ξ_s, follows the same pattern for both. It starts with a stronger income effect that decreases through time. The agriculture elasticity ξ_a is increasing (i.e. less negative) as income grows. The difference between both specifications is the speed up after the mid 1970s of the GSG. This increase improves the fit to the data necessary to capture the growth of agricultural consumption after the mid 1970s. The main difference between both specifications is in the behavior of manufacturing elasticity ξ_m. In the GSG specification, ξ_m is persistently declining (i.e. becoming more negative) whilst it is increasing (i.e. less negative). So, the manufacturing good is becoming more income inelastic according to the GSG specification, but it is becoming less income inelastic according to the SG specification. Figure (1.3b) illustrates the monotonic behavior of the SG income elasticities where ξ_i converges to zero in the three sectors. This dynamic of the income elasticities captures the asymptotic homotheticity associated to the SG preferences[18].

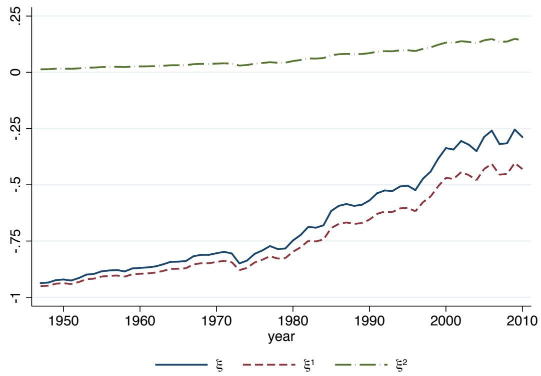
Now I discuss the components of the income elasticity for the GSG. The first term, $-\mathbf{A}_i p_i \left(\frac{\mathbf{B}}{e}\right)\frac{1}{\omega_i}$, is denoted by ξ_i^1 and the second, $\mathbf{D}_i p_i \left(\mathbf{A}\left(\frac{\mathbf{B}}{e}\right) - \epsilon\right)\frac{1}{\omega_i}\left(\frac{e}{\mathbf{B}} - \mathbf{A}\right)^{-\epsilon}$, denoted by ξ_i^2. The first term simply corresponds to the income elasticity in the SG specification, even though it may have distinct values because the parameters may be different. Therefore, ξ_i^1 also has a monotonic behavior and it becomes weaker over time for the three sectors. The second term, ξ_i^2, generates the sustained income effect inhibiting the elasticities to go to zero that can be observed for the three sectors.

further discussion.

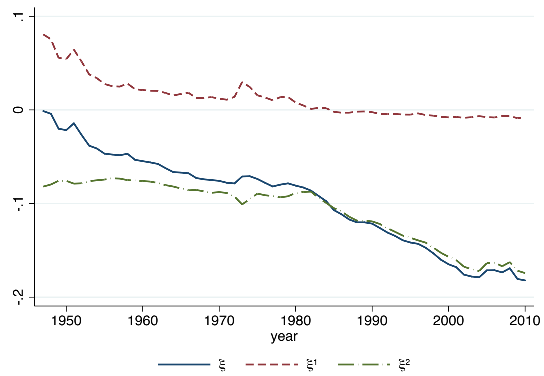
[18]Notice that if preferences were homothetic, income elasticity ξ_i would be equal to zero for all sectors. The homothetic specification corresponds to the case where $\mathbf{A} = 0$ and $\mathbf{D} = 0$. From equation (1.5), it is easy to notice that $\partial \omega_i / \partial e = 0$.

Figure 1.4: Income Elasticity by Sector

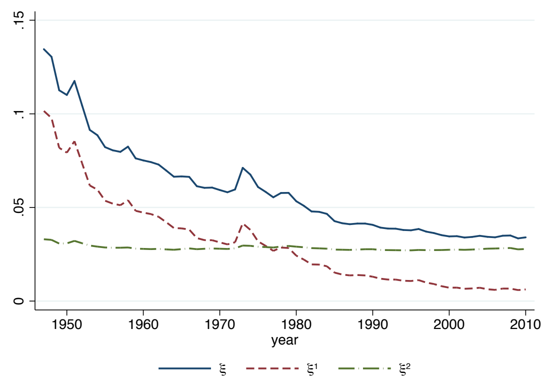
(a) Agriculture



(b) Manufacturing



(c) Services



Note: The graphs show the income elasticity for each sector and their two terms. The first term is $\xi_i^1 = -\mathbf{A}_i p_i \left(\frac{\mathbf{B}}{e}\right) \frac{1}{\omega_i}$. The second term is $\xi_i^2 = \mathbf{D}_i p_i \left(\mathbf{A}\left(\frac{\mathbf{B}}{e}\right) - \epsilon\right) \frac{1}{\omega_i} \left(\frac{e}{\mathbf{B}} - \mathbf{A}\right)^{-\epsilon}$. For all sectors, the second term generates sustained income effects.

First, consider the income elasticity for agrilculture, ξ_a. Figure (1.4a) shows that ξ_a^2 is actually positive and increasing. Second, consider the elasticity for manufacturing, ξ_m. While the first term, ξ_m^1, is bigger than zero and converges to zero, the second term is actually decreasing (i.e. becoming more negative). The sustained decline of ξ_m^2 since the early 1980s explains the overall behavior of the income elasticity. Finally, the two terms of the services income elasticity have different patterns. The first term, ξ_s^1, monotonically converges to zero. The second term, ξ_s^2, is flat and roughly constant. If this pattern follows into the future, ξ_s^2 would set a positive lower bound that the income elasticity of services would converge to. These graphs show that the nonlinear income effects will likely have important impacts in the future dynamics of the income elasticities and consumption demand.

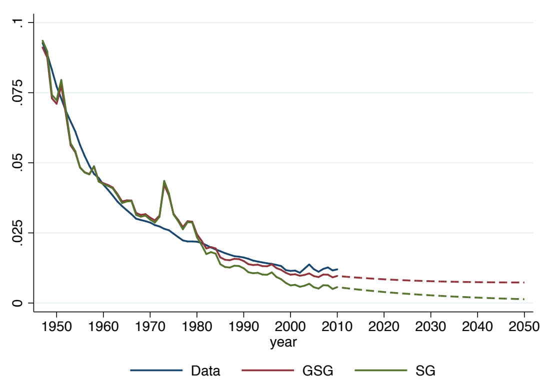
1.5 Application

In this section, I make a simple computational exercise to explicit the differences of the two specifications in the long run. What do the different preference specifications imply for the evolution of sectoral consumption of the U.S. economy? Assuming that prices p_i and consumption expenditure e grow at the average growth rate of the postwar period, I forecast the expenditure shares and income elasticities until 2050 for both specifications.

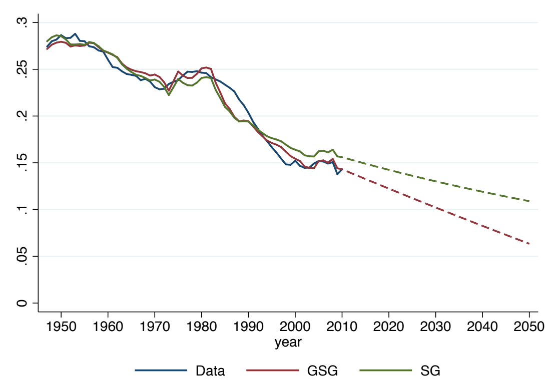
The consumption shares from each specification follow different long run patterns. The agricultural consumption share declines faster with the SG specification than the GSG. Recall that the parameter $\bar{c}_a$ estimated for the SG specification is higher than for the GSG. By 2050, agricultural expenditure share ω_a would be 0.1% and 0.7% for the SG and GSG, respectively.

Figure 1.5: Consumption Share by Sector

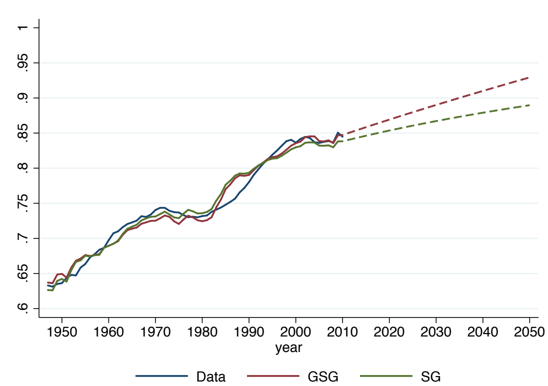
(a) Agriculture



(b) Manufacturing

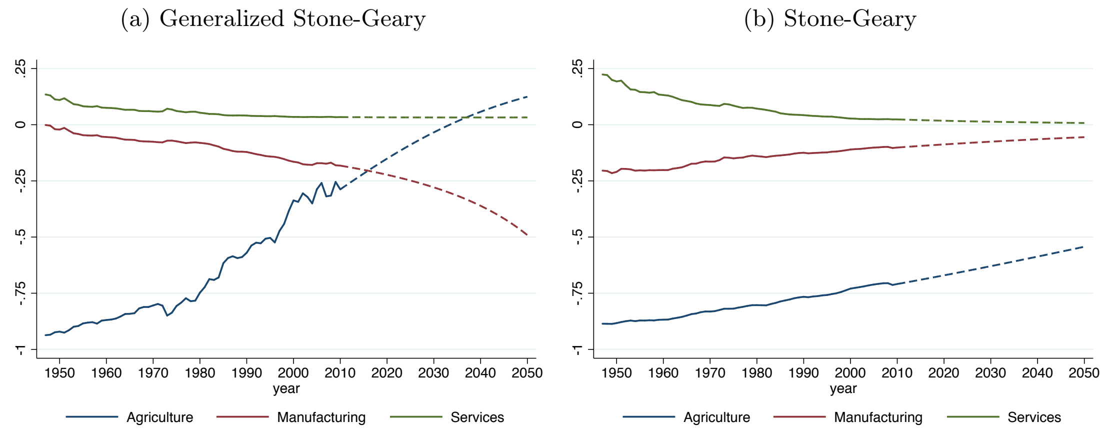


(c) Services



Note: The graphs show the consumption shares for each preference specification and the forecasted future values from 2010-2050.

Figure 1.6: Income Elasticity



Note: The income elasticity is ξ_i. The elasticity for the Stone-Geary specification is monotone and becomes weaker over time, converging towards zero.

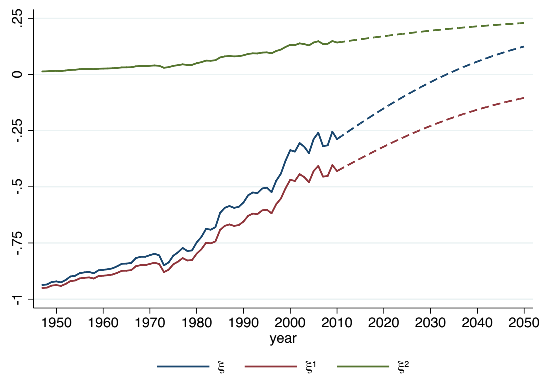
The projected manufacturing and services consumption shares for the SG specification level off as income grows with the SG specification. Notice that this does not happen with the GSG. Showing the long run impact of sustained income effects for consumption allocation. The manufacturing consumption share clearly declines faster with the GSG reaching 6.3% in 2050 while it reaches 10.8% with the SG. The services consumption share grows faster with the GSG than in the SG and their projected shares are 93% and 88.9%. This difference is mainly explained by the sustained income effect.

Here, I follow the same steps of Section (1.4.2). First, I compare the income elasticites for both specifications, then I discuss only the GSG income elasticities. Figure (1.6) shows them for both specifications. As expected, the income elasticities of the SG specification converge to zero. Once more, it exemplifies its asymptotic homotheticity property. This pattern makes clear that income effects become less important as expenditure grows. The GSG income elasticities behave very differently. The income elasticity for agriculture increases up to the point of actually becoming positive and being the highest of the three sectors. The income elasticity of manufacturing would decline (i.e. more negative) throughout the entire period, turning into a more income inelastic good. The income elasticity of services is always positive, as in the SG specification.

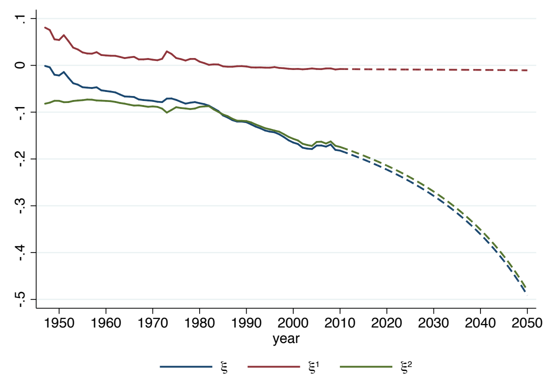
Figure (1.7) depicts the income elasticities for each sector. As in Section (1.4.2), I again separate the two terms that determines the income elasticity. Notice that for the future paths, the additional term ξ_i^2 of the GSG plays the major role in all three sections. In the agricultural income elasticity, the first term ξ_a^2 converges towards zero, as expected. The increase in the elasticity, ξ_a, up to the point of becoming positive comes from the term ξ_a^2

Figure 1.7: Income Elasticity by Sector

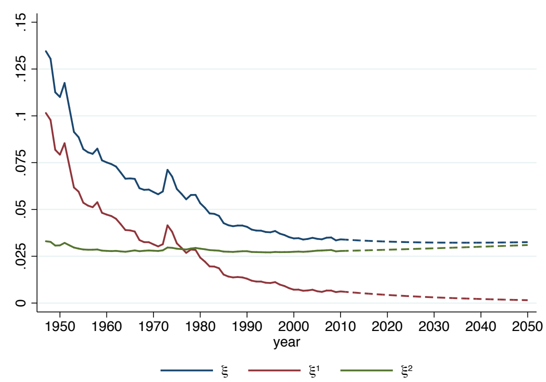
(a) Agriculture



(b) Manufacturing



(c) Services



Note: The graphs show the income elasticity for each sector and their two terms. The first term is $\xi_i^1 = -\mathbf{A}_i p_i \left(\frac{\mathbf{B}}{e}\right)\frac{1}{\omega_i}$. The second term is $\xi_i^2 = \mathbf{D}_i p_i \left(\mathbf{A}\left(\frac{\mathbf{B}}{e}\right) - \epsilon\right)\frac{1}{\omega_i}\left(\frac{e}{\mathbf{B}} - \mathbf{A}\right)^{-\epsilon}$. For all sectors, the second term generates sustained income effects.

that rises throughout the entire period. Consider now the manufacturing income elasticity. The first term, ξ_m^1, converges to zero wile the second term drives all the decline of ξ_m. This declining dynamics explains the lower forecasted manufacturing consumption share. Finally, the services income elasticity does not converge to zero, but to the lower bound imposed ξ_s^2. The ξ_s^2 is also roughly constant throughout the forecasted period. This exercise shows the importance of sustained income effects in forecasting the future behavior of consumption demand and how the process of structural transformation in the U.S. may continue in the next decades.

1.6 Conclusion

This paper presents an extension of the Stone-Geary preferences that accomodates a long run demand driver of structural transformation. This extension generates nonhomothetic demand for every level of income and it does not become asymptotically homothetic as income grows. In the estimation of the GSG, the substitution parameter σ also has a fairly low value, but the income effects do not vanish. I point out that I focused the analysis at one specific functional form to generate persistent income effects. Other functional forms of $\mathbf{D}$ could potentially overturn the results of the paper.

Chapter 2

Structural Transformation, Energy-Saving Productivity and Carbon Emission in the U.S.

2.1 Introduction

Economic growth has been a crucial determinant of U.S. energy use and, as consequence, of carbon emission since 1950. At the same time, carbon intensity (carbon emission per output) continuously declined. Also during this period the U.S. economy has gone through a large reallocation of employment and production from goods towards services. Even though these two topics have been widely researched, their interaction has received less attention in the economic literature. The key idea of this paper is that structural transformation - the reallocation from goods production to services - and the increase in energy-saving productivity are the determinant forces of the decline in carbon intensity (carbon emission per output) in the U.S. from 1950 to 2015. Because services require relatively less energy for production, shifts toward this sector decreases the necessary energy for production. Accordingly, even with the same technology, simply switching production from goods to services decreases carbon intensity. Energy saving productivity, on the other hand, reduces the amount of energy input for each unit produced.

Throughout the paper I assume the same production function for both the goods and services sectors. The production function uses labor and energy as input. More specifically, I assume that both sectors have a Leontief production function. One component of the production function is linear in energy use and the other component is linear in labor. Previous studies have found very low elasticity of substitution between energy and other inputs of production such as labor (and capital), thus supporting my assumption of perfect complementarity. For example, Hassler *et al.* (2016) estimates a CES production function using aggregate data and find the elasticity of substitution between energy and other inputs such as capital-labor to be fairly inelastic, with a value of 0.0013. van der Werf (2008) estimates the elasticity of substitution for a group of countries and also finds evidence of very low elasticity between energy and other inputs. Assuming a production function form allows me to compute both the labor productivity and the energy-saving productivity as residuals from the data series. If energy-saving productivity is constant, an increase in sector production is only possible with an increase in energy use. But if energy-saving productivity increases, higher production does not necessarily require more energy. Energy-saving productivity of both goods and services sectors grew at very low rates until mid 1970s. For the 1950-1974 period, energy-saving productivity growth in the goods and services sectors was 0.3% and 0.5%, respectively. From 1975-2015 energy-saving productivity had a faster growth trend in both sectors. In this period, growth rates were 2.3% and 1.8% in the goods and services sectors, respectively. This finding is consistent with the energy-saving productivity calculated by Hassler *et al.* (2016) using a constant elasticity of substitution

(CES) aggregate production function [1]. Hassler et al. find the growth of energy-saving productivity was 0.1% from 1950 to 1973 and 2.54% from 1974 to 2010.

In the paper, I use a multi-sector model with two objectives: isolate the effects of increased energy-saving productivity in the economy and predict the impacts of a carbon tax. The model builds on the standard structural transformation framework with multiple sectors - goods and services - and nonhomothetic preferences over goods and services, represented by the utility function proposed by Pakos (2011). With these preferences both goods and services are normal, services are income elastic (a luxury good) but goods are income inelastic. In this manner, the nonhomotheticity implies that the relative demand for goods with respect to services declines as income rise. This utility function is particularly suitable in the context of this paper because it generates nonhomothetic demand for every level of income. It is important to emphasize that other utility functions with such property has been used in the literature. To match the process of structural transformation for a panel of countries, Comin *et al.* (2015) have introduced the implicit nonhomothetic CES preference in the context of structural transformation. This utility function also has the property that the Engel curves do not level off as income grows; that is, demand is nonhomothetic for every level of income. Using the implicit nonhomothetic CES, Duernecker *et al.*(2017) identifies the impacts of labor reallocation to the services sector on future aggregate productivity growth. In a related paper, Buiatti *et al.* (2017) also use the implicit nonhomothetic CES to study the differences in labor productivity of the services sector between U.S. and Europe. These preferences contrast with the commonly used generalized Stone-Geary preferences (Kongsamut *et al* (2001), Dennis and Iscan (2007) and Herrendorf *et al.* (2013). Stone-Geary type of preferences generates nonhomothetic effects by imposing subsistence (or endowments) levels. These exogenous subsistence levels generate large nonhomothetic effects for low levels of income, but these effects vanish as income grows. As consequence, these preferences are assymptotically homothetic.

The structural transformation literature focus on unequal productivity growth between sectors and non-homothetic preferences as the drivers of the reallocation of production and labor between sectors. Here, I use the model to sort out the contribution of unequal productivity and non-homothetic preferences from energy-saving productivity. I find that energy-saving productivity is responsible for 6.1% of the decline in the labor share of the goods sector in 2015. I also find that energy-saving productivity is responsible for 6.2% of aggregate consumption level; that is, in the absence of energy-saving productivity growth, aggregate consumption would be 6.2% lower than observed in 2015. In addition, I also study the effects of energy-saving productivity in the decline of carbon intensity. I find that

[1] The authors assumed that fossil fuel was the only source of energy.

structural transformation explains only 3.9% of the decline in carbon intensity in the 1950-2015 period. That is, unequal productivity growth together with nonhomothetic preferences is responsible for only 3.9% of the decline in carbon intensity. I also find that energy-saving productivity explains 71.5% of the decline in carbon intensity between 1950 and 2015. Focusing only on the 1975-2015 period, energy-saving productivity is responsible for 83.9% of the decline. In the literature, researches focusing on energy intensity have found comparable results [2]. For the 1958-2000 period, Wing (2008) found that inter-industry reallocation was the main driver of the reduction in energy intensity in the U.S., but efficiency gains were an important factor after 1980. Focusing on Latin American countries, Jimenez and Mercado (2014) find that efficiency improvements drive the decrease in energy intensity and that reallocation of production does not represent a clear source of change. Huang (1993) studies the impact of structural transformation and industry level energy intensity on the decline of aggregate energy intensity for China during the period of 1980-1988. Huang finds that the decline is mostly due to decreases in industry level energy intensity and structural transformation had little impact on energy intensity. In a related work, using a two-sector structural transformation framework, Gertz (2015) discusses the impact of structural transformation on carbon intensity. In the simulations, Gertz predicts that structural transformation in China will be responsible for 3/4 of the decline in carbon intensity in the next 30 years.

I also analyze the effects of imposing a tax on energy demand. Given the estimated parameters, I find a somewhat counterintuitive energy use dynamics. Energy use initially increases and in the subsequent periods it decreases at a higher level than the case without tax. The increase of the after-tax energy price drives up the price of both goods and services. Because of the reduced income, demand for both goods and services decrease. In addition, since goods production is more energy intensive than services, the price of goods relative to services increases. The higher relative price induces demand away from goods toward services. But, since goods is income inelastic, reduced income causes an increase in the expenditure share of goods and postpones the reallocation of labor away from the energy intensive goods sector. The final effect is an increase of the labor share in the energy intesive goods sector. In the policy exercise, I set a tax on energy demand based on the social cost of carbon provided by the Energy Information Agency that increases energy price by 40%. In the exercise, Aggregate consumption is 3.5% lower compared to the case without the tax and the labor share in the goods sector increases 1.61% despite reduced demand. The increase in labor is necessary to finance the after-tax higher costs of energy for production. Using a one-sector model, Atkeson and Kehoe (1999) find that doubling energy price leads to a 33% drop in output. On the other hand, Jorgenson *et al.* (2013) uses a multi-sector model to evaluate

[2] More than 80% of carbon emission is consequence of energy use. So, the decline in carbon intensity is closely related to the decline in energy intensity.

many different environmental policies. They find that these policies would have low impact on household consumption levels and welfare. In the model I abstract from iteractions of the tax with other possible taxes. In the economic climate literature, introducing a tax on carbon emission is argued to involve a double dividend: it diminishes carbon externality and it reduces the distortions associated to other taxes (see Jorgenson *et al.* (2013)).

This paper has overlaps with the existing economic literatures on structural transformation and on environmental macroeconomics. Much of the environmental macroeconomic literature builds on the one-sector neoclassical growth model (e.g. Nodhaus (1992, 2014) and Golosov *et al.* (2014), but little attention has been paid on sectoral composition effects on carbon emission or how economy's structure could affect policies. On the other hand, structural transformation models usually ignore energy use and carbon emission, and focus mainly on labor allocation across sectors (just to cite a few, Ngai and Pissarides (2007), Acemoglu and Guerrieri (2008) and Herrnedorf *et al.* (2013)). Notable exceptions are Engstrom (2016), Gertz (2015) and Stefanski (2014). Engstrom (2016) discusses optimal carbon policy in the context structural transformation and heterogeneous damages among sectors. Engstrom results also suggest an important role for the elasticity of substitution between sectors, but in the context of the optimal consumption of fossil fuel. Stefanski (2014) uses a structural transformation model to infer implicit tax/subsidies in fossil fuel prices for a panel of 170 countries. Stefanski finds that up to 36% of global carbon emissions between 1980 and 2010 were driven by subsidies and that GDP was up to 1.7% lower because of these implicit subsidies. Gertz (2015), as previously cited, discusses structural transformation in the context of the chinese economy and find that structural transformation has an important role in the decline of carbon intensity. An important difference between this work and Gertz is that Gertz does not consider energy-saving productivity. The main adjustment of the firm when facing higher energy costs is to substitute it away for labor.

In the next Section, I present the stylized facts on carbon emission and structural transformation. The first fact is the increase of carbon emission level until 2007. The second fact is the decline in carbon intensity throughout the 1950-2015 period and its close relation to energy intensity. Related to structural transformation, the labor share allocation between sectors. In Section 3, I present the energy-saving productivity series for the U.S. assuming a specific production function. Section 4, I build the model and characterize its equilibrium conditions. In Section 5, I explain the calibration and estimation of the parameters, and discuss the estimation results. Section 6 discusses the fit of the model for the U.S. economy and the importance of energy-saving productivity in explaining the decline in carbon intensity. In this section I also discuss the tax policy exercise and discuss the results. Section 7 concludes.

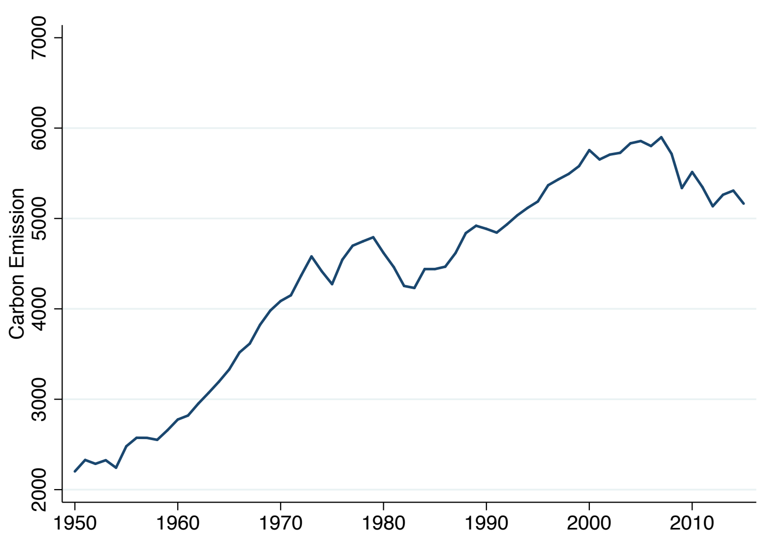
2.2 Stylized Facts

Carbon emission patterns and reallocation of production from goods to services in the US economy since 1950 are well documented, but their relation has received much less attention in the economic literature. The first fact is the growth of carbon emission levels from 1950 to 2007 and its following slight decrease. The second is the decline in carbon intensity - defined as carbon emission per output - throughout the entire period. In this section I discuss these two facts on carbon emission in the US from 1950-2010 and their relation with the reallocation of production [3].

Figure (2.1) plots the carbon emission level for 1950-2015. In 1950 carbon emission totalized 2382 million metric tons of carbon dioxide (MMt CO2) and it increased up to 5898 MMt CO2 at its peak in 2007. In 2015, its level was 5164 MMt CO2 about 14% below its peak. Notice there are two medium run trends in the data. The first trend from 1950 to 1979 carbon emission grew by 80% with average growth rate of 2.75%. The second from 1983 to 2007 carbon emission grew by 40% with average growth rate of 1.65%.

Figure (2.2) plots carbon intensity for 1950-2015. Carbon intensity declined from a level of approximately 0.001 metric tons of carbon dioxide (Mt CO2) per output[4] in 1950 to approximately 0.0003 Mt CO2 per output in 2015. Notice that declining carbon intensity

Figure 2.1: Carbon Emission Level, 1950-2015

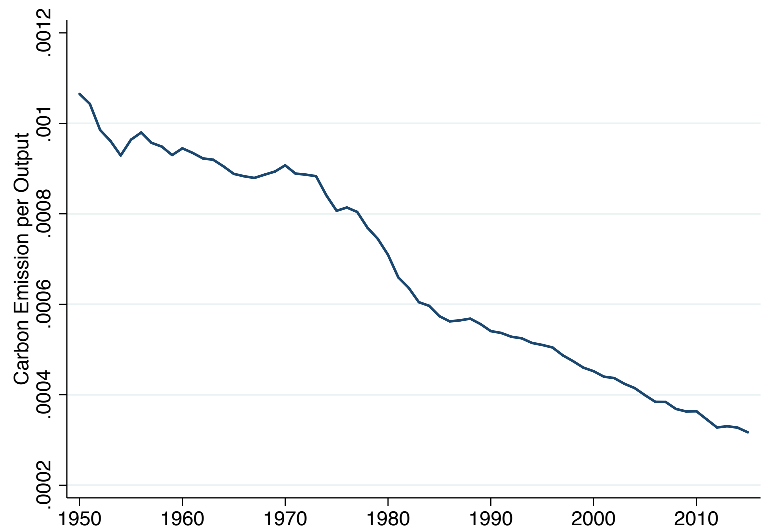


Note: Carbon emission data is in million metric tons of carbon dioxide (MMt CO2). The plot shows the increase in carbon emission up to mid 2000s. Carbon emission level per year data is from EIA Annual Energy Review and Monthly Energy Review.

[3] I only consider carbon emission from energy use. See EIA Annual Energy Review.

[4] Output is in US$ 2009

Figure 2.2: Carbon Intensity, 1950-2015



Note: Carbon intensity is carbon emission per output. Carbon emission is million metric tons of carbon dioxide (MMt CO2). Output is in million of US$ 2009. Carbon emission data comprises emisison from energy use. Data on emission is from Energy Information Agency (EIA) and data on output is from Bureau of Economic Analysis (BEA). See Appendix (1) for a further description of the data. Figure 2 shows the continuous decline in carbon intensity throughout the period.

happened throughout the period, but it was particularly fast during the period of high energy price from 1975 to 1985. The decline has averaged 1.82% per year for the entire period and 2.0% for 1985-2015 [5].

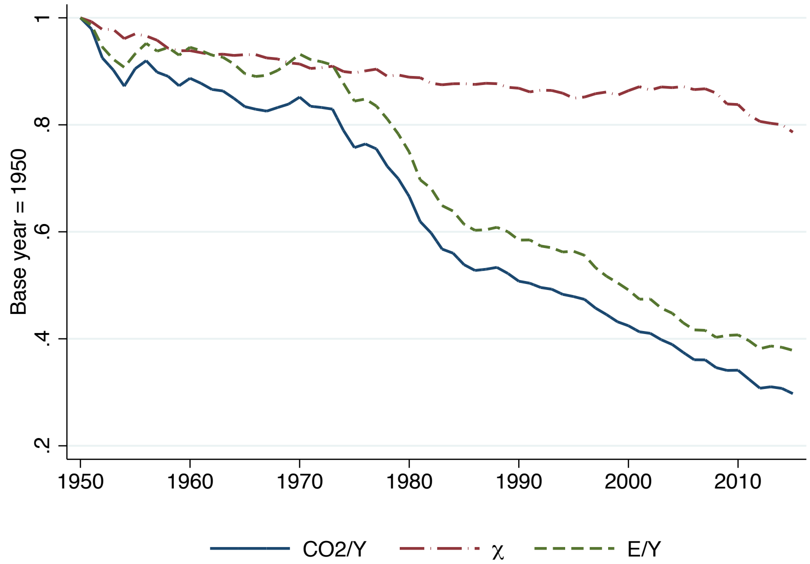
Now I will discuss the relation between carbon emission and energy use. Following Stefanski (2014), I consider the carbon-energy relation $\mathcal{P} = \chi \cdot E$ where $\mathcal{P}$ is carbon emission (pollution), E is total energy use and χ is the emissions per energy unit which is called 'energy impurity'. Given the data on carbon emissions and energy use, energy impurity can be calculated as a residual. Dividing both sides by output, carbon intensity is related to energy intensity and impurity:

$$\frac{\mathcal{P}}{Y} = \chi \, \frac{E}{Y}$$

Figure (2.3) shows that both energy intensity and energy impurity have fallen since 1950. Additionally, carbon intensity follows energy intensity dynamics very closely, particularly afther mid 1970s. In this carbon intensity decompostion energy impurity is a residual that captures changes in the energy source. A decrease in χ may represent a substitution among different fossil fuels or a substitution of energy production from fossil fuel for carbon free like nuclear or hydro. A decrease in the use of "dirty" coal with an equivalent increase in natural gas would be captured as a decrease in energy impurity since coal releases more carbon for

[5] For a discussion of carbon intensity since the early 1800s in the US, see Tol *et al.* (2009). For a discussion about the long run patterns of carbon intensity for different countries, see Stefanski (2014).

Figure 2.3: Carbon-Energy Decomposition, 1950-2015



Note: Figure (2.3) decomposes carbon intensity into energy intensity (E/Y) and energy impurity χ. The components are normalized for 1950 as base year. It illustrates that until mid 1970s energy intensity and energy impurity were important for the decline. After mid 1970s, carbon intensity and energy intensity are closely related.

the same amount of energy content [6]. This substitution between different fossil fuels may have a relevant impact on energy impurity because fossil fuel counts for more than 80% of US energy source. Substitution away from fossil fuel toward carbon free energy sources such as nuclear or hydro also decreases χ because there is no release of carbon as consequence of energy production.

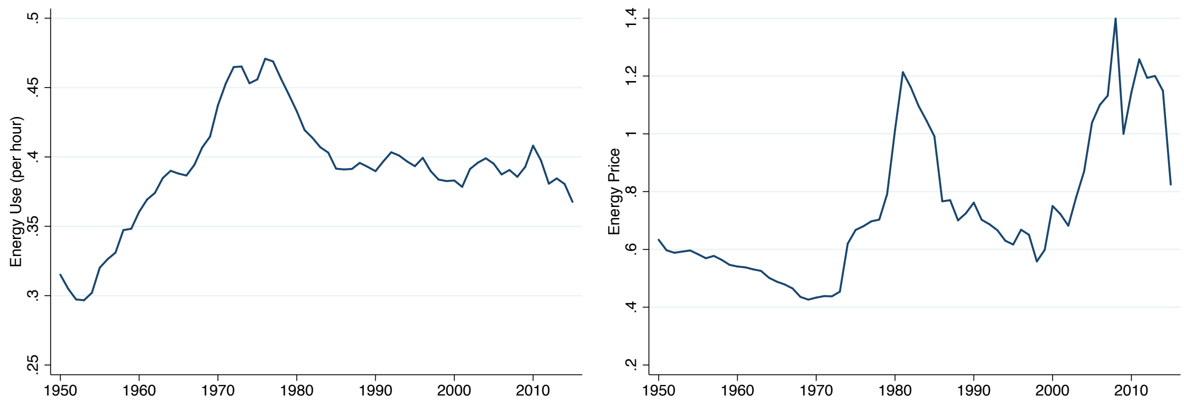
Figure (2.4a) shows energy use per hour. It increases up to mid 1970s, followed by a fast decrease until mid 1980s. Since then, it has only slightly declined. Notice that even though energy use per hour has been roughly constant, there has been output growth per hour during this period. The relationship of energy use per hour and energy price, at least until the mid 1980s, is apparent. Figure (2.4b) plots the price of energy. Evidently, energy price has large fluctuations in its price, oil in particular. Despite its large effects in the economy, the large increase in energy price of the 1970s is not the highest energy price for the 1950-2015 period. The peak actually happened in 2008 before the recent crisis.

Now I turn to the discussion of structural transformation. Structural transformation defined as the reallocation of production across the broad economic sectors agriculture (a), manufacturing (m) and services (s) is a well documented fact of economic growth. The two common measures of the structural transformation process are the shares of labor across

[6] According to the EIA, coal emits 205 pounds of CO2 per million Btu of energy while natural gas emits 117.

Figure 2.4: Energy Use and Energy Price

(a) Energy Use (per hour)   (b) Energy Price



Note: Panel (a) plots energy use (per hour). Energy use is in million Btu. Panel (b) plots the price of energy. Aggregate energy price is the ratio of energy use measured in current prices to energy use measured in constant price. A full explanation of the sources and methods used to construct the data is in Appendix 1.

sectors and value-added shares. Both measures display the same dynamics for the 1950-2015 period in the US: a decrease in agriculture and manufacturing, and an increase in services[7]. Because I am studying structural transformation from 1950-2015, I will aggregate both agriculture and manufacturing sector production and call it the goods sector (g) [8]. Figure (3.2) plots employment shares in the goods and services sectors over time. Employment share in the goods sector decrease from its peak level in 1950 of 38% to 13.8% in 2015. Equivalently, employment share in services increase from 62% to 86.2%. As the Figure (3.2) shows, the process of reallocation of labor among sectors has been continuous without any large change in the trends.

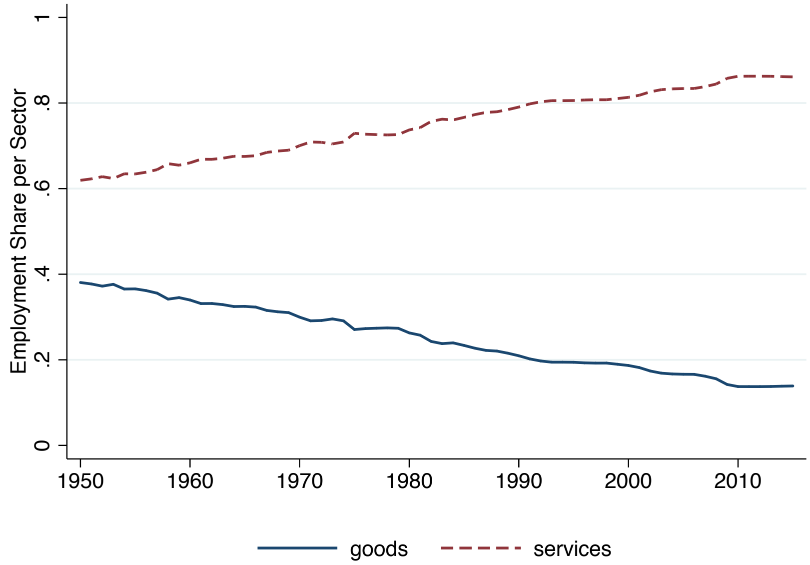
Another key feature of the data is the increasing trend in the price of services (p_s) relative to goods (p_g) since 1950. Figure (2.6a) plots the relative price normalized to one in 1950. There is a sharp drop in the trend during the 1970s, likely as consequence of the increase in energy price of the period. If goods are more energy intensive in production[9], then energy price changes have larger effect on the price of goods than on the price of services. At the same time, there is an increasing trend in the (real) value-added of services relative to goods. Given the relatively low export levels, this increase is associated with an increasing trend

[7]Strucutral transformation usual stylized facts are the continuous decline in agriculture, a hump shape in manufacturing and an increase in services. This pattern is also observed in the US for a longer period as discussed in Buera and Kaboski (2009). For a further discussion of the stylized facts, see Maddison (1980) and Herrendorf *et al.* (2014)

[8]See Appendix 1 for more details on data.

[9]Goods are actually more energy intensive in production. This will be further discussed in the next section.

Figure 2.5: Employment Share by Sector, 1950-2015



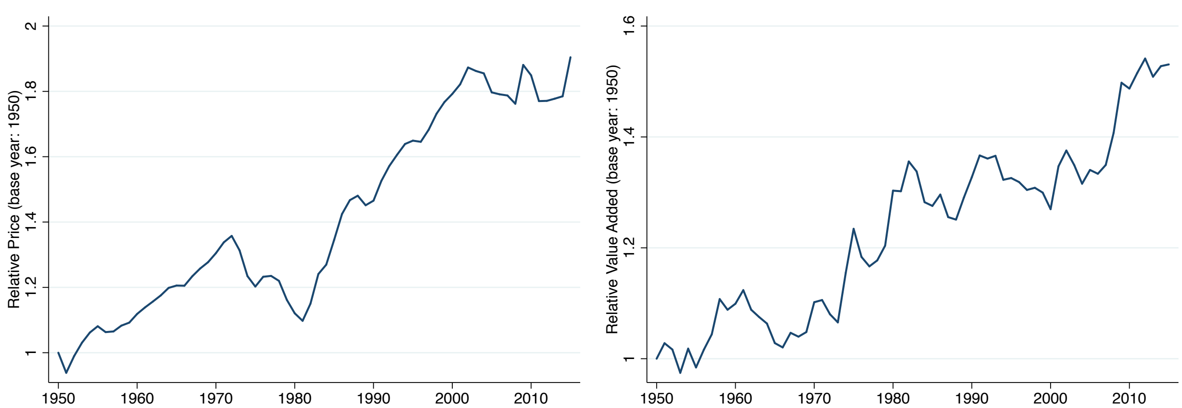
Note: The figure plots the employment share in the goods and services sectors. It shows the decline in the employment share in the goods sector and the increase in services. Employment shares are calculated using part time and full time workers from NIPA. See Appendix 1 for more details on the data.

in consumption of services relative to goods[10]. Notice that the increase in value-added of services relative to goods happens exactly in the sector with increasing relative price. These two facts together suggest that there is an increase in the consumption of services relative to goods whilst their relative price is increasing.

Figure 2.6: Relative Price and Relative Value-Added

(a) Relative Price

(b) Relative Value-Added



Note: Panel (a) plots relative price of services to goods p_s/p_g. Panel (b) plots the relative value-added of services to goods. Relative price is the value-added price index of services sector relative to price index of goods sector. See Appendix 1 for more details on the data.

[10]See Herrendorf *et al.* (2013) for further discussion on how much of value-added is used for consumption and how much is used for invesment.

2.3 Energy-Saving Productivity

For the period in analysis, a well known structural transformation fact is the fast growth in the goods sector productivity and the slow growth in services productivity [11]. Energy-saving productivity, on the other hand, hasn't received as much attention in the macroeconomic literature. To measure the energy-saving productivity, I assume that both sectors use a Leontief production function. One component is linear in energy use and the other is linear in labor. As discussed in the Introduction of the paper, previous studies have found very low elasticity of substitution between energy and other inputs of production[12]. The production function for the goods and services sectors is assumed to be, for each $i \in \{g, s\}$:

$$Y_i = \min\{A_i l_i, A_i^e e_i\}$$

where Y_i is output [13], l_i is labor input, e_i is energy input, A_i is sector specific labor productivity and A_i^e is sector specific energy-saving productivity. Using time series data on output, labor and energy inputs, the productivity levels A_i and A_i^e are computed as residuals [14] [15]. For ease of discussion, from now on I will refer to A as TFP and A^e as ETFP.

Figure (2.7) shows productivities A and energy-saving productivities A^e for both sectors (normalized by 1950). Both sectors TFPs look like the productivities patterns previously documented in literature and TFP in goods sector grows (much) faster than services. The average growth rates are 2.88% and 1.12% in the goods and services sectors respectively. The high growth rate in goods TFP is mainly consequence of the fast agriculuture sector TFP growth that in this period increased more than 9-fold. The ETFPs follow a different pattern from the TFPs. Figure (2.7b) shows that ETFPs were roughly constant up to mid 1970s and, since then, they have increased for both sectors with average growths of 2.3% and 1.83% for goods and services, respectively. [16]

Despite the higher growth rate of ETFP in goods sector, Figure (2.8a) shows that ETFP

[11] Maddison (1980) had already pointed out this fact. See Herrendorf *et al.* (2014) for a detailed discussion on productivity growth.

[12] Hassler *et al.* (2016a) estimates a CES production function of the form:

$$Y = \left[(1-\nu)(Ak^{\alpha}l^{1-\alpha})^{\frac{\varepsilon-1}{\varepsilon}} + \nu(A^e e)^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}}$$

The authores estimate ε equal to 0.0013. Ready (2016) and Stern and Kander (2012) also use a similar production function.

[13] Output Y is sector value-added plus expenditure in energy in 2009 dollars. The data is described in more detail in Appendix 1.

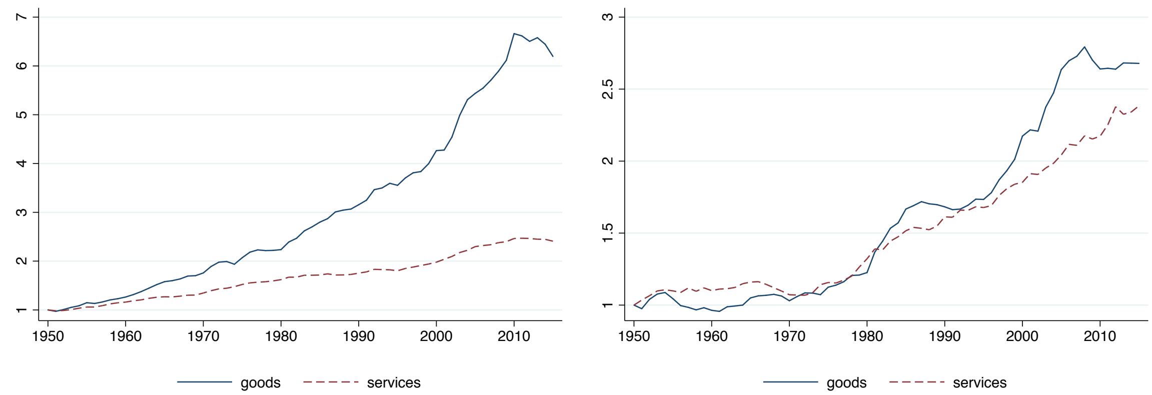
[14] A full explanation of the sources and methods used in the data construction is given in the Appendix

[15] For a further discussion on the properties of production functions and structural transformation, see Herrendorf *et al.* (2015).

[16] See Appendix 2 for aggregate production function TFPs and ETFPs.

Figure 2.7: Sector Productivities and Energy-Saving Productivities (normalized for 1950)

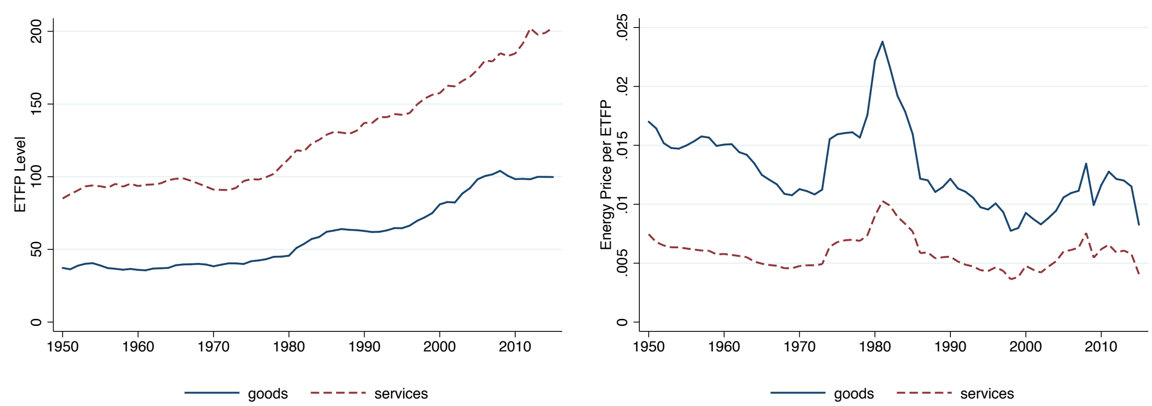
(a) Sector TFP A (b) Sector ETFP A^e



level in services is clearly much higher than in goods sector. Thus, in the services sector it is necessary less energy than in the goods sector to produce the same output. For comparison, services ETFP was about 2.8 times goods ETFP in 1950 and in 2010 it had decreased to about 2 times. Hence, for the same level of production, services required less than half of the energy level. Given the production function assumed, the energy cost for each unit of production is the energy price divided by its productivity p^e/A^e_i, as depicted in Figure (2.8b). Regardless of the high price of energy, the cost of energy to produce one unit of good or service is actually lower in 2015 than in the 1950s and 1960s because of the increase in ETFPs. In the goods sector it decreased from 0.017 in 1950 to 0.008 in 2015, and in the services sector from 0.007 to 0.004. For both sectors, the marginal cost of energy peaked in 1981, with a level more than the double of the 2015.

Figure 2.8: ETFPs and Energy per ETFP

(a) ETFP Level A^e (b) Energy Price per ETFP A^e



Note: Panel (a) plots energy-saving productivity A^e level by sector. In 1950, energy-saving productivity in services sector was 2.8 times in goods sector. In 2015, it was 2 times. Panel (b) plots energy price per sector energy-saving productivity, p^e/A^e. It represents the energy cost necessary for one unit of production.

2.4 Model

In the model, the economy has two sectors, each produces a different good – goods (g) and services (s) – at every period[17]. The representative firm of each sector uses labor and energy as inputs. Energy is imported from abroad at an exogenous world price p_t^e and paid with exports of ouput, assuming trade is balanced for each sector in every period. The representative household consumes goods and services, and supplies one unit of labor inelastically. The price of each consumption good is denoted by p_{it} and wage is w_t.

2.4.1 Production

Sector $i \in \{g, s\}$ produces output Y_i according to the Leontief production function discussed above:

$$Y_i = \min\{A_i l_i, A_i^e e_i\} \tag{1}$$

where Y_i is output, l_i is labor input, e_i is energy input, A_i is sector specific labor productivity and A_i^e is sector specific energy-saving productivity.

The firm in each sector behaves competitively in goods and inputs markets. At each period t, it takes price p_{it}, wage w_t, and energy price p_t^e as given and choose input demand $\{l_{it}, e_{it}\}$ to solve its static profit maximization problem:

$$\begin{aligned} \max_{\{l_{it}, e_{it}\}} \ & p_{it} Y_{it} - w_t l_{it} - p_t^e e_{it} \\ \text{s.t.} \quad & Y_{it} = \min\{A_{it} l_{it}, A_{it}^e e_{it}\} \end{aligned}$$

In every period energy is imported and paid for with output. The value of output produced equals the value used to pay for energy and the output sold to household:

$$p_{it} c_{it} + p_t^e e_{it} = p_{it} Y_{it}, \quad i \in \{g, s\} \tag{2}$$

Labor is assumed freely mobile between sectors and feasibility requires that in each period:

$$l_{gt} + l_{st} = 1 \tag{3}$$

Carbon emission is determined through the carbon-energy relation $\mathcal{P}_t = \chi_t \cdot E_t$ where $\mathcal{P}_t$ is carbon emission (‘pollution’), χ_t is energy impurity and $E_t = e_{gt} + e_{st}$ is total energy.

[17] Goods include the usually defined agricultural and manufacturing goods.

2.4.2 Household

The economy has a representative household that lives for infinite periods with preferences over consumption of goods and services:

$$\sum_{t=0}^{\infty} \beta^t \log(C_t)$$

where $\beta \in (0,1)$ is the discount factor and C_t is the consumption aggregator introduced by Pakos (2011):

$$C_t = \left[b\, c_{gt}^{\frac{\sigma-1}{\sigma}} + (1-b)\, c_{st}^{\frac{\sigma-\eta}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{4}$$

where $b \in (0,1)$, $\sigma \geq 0$ and $\eta \in \mathbb{R}$. Parameter η equals the ratio of period expenditure elasticity of goods and services, and it corresponds to homothetic preferences if $\eta = 1$. If $\eta < 1$, goods are income inelastic while services are income elastic. In this case, for a given relative price, as income grows, the demand for services increases more than the demand for goods[18].

Household income includes labor income and return on rented capital, which she spends on consumption and investment. So, the household budget constraint is:

$$\sum_{i \in \{g,s\}} p_{it} c_{it} = w_t \tag{5}$$

The household problem is to choose consumption of goods and investment that maximizes lifetime utility subject to the budget constraint.

Definition: Competitive Equilibrium
A competitive equilibrium is a sequence of prices $\{w_t, p_{it}\}_{t=0}^{\infty}$, household's allocation $\{c_{it}\}_{t=0}^{\infty}$, firm's allocation $\{l_{it}, e_{it}\}_{t=0}^{\infty}$, carbon emission $\{\mathcal{P}_t\}_{t=0}^{\infty}$ s.t. given energy price $\{p_t^e\}_{t=0}^{\infty}$:

(1) given prices, household's allocation solves its problem

(2) given prices, firms' allocations solve their respective problems

(3) resource constraints are satisfied

(4) labor market clears

(5) carbon emission dynamics from energy use

[18] This is the case consistent with what is observed in the data.

2.4.3 Characterization of Equilibrium

I focus on the case with production in the two sectors so that the solution to firm's problem is interior. Then, Leontief production function can be replaced by equality:

$$A_i l_i = A_i^e e_i \tag{6}$$

The static profit maximization problem of the firm can now be written as:

$$\max_{\{l_{it}, e_{it}\}} p_{it} A_{it} l_{it} - w_t l_{it} - p_t^e e_{it}$$
$$\text{s.t.} \quad A_{it} l_{it} = A_{it}^e e_{it}$$

From sector firm's demand of labor, after normalizing wages to $w_t = 1$, equilibrium prices are:

$$p_{it} = \frac{1}{A_{it}} + \frac{p_t^e}{A_{it}^e} \tag{7}$$

where, as usual, marginal revenue equals marginal cost. Notice that the marginal cost includes the extra cost of energy required to increase production; that is, the firm considers this additional cost of energy when deciding to increase its demand for labor.

Household sectoral consumption expenditure equals the value of sector production minus sector expenditure in energy:

$$p_{it} c_{it} = p_{it} Y_{it} - p_t^e e_{it} \tag{8}$$

Defining household consumption expenditure as $\omega_{it} = (p_{it} c_{it})/(\sum_i p_{it} c_{it})$ implies that:

$$\omega_{it} = l_{it} \tag{9}$$

that is, the share of household expenditure in consumption of sector i equals the labor allocation in the sector.

Now I turn to the household problem. The first order conditions determines the marginal rate of substitution between goods and services:

$$\frac{1-b}{b} \frac{\sigma - \eta}{\sigma - 1} \frac{c_{st}^{-\frac{\eta}{\sigma}}}{c_{gt}^{-\frac{1}{\sigma}}} = \frac{p_{st}}{p_{gt}} \tag{10}$$

As usual, the marginal rate of substitution equals relative price p_s/p_g. It reflects the substitution and income effects determining the relative consumption allocation for household[19].

[19]Note equation (10) can be rewritten as $c_{gt} = \left(\frac{p_s}{p_g}\right)^{\sigma} c_s^{\eta} \left(\frac{b}{1-b} \frac{\sigma-1}{\sigma-\eta}\right)^{\sigma}$.

2.5 Quantitative Analysis

In this section, I will use the model to analyze salient features of the U.S. data including labor allocation across sectors, energy use, relative price and relative consumption. In the counterfactual exercise, I use the model developed in the previous section to quantify the effects of energy-saving productivity in the economy. I then use the model to predict the impacts on introducing a tax on energy demand.

The parameters choice for the benchmark economy involves selecting values so that the benchmark model matches key features of the data. The model has only three parameters (σ, η, b) to be estimated. First, given values for σ and η, b is chosen to match the share of labor in the goods sector in 1950. Second, given a value of b, σ and η are jointly chosen to match as close as possible the labor shares. The values for σ and η are 0.15 and 0.45 respectively. Given the values of σ and η, $b = 0.00105$.

For the computational exercises, the TFPs A were normalized to one in 1950. The ETFPs A^e were adjusted such that the relative productivities A/A^e in each sector were equal to the data. The marginal cost of energy p^e/A^e were adjusted accordingly as well. After these normalizations, I feed the model with these productivities and the series of marginal cost of energy. Notice that the variables calculated in the model are normalized per hour worked.

2.5.1 U.S. Economy: 1950-2015

In this section I discuss the match of the model with the data. The model is able to generate an increase in the relative quantity consumed of services relative to goods c_s/c_g at the same time that relative price p_s/p_g increases. Figure (2.9) plots the results. This increase in relative consumption concomitant with the increase in relative price is only possible because household preference is nonhomothetic. To see why, consider the case in which household preference is homothetic $\eta = 1$. Given that the CES utility function is inelastic, i.e. $\sigma < 1$, nominal and real shares of consumption necessarily move in opposing directions. Consider an increase in the relative price. Because household has preference for balanced consumption, there is a nominal increase in the consumption of services[20] relative to goods whereas the consumption of services relative to goods decrease. So, preference featuring nonhomotheticity with (high) income effect is necessary to match the data. In the model, household preference has high income elasticity of services relative to goods and this is characterized by $\eta < 1$. Given an increase in aggregate consumption, consumption of services increases more than of goods. As a result, relative consumption c_s/c_g grows despite higher relative price p_s/p_g. Figure (2.9a) compares data (solid line) and model (dashed line)

[20] Nominal consumption is $p_i c_i$.

Figure 2.9: Relative Price and Relative Consumption

(a) Relative Price (b) Relative Consumption

Note: Panel (a) plots the relative price of services to goods p_s/p_g in the data and the model. The model closely matches the data, including the drop of the 1970s. Panel (b) plots relative consumption. In the model, the value of consumption in each sector equals its value-added. So, I compare model relative consumption to the relative value-added.

relative price, and model relative price closely matches the data. Notice that in the model, the value of consumption in each sector equals the value-added of the sector. For consistency between model and data, I compare model relative consumption to relative value-added in the data. For most periods, model relative consumption is a little higher than the data, but it follows the same pattern.

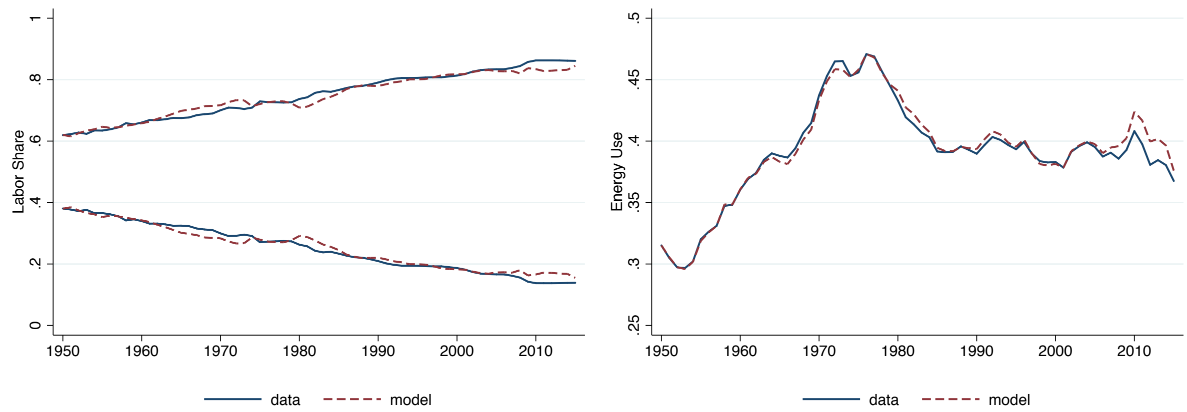
Figure (2.10) plots the shares of labor in the data (solid lines) and implied by the model (dahsed lines). The labor shares from the model closely match the process of structural transformation of the U.S. over the period. In the benchmark case, the model implies a decline in the share of labor in the goods sector from 38% in 1950 to 16.6% in 2015 whereas the share in the data is 13.9%. In the services sector, it increased from 62% to 83.4% in the model whilst in the data to 86.1%.

In Figure (2.10b), I compare energy use (per hour) implied by the model and the data. Because of the production function, energy use depends directly on the labor allocation. As a result of the good match of the model's labor allocation, it also closely reproduces aggregate energy use[21]. For the periods in which, labor allocated in the goods sector in the model is higher than in the data, the model also predicts energy use in the goods sector to be higher than in the data. Given that goods production requires more energy than services, a higher labor share in goods compared to the data overpredicts the energy use. The opposite happens if good's labor allocation in the model is lower than in the data. Only after 2003 there is a persistent discrepancy between model and data with energy use slightly higher

[21]From the production function assumption, energy use is just $e_i = (A_i/A_i^e)l_i, i \in \{g, s\}$.

Figure 2.10: Labor Shares and Energy Use

(a) Labor Shares (b) Energy Use



Note: Panel (a) plots the share of labor in each sector. The model closely matches the data. From 2005-2015 it slightly overpredicts labor share in the goods sector. Panel (b) plots the energy use. It also closely matches the data.

than in the data.

2.5.2 Counterfactual: The Role of Energy-Saving Productivity

In this section I discuss the impacts of energy-saving productivity growth in the U.S. economy. To quantify their effects, I consider the counterfactual case in which there is no growth in ETFP; that is, A_i^e, $i \in \{g, s\}$, are constant at their 1950 levels. The other exogenous variables, labor productivity A_i and energy price p^e, are asssumed to be as observed in the data[22]. I use this counterfactual to quantify the impact of ETFP in variables of interest such as relative price, labor allocation, aggregate consumption, energy use and to discuss the decline of carbon intensity.

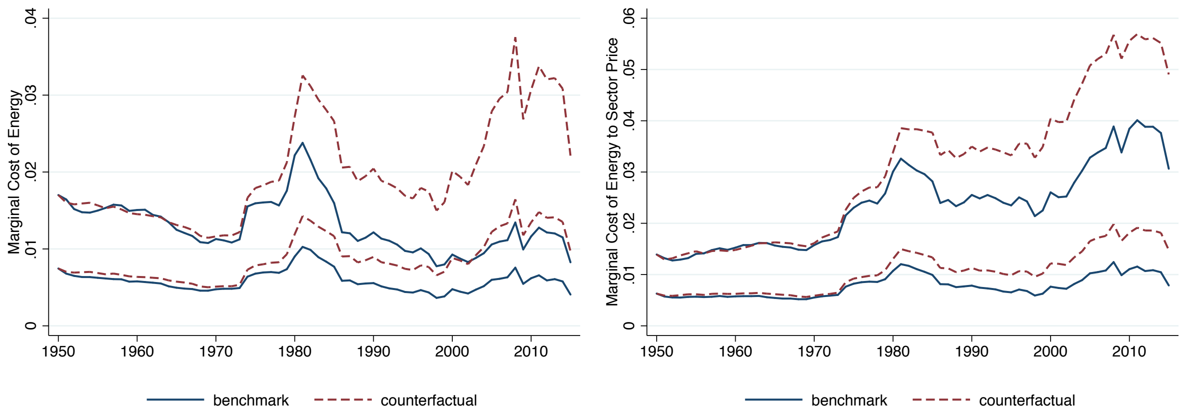
First, recall that sectoral prices p_i equals the marginal cost of labor per unit produced $1/A_i$ plus the marginal cost of energy p^e/A_i^e. If ETFP is higher, then an increase in energy price does not necessarily, or at least it has a small, impact the cost of producing an extra unit. However, if it is constant, then the increase in price has large effects on the cost of production and on sectoral prices. Figure (2.11) plots the marginal cost of energy for both sectors. In the benchamrk model[23] (blue solid line), the marginal cost of energy in the goods sector decreased from 0.017 in 1950 to 0.008 in 2015, less than half of the value despite higher energy price. In the benchmark model, the highest level occured in 1981, with the marginal energy cost equal to 0.023. In the counterfactual, this cost would be 0.022 in 2015

[22]Throughout the rest of the paper I will call the model allocation from previous section as benchmark model and the allocation from this section as counterfactual model.

[23]Noice that the marginal cost of energy p^e/A^e in the benchmark is equal to the data.

Figure 2.11: Counterfactual - Marginal Cost of Energy

(a) Marginal Cost of Energy (b) Marginal Cost of Energy to Price



Note: Panel (a) plots the marginal cost of energy p^e/A^e for each sector. Panel (b) plots the marginal cost of energy to sector price $(p^e/A^e)/p$. In the counterfactual case, the energy cost per unit relative to sector price increases considerably more in the goods sector than in the services. In both sectors, marginal cost of energy has a similar pattern, but price of goods decline faster than of services.

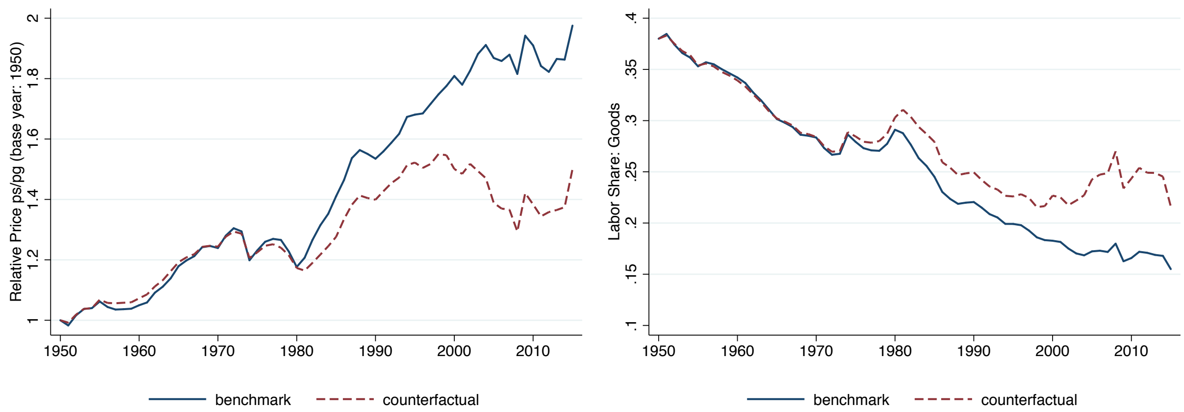
and 0.037 in 2008, the highest level. In 1981, the counterfactual value would be 0.023. In the services sector, it decreased from 0.007 in 1950 to 0.004 in 2015. In the counterfactual, the peak also occurred in 2008 with a level of 0.016. This large increase in energy marginal cost coincides with the peaks in energy prices. In Figure (2.11b), I compare the marginal energy cost relative to the sector price $(p^e/A_i^e)/p_i$. Despite the decrease in the marginal cost of energy, there is, in general, an increase in the marginal cost of energy relative to sector price. This is consequence of the decrease in the sector prices p_i. During the 2000s, the relative cost of energy was actually higher that in the early 1980s.

In Figure (2.12a), I compare the effects of ETFP on relative prices p_s/p_g. In the counterfactual, the increase of the marginal cost of energy is so large, compared to the increase in TFP, that it reverts the trend on relative prices. From the late 1990s until the mid 2000s, the price of services would actually decrease relative to goods. Notice that in the counterfactual, the sector prices are higher than in the benchmark case. To discuss the effects of ETFP, consider the goods sector. The constancy of A_g^e has different effects. First, goods price p_g is higher and household demand for goods is then lower. The higher price induces a decline of labor allocated to the sector. Second, given that an increase in price reduce household affordable consumption[24], nonhomotheticity parameter $\eta < 1$ implies an increase in the relative demand for goods. Third, the energy cost per unit relative to sector price grows; that is, it requires more goods to pay for the energy needed to produce an extra unit.

[24]Given the assumption that wage equals one in every period and labor equals one, income also equals one in every period $wl = 1$.

Figure 2.12: Counterfactual - Energy Price and Labor Shares

(a) Relative Price (b) Labor Share: Goods



Note: Panel (a) plots relative price of services with respect to goods p_s/p_g. Panel (b) plots the labor share allocated to the goods sector. In the counterfactual, the increase in energy price is large enough to increase goods price after 2000. This increase is so large that it actually reverses the process of structural transformation.

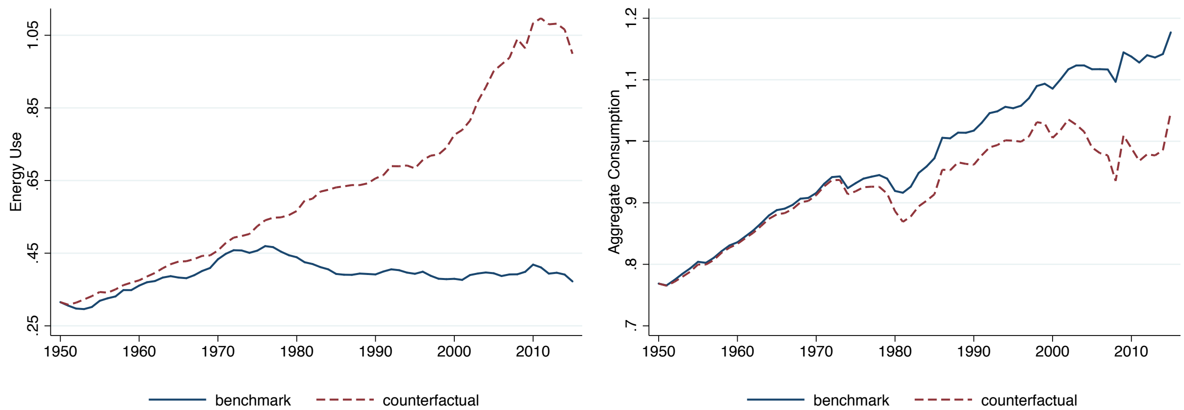
This effect also induces an increase of labor allocated to the goods sector. If the second and third effects dominate the first, the increase of goods price relative to services leads to an increase of labor allocated to the goods sector.

In the model, labor allocation equals expenditure share, from equation (9). Because of the preference for balanced consumption, $\sigma < 1$, expenditure share increases with price. That is, if the price of goods increases relative to services, as in the counterfactual after the late 1990s, then household expenditure share on goods increases. Consequently, labor allocated to goods production also increases. In the counterfactual, despite its small cost relative to labor, the increase in energy price is large enough that it changes the trend in relative prices p_s/p_g. As a result, it slows down the process of structural transformation and labor towards goods stays roughly constant after 2000. In 2015, labor share in the goods sector is 21.6% in the counterfactual compared to 15.5% in the benchmark. Therefore, ETFP is responsible for 6.1% of the decline in the labor share of goods.

The effect on energy use is clear from Figure (2.13a). In the counterfactual, energy use would be much higher, about 2.5 times the level observed in 2015. This high value is consequence of two effects. First, without improvements in ETFPs, each unit of production requires more energy. Second, more labor is allocated towards goods production compared to the benchmark case. Because goods production is energy intensive, both effects enforce each other and it generates such large increase in energy use. Figure (2.13b) plots aggregate consumption C. The effects are particularly large after the 2000s and confirm the welfare

Figure 2.13: Counterfactual - Energy Use and Aggregate Consumption

(a) Energy Use (b) Aggregate Consumption



Note: Panel (a) plots energy use is million Btu per hour. Energy increase up to mid 1970s and decreases afterwards. The model follows the pattern of the data. Model underestimates the data until 1998 and it slightly overestimates data afterwards. Counterfactual model indicates energy use would be much higher without energy-saving productivity growth. Panel (b) plots aggregate consumption is the level of C aggregated over consumption of goods c_g and services c_s. Aggregate consumption would be 6.2% lower in the counterfactual in 2015.

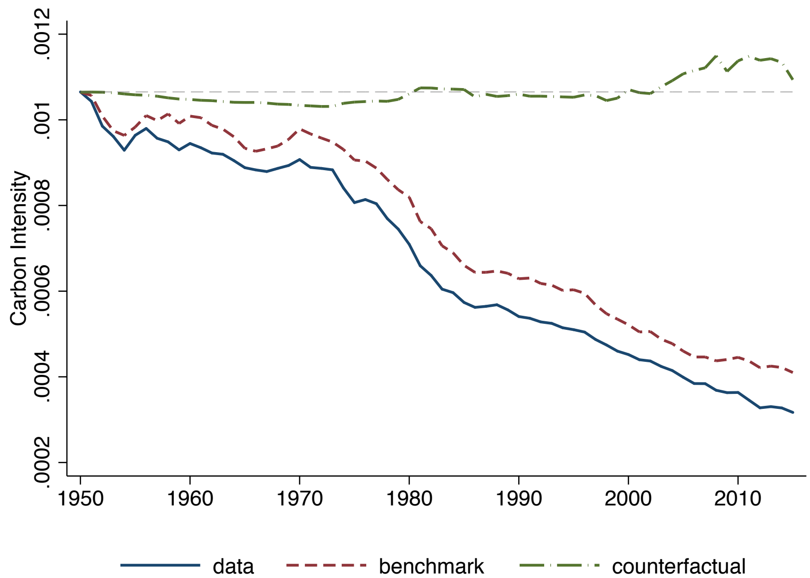
impacts of the increase in ETFP. In the counterfactual, aggregate consumption would be considerably lower, with 93.8% of the benchmark level. That is, ETFP is responsible for 6.2% of the aggregate consumption level.

I now use the model to account for the importance of ETFPs on the decline of carbon intensity. Figure (2.14) shows how well the model explains the decrease in carbon intensity and how much is due solely to the energy-saving productivities. First, I compute the carbon intensity from the benchmark model with energy impurity χ fixed at 1950 level. The difference between carbon intensity from the data (solid line) and from the model (dash line) is interpreted as the result of changes in energy impurity χ. Then, I compute carbon intensity in the counterfactual assuming energy impurity χ fixed at the 1950 level as well. The difference between the carbon intensity generated by the benchmark model and counterfactual (dot-dash line) represents the importance of ETFPs on the decline of carbon intensity. Notice that, without increasing ETFPs, carbon intensity would be much higher as consequence of the high energy use. In the counterfactual, aggregate carbon intensity can be written as:

$$\frac{\mathcal{P}_t}{Y_t} = \chi_{50} \frac{\frac{A_{gt}}{A^e_{g50}} l_{gt} + \frac{A_{st}}{A^e_{s50}} l_{st}}{A_{gt} l_{gt} + A_{st} l_{st}}$$

Because ETFP in the goods sector is lower than in the services sector, $A^e_g < A^e_s$, the difference of relative TFP growth, A/A^e, between goods and services is higher than the

Figure 2.14: Carbon Intensity Decomposition, 1950-2015



Note: Carbon intensity is carbon emission per output. Carbon emission is million metric tons of carbon dioxide (MMt CO2). Output is in million of US$ 2009. The solid line is carbon intensity from the data. The dashed line is carbon intensity from the benchmark model assuming energy impurity χ fixed at 1950 level. The dot-dashed line is carbon intensity from the model assuming energy impurity χ and energy-saving productivities A_i^e fixed at 1950 level. The difference between data and benchmark model represents the importance of energy impurity on the decline of carbon intensity. The difference between benchmark model and counterfactual represents the importance of energy-saving productivities on the decline of carbon intensity.

difference between TFP, A, growth. If labor shares were fixed at their 1950 level, energy use (numerator) would grow faster than output (denominator) and energy intensity would be higher. Therefore, carbon intensity increases if the difference of growth rates between relative TFP and TFP offsets the effect of labor reallocation.

Table (I) shows the average percentual explanation per period intervals. In 1974, carbon intensity had declined 21% compared to 1950. Of this decline, energy-saving productivities account for 12.6% (or 59.8% of the change). Structural transformation accounts for 2.5% (or 11.9% of the change). In 2015, carbon intensity had declined 70% compared to 1950. Of this decline, energy-saving productivities account for 61.25% (or 87.5% of the change). Structural transformation accounts for -3.8% (or -2.66% of the change). These negative values capture the increase in energy intensity.

Table I: Carbon Intensity Decomposition, 1950-2015

	1950-2015	1950-1974	1975-2015
Structural Transformation	3.9%	12.3%	-1%
Energy-Saving	71.5%	50.2%	83.9%
Energy Impurity	24.6%	37.5%	17.1%
	100%	100%	100%

Note: Table (I) shows how much of carbon intensity decline is explained by structural transformation, energy-saving productivity and energy impurity. The values are the average explanation for each period. The first column shows the average percentual explanation for the entire period. The second column shows the average for 1950-1974. The third shows the average for 1975-2015. After 1975, energy-saving productivity explains 83.9% of the decline in carbon intensity.

2.5.3 Policy Experiment

In this section I describe the effects of imposing a per unit tax on energy demand in 2016[25]. In the model, carbon emission is solely consequence of energy use. Therefore, a tax on energy demand is equivalent to imposing a tax on carbon emission. I consider different tax scenarios based on the social cost of carbon (SCC) provided by the Energy Information Agency (EIA). To perform this policy exercise, I assume a future behavior for the exogenous variables of the model from 2016 to 2050. These variables are the future paths of TFPs, ETFPs, energy price and energy impurity χ. I assume both the TFPs and ETFPs grow at their 1975-2015 average growth rates. The TFPs average growth rates were 3% and 1.46% in goods and the services, respectively. From 1975-2015 ETFPs growth rates were 2.21% and 1.84%. The price of energy is assumed to grow at 2% per year.

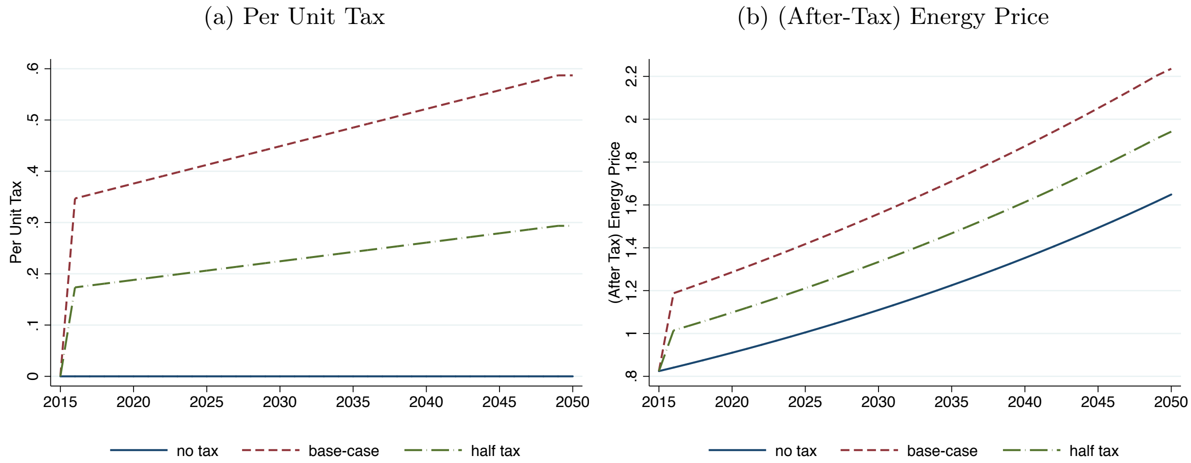
Let τ be a per unit tax implemented on energy demand. The price in sector $i \in \{g, s\}$ is now:

$$p_{it} = \frac{1}{A_{it}} + \frac{p_t^e + \tau_t}{A_{it}^e}$$

Figure (2.15a) plots the different tax scenarios. The base-case per unit tax is calculated using the amount of CO2 per unit of energy (million of Btu) and the SCC of a ton of CO2 provided by EIA. I first calculate the amount of CO2 per unit of energy (million of Btu) using a predicted energy impurity χ. Energy impurity χ is assumed to decrease at its declining average rate of 1.77% per year. Given the amount of CO2 (in tons) in an unit of energy, I set the per unit tax equal to the SCC in an unit of energy. For the exercise, I use the SCC

[25] It is instructive to make a comment on theoretical aspects of the model. In the model, carbon emission is only a byproduct of energy use and generates no externality. This assumption is motivated by the focus on the carbon emission determinants and not on the optimal policies to cope with potential negative effects. As consequence, first welfare theorem holds in the framework and, on the grounds of the model, there is no motivation for policy implementation with the objective of achieving a Pareto superior allocation.

Figure 2.15: Energy Tax and After-Tax Price

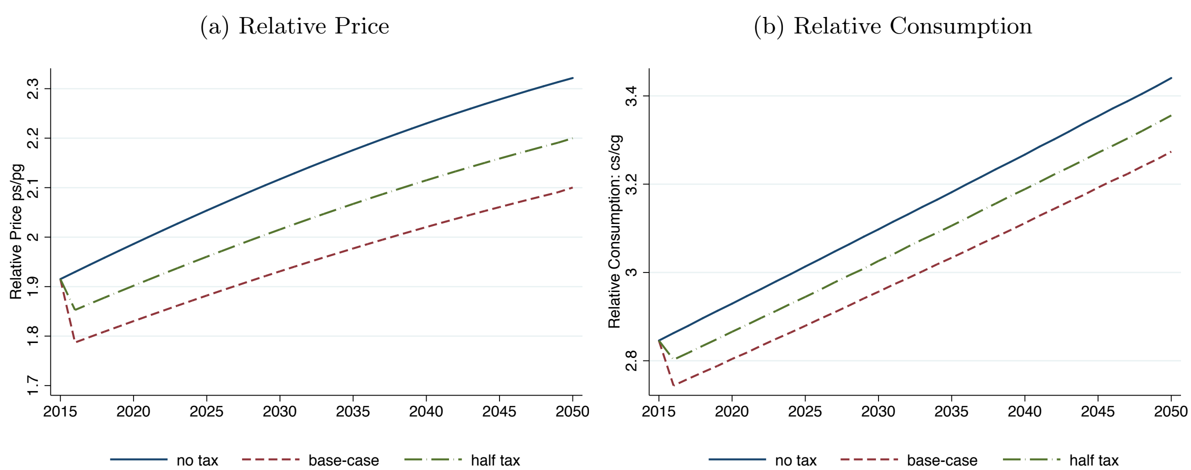


Note: Panel (a) plots the per unit tax τ. Panel (b) plots the (after tax) energy price $p^e + \tau$. The per unit tax equals the SCC per energy. See text for details on how τ is calculated. Energy price is assumed to increase 2%.

associated with discount rate of 2.5% and value of \$56 per ton of CO2 in 2015. For the years that the SCC were not provided, I linearly interpolated the values. The base-case tax generates a 41.2% increase in the after-tax energy price. I also consider the case in which the tax is set to half of the base-case. Figure (2.15b) plots the associated paths of after-tax prices.

The tax on energy demand increases the price of both goods and services and, as consequence, demand for both falls. Because income is normalized to one, $wl = 1$, the quantity

Figure 2.16: Relative Price and Relative Consumption



Note: Panel (a) plots the relative price of services with respect to goods p_s/p_g. Panel (b) plots the relative consumption c_s/c_g.

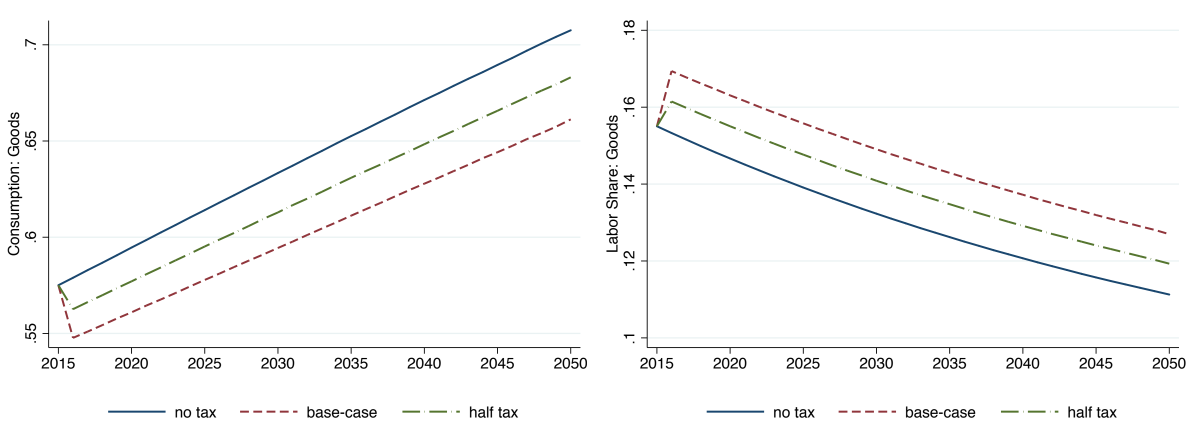
of affordable consumption is now lower. First, the production of goods has higher marignal cost of energy p^e/A_g^e, the price of goods p_g increases more than the price of services p_s. So, the relative price p_s/p_g falls and substitution effect implies a decrease in the demand of goods relative to services. Second, because services is income elastic, the decrease in demand for services is larger than for goods. Given that goods and services are very complementary in consumption and services has high income elasticity, the income effect dominates substitution effect and relative demand for services, c_s/c_g, decreases.

As production in the goods sector is more energy intensive[26], the per unit tax impacts more the costs of production in the goods sector than in the services. Figure (2.17b) plots labor share in the goods sector. Notice that l_g increases and, as direct consequence, it decreases in services. Because after-tax goods consumption c_g is lower, this increase of labor is solely to finance the after-tax higher energy costs. In the services sector, even though labor l_s decreases, because consumption of services also falls, labor allocated to finance energy expenditures has also increased. As the tax impacts the cost of production, both sectors require more labor just to finance the higher costs. In both sectors, more output $p_i A_i l_i$ will be necessary to pay for a given level of energy use. Therefore, firms in both sectors will demand more labor just pay for this higher energy cost.

The fall in after-tax relative price p_s/p_g causes an increase in the expenditure share of goods because of the complementarity in consumption. In terms of the model, this increase in expenditure share has a one-to-one relationship to the labor share the goods sector, that can be seen from equation (9). So, for given levels of TFP and ETFP, imposing a tax on

Figure 2.17: Consumption and Labor Share: Goods

(a) Consumption: Goods (b) Labor Share: Goods



Note: Panel (a) plots the consumption level of goods c_g. Panel (b) plots the price of goods p_g.

[26] Notice that energy intensity of production is simply the inverse of ETFP, $e_i/Y_i = 1/A_i^e$.

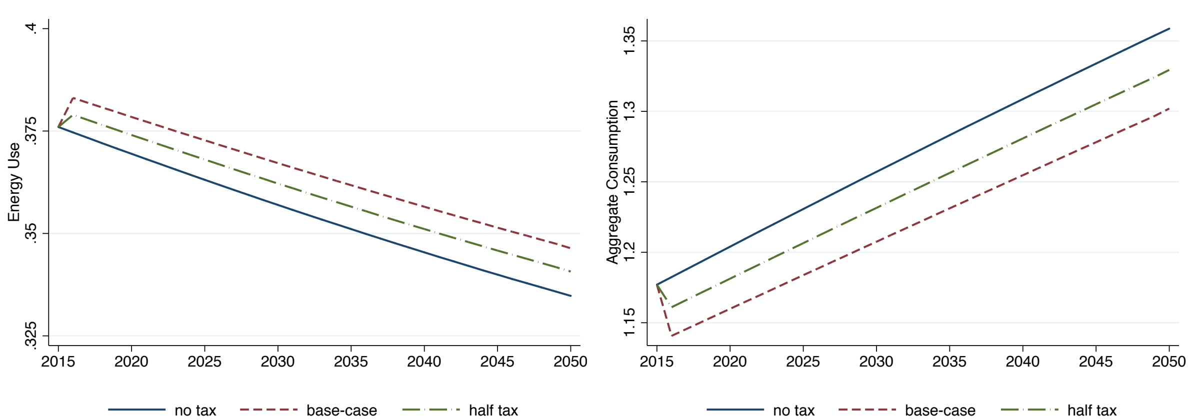
energy demand actually increases the allocation of labor in the energy intensive sector.

Figure (2.18) plots energy use for the different tax scenarios. Note that energy use actually increases despite the fall in demand for goods and services. This increase comes from higher production in the goods sector. In the first period, total energy in the base-case is 1.88% higher than the no tax case. After the first period, energy use falls, but at a higher level compared to the no tax case. Because both the consumption of goods c_g and services c_s fall, aggregate consumption also decreases. In the first period, aggregate consumption is 3.5% lower compared to the no tax case in the first period and it only achieves the 2015 level again in 2025.

Notice that in the model income is normalized to one since $wl = 1$ for every period. So, the dynamics of the model should be interpreted with respect to a given level of income. The result above states that, for a given level of income, more energy is used after the tax is imposed. It calls attention to the fact that the U.S. economy is in a process of transition from goods production towards services production. The tax on energy demand postpones this reallocation away from the energy intensive goods sector. The argument relies crucially on the low substitutability of consumption and the perfect complementarity of the production function. The high complementarity implies that changes in relative prices have little effect on relative consumption choice of household. As a result, the high income elasticity of services relative to goods is predominant effect on allocation. Another aspect of the result worth mentioning is the assumption of exogenous growth rates for energy-saving productivity. Changes in energy price does not affect firm's incentives to decrease its use,

Figure 2.18: Energy Use and Aggregate Consumption

(a) Energy Use (b) Aggregate Consumption



Note: Panel (a) plots the energy use e. Panel (b) plots aggregate consumption C. The tax generates an initial increase in energy use and an initial decrease in aggregate consumption.

unless through reduced production. But, given the timing of the increase in energy-saving productivity and the large increase in energy price throughout the 1970s, the two are likely related.

2.6 Conclusion

The U.S. economy has passed through large reallocation of production and employment among different sectors since 1950. In this paper, I study the impacts of energy-saving productivity from the lens of a structural transformation model. I use the model to isolate the effects of energy-saving productivity in the decline of labor in the goods sector, its impact on aggregate consumption and how much it is responsible for the decline in carbon intensity. I find that energy-saving productivity is responsible for 6.1% of the decline in labor share in the goods sector. I also find that if there was no growth in energy-saving productivity, aggregate consumption would be 6.2% lower. In addition, I find that energy-saving productivity explains most of the decline in carbon intensity. I also use the mode to study the effects of imposing a tax on energy demand.

An interesting extension is to endogeneize energy-saving productivity through a price-induced technical change mechanism. This would allow to better predict its future behavior and, as consequence, the future path of carbon emission under different economic growth scenarios. In addition, an endogenous energy-saving productivity model would allow to improve the design of policies that could potentially accelerate its growth. For example, I have assumed that energy-saving productivity is independent of energy price. But, if there is a positive relation, the efficacy of an energy tax would be higher because it would also accelerate the growth in energy-saving productivity. Recent work by Hassler *et al.* (2016) has introduced endogenous change in energy-saving productivity in a one sector framework.

Chapter 3

Structural Transformation and Labor Productivity in Brazil

3.1 Introduction

The Brazilian economy has undergone substantial transformations in the last six decades. Labor has reallocated away from agriculture and towards manufacturing and services. Alongside this structural transformation, the Brazilian economy experienced both periods of booms and busts. In this paper, we study the behavior of labor productivity (here defined as output per worker) in Brazil considering the varying levels of economic growth and the structural transformation process.

Due to the disparity in economic performance, the natural approach to study the Brazilian economy in the past 60 years is to analyze its performance in two sub-periods, 1950-1980 and 1980-2010. While during the first sub-period the Brazilian economy was booming, during the second it could barely keep the gains from the previous years. From 1950 to 1980, Brazil was a fast-growing economy with labor productivity increasing by more than 3-fold. Brazil seemed to be in the process of catching up with the most developed economies. In particular, its output per worker relative to that of the U.S. raised from 19.4% to 27.5%. However, in the second sub-period, Brazil experienced a recession followed by a slow growth phase. GDP growth rates plummeted and the labor productivity gap with the U.S. increased. During this sub-period, the economy was falling behind the U.S. and, by 2010, Brazilian output per worker was equivalent to 20% of the American one.

The 1950-2010 period is also characterized by the monotonic decline of the share of labor in agriculture and the monotonic increase of the share of labor in services. Labor share in manufacturing increases in the first sub-period and decreases in the second. While, the catching up phase coincides with the increase in manufacturing labor share, the falling behind phase coincides with the decrease in manufacturing. This association between the economy's performance and manufacturing figures constantly in academic and public discussions. A recurring issue is what public policies could do to reverse this decline of manufacturing labor share. The appropriate answer depends on what is driving this process. To help shed some light in this debate, this paper discusses the main forces behind the process of structural transformation and their impacts on aggregate productivity in the Brazilian economy. Theories of structural transformation approach it using supply and demand drivers, and we build a structural transformation model able to decompose the contribution of these two drivers[1].

More specifically, we use a standard structural transformation model with three sectors – agriculture, manufacturing and services – and assume household preferences are nonhomothetic. Nonhomotheticity implies that changes in income will lead to changes in expenditure

[1] And also the contribution of the wedges (distortions).

shares even if relative prices are constant[2]. Household preferences are represented by the implicit nonhomothetic constant elasticity of substitution (CES) utility function introduced in the structural transformation literature by Comin *et al.* (2015). This utility function is particularly suitable in the context of this paper because it generates nonhomothetic demand for every level of income. Given the large increase of income in the Brazilian economy throughout the period, the property of constant income elasticity helps to match the model to the data. This utility function contrasts with the commonly used generalized Stone-Geary class of utility functions (Kongsamult *et al.*, 2001, Dennis and Iscan, 2007, and Herrendorf *et al.*, 2013) that generates nonhomothetic effects by imposing subsistence (or endowment) levels. These exogenous subsistence levels generate large nonhomothetic effects for low levels of income, but these effects vanish as income grows. As a consequence, these preferences are asymptotically homothetic. In addition, the implicit nonhomothetic CES has the property that the elasticity of substitution between the consumption goods does not depend on their income elasticities, a property unique to this utility function[3].

In our estimation, we find that households have a preference for balanced consumption; that is, the different consumption goods are complements. This complementarity implies that the expenditure share of a good increases with its price and, as a consequence, labor moves towards the sector with increasing relative price. Another finding of our estimation is that manufacturing has higher income elasticity of demand than agriculture and lower income elasticity than services. Thus, following an increase in income, consumption of services increases more than consumption of manufacturing goods, and both services and manufacturing consumption increase more than agricultural consumption. This estimation result is in line with the literature on structural transformation.

Our simulated economy is able to successfully replicate the labor shares dynamics and the aggregate labor productivity for the entire 1950-2010 period. In particular, our model reproduces the hump-shaped labor share of manufacturing and the behavior of the labor share in agriculture and services. Moreover, our simulated economy mimics the data displaying the two marked sub-periods: the first one in which aggregate productivity exhibits strong growth, and the second in which it stagnates.

We also use the model to gain further insights about the main mechanisms driving the structural transformation process in Brazil. Our main contribution is to decompose the sources of labor reallocation. To do so, we adapt the methodology from Chari, Kehoe and McGrattan (2007) and use the model to quantify how much of the variation in labor shares

[2] An example of nonhomothetic behavior is the empirical fact that the richer the households are, the smaller is their expenditure share with agricultural goods, despite the decline of its relative price.

[3] Among those used in the structural transformation literature, to the best of our knowledge.

can be accounted for by income growth, relative price changes and wedges[4]. We find that during the first sub-period, income growth is responsible for basically all the reallocation of labor. During the second sub-period, changes in relative prices become the main driver of structural transformation, though income growth is still quantitatively relevant. For both sub-periods, the sectoral wedges had only a small impact. We emphasize that decomposing the forces that drives the reallocation of labor between income growth, changes in relative prices and wedges is only possible because the elasticity of substitution and income elasticities are independent[5].

Finally, we perform three counterfactual exercises by varying sectoral labor productivity and wedges. First, we ask how the Brazilian economy would have behaved if manufacturing productivity had grew at the U.S. growth rates to evaluate the importance of labor productivity in the manufacturing sector. Between 1950 and 1980, manufacturing labor productivity in Brazil grew faster than in the U.S. and, also, than in agriculture and services sectors. Between 1980 and 2010, however, manufacturing productivity grew only slightly. We find that aggregate productivity would be 15.3% lower than observed in 1980 and about the same level in 2010. In the second counterfactual, we ask how the Brazilian economy would have behaved if services productivity was constant at its 1980 level. From 1980 to 2010, the behavior of services productivity was disastrous, declining to a level close to the one observed in 1950. We find that aggregate productivity in 2010 would be 28.8% higher than in the data. In our last counterfactual exercise, we assess the importance of the wedges, here measured as the distortions in labor demand. We find that the manufacturing wedge has limited effect in the allocations of the model and, although the services wedge has a larger effect, it is still modest compared to the effects of productivity and income growth.

This paper closely relates to a vast structural transformation literature that goes back to Kuznets (1957), who documented the levels and trends of value-added and employment shares across different sectors of the economy. Since then, numerous studies have examined the role of labor productivity across sectors and that of productivity differences across countries to explain the process of structural transformation. Some of these theories rely on unequal productivity growth across sectors and their effects on relative prices. A few examples are Baumol (1967) and Ngai and Pissarides (2007). Another branch of the literature assesses the importance of nonhomotheticicities in the growth process such as Echevarria (1997) and Kongsamut *et al.* (2001). Most of the papers consider supply and demand drivers of structural transformation in their framework such as Dennis and Iscan (2009), Buera and

[4] In this paper, wedges are distortions in the demand for labor that account for the differences between the model labor allocation and the data.

[5] Notice that the Stone-Geary preferences do not have this property. Under these preferences, the elasticity of substitution depends on the income elasticities that change with income.

Kaboski (2009), Duarte and Restuccia (2010), and Herrendorf *et al.* (2014), just to cite a few. Our paper combines the sectoral production structure used by Duarte and Restuccia (2010) with the nonhomothetic CES utility function used by Comin *et al.* (2015)[6].

The subset of this literature that specifically studies structural transformation in Brazil is especially relevant for our paper. The work of Ferreira and da Silva (2015) that studies the process of structural transformation for a group of Latin American countries, including Brazil, is the paper most closely to ours. They find that services labor productivity explains a sizable portion of the economy's stagnation of the later decades. The main difference between our paper and Ferreira and da Silva's is the decomposition of the sources of labor reallocation. Firpo and Pieri (2013) focus solely on the Brazilian economy and find that labor reallocation was the main force behind the economic growth between 1950 and 1970. After this period, the authors find that most of the increase came from within-sector component. Finally, Cai (2015) quantifies the role of labor market distortions in four countries (Brazil, India, Mexico, and the U.S.) and finds that Brazil has the largest frictions in all sectors. However, he concludes that improving labor market efficiency contributes little to the reallocation of labor. The measured distortion for Brazil contributed only to a 1% faster decline in the share of labor in agriculture.

The rest of the paper is organized as follows. Section 3.2 contains the main stylized facts on growth and structural transformation in Brazil. Section 3.3 develops the model and explains its main properties and the parameters selection. Section 3.4 presents and discusses the results for our benchmark economy. Section 3.5 measures the distortions in the Brazilian economy and section 3.6 performs the decomposition exercise. Section 3.7 analyzes the importance each sector's labor productivity to overall aggregate productive by means of counterfactual exercises. Section 3.8 concludes.

3.2 Data and Facts

In this section, we document the stylized facts of the structural transformation process in Brazil from 1950 to 2010. We use the Groningen Growth Development Centre 10-Sector Database for sectoral value-added and employment data. This database defines each sector of economic activity according to the international standard industrial classification of economic activities of the United Nations (ISIC 3). Using these data, we construct production and labor input series for our three broad sectors – agriculture, manufacturing, and services[7].

[6] After Comin *et al.* (2015), Buiatti *et al.* (2017) also used the implicit nonhomothetic CES to study the process of structural transformation and services productivity differences between the U.S. and Europe.

[7] Agriculture corresponds to ISIC code AtB (agriculture, forestry, hunting and fishing), manufacturing to C-F (mining and quarrying, manufacturing, construction and, electricity, gas and water supply), and services correspond to all the other sectors.

We then incorporate population data from the Penn World Tables version 9.0 (PWT) and real GDP per capita from the Maddison project[8] into our time series dataset. All data have been filtered using the Hodrick-Prescott filter with a smoothing parameter equal to 100.

3.2.1 An Overview of the Brazilian Economy

From 1950 to 1980, Brazil experienced a fast paced labor productivity growth, measured as output per worker[9]. In 1950, output per worker was $5,704 (in 2005 local prices) and in 1980 it had more than tripled to $19,216. Then, from 1980 to 2010, the Brazilian economy was characterized by a decade-long recession[10] where output per worker declined through the mid 1990s and a slow recover afterwards. As a result, output per worker in 2010 was $19,931, only slighlty higher than in 1980. Figure (1a) plots output per worker for 1950-2010 in 2005 local prices. The graph illustrates the fast growth pre-1980s and the stagnation post-1980. In particular, aggregate labor productivity only reached its maximum 1980s level again in 2008. The Brazilian output per worker grew at a 4.04% annual rate on average in the first sub-period and a modicum 0.16% rate post-1980(see Table (I)).

The fast increase of aggregate productivity growth from 1950 to 1980 narrowed the gap between the Brazilian and the American productivities, as displayed in Figure (3.1b). In 1950, the Brazilian GDP per worker was equivalent to 18.6% of that in the United States. By 1980, this ratio increased 1.4-fold and the Brazilian GDP per worker was 26.7% of the American one. In the following years, however, the Brazilian economy lost some of the gains conquered in the first sub-period and had its GDP per worker relative to the U.S. reduced

Table I: Output per Worker in Brazil

Period	first and last years levels (2005 local prices)	annual growth rate (period average)
1950 - 1980	5,704 - 19,216	4.04%
1980 - 2010	19,216 - 19,931	0.16%
1950 - 2010	5,704 - 19,931	2.08%

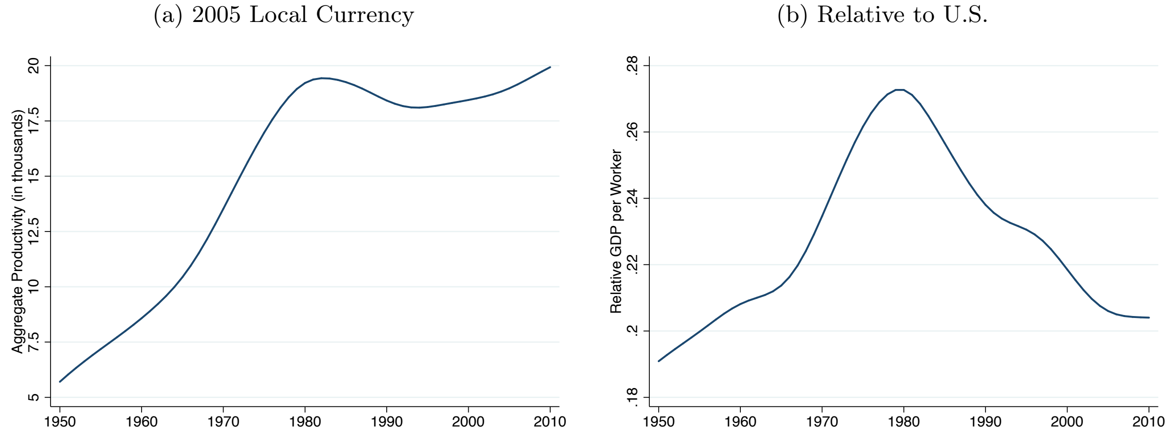
Note: Table (I) shows output per worker growth in Brazil. It shows the first and last year levels and growth rate per period. Output per worker and employment data were calculated using Groningen 10 sector database.

[8] The real GDP per capita is in 1990 Geary-Khamis international dollars.

[9] Following the literature on structural transformation in Brazil, such as Ferreira and da Silva (2015), we adopt output per worker as our productivity measure due to the unavailability of data on hours worked by sector.

[10] Brazil experienced a depression, as defined by Kehoe and Prescott (2002); that is, a large and persistent deviation of aggregate output per working-age person from its trend, such that it falls at least 15% within the first decade and remains at least 20% below trend. For more on the Brazilian depression of the 1980s, see Bugarin *et al.* (2007).

Figure 3.1: Brazilian GDP per Worker



Note: Panel (1a) displays the value-added per worker (2005 local currency, in thousands). Panel (1b) displays the value-added per worker in Brazil relative to the U.S.

to 20% by 2010.

The behavior of the Brazilian economy throughout these 60 years follows a pattern common to most Latin American countries. In a first phase, these economies were taking off into growth and benefiting from worldwide trends such as a more urban population, lower dependence on agriculture, and increased educational attainment levels. However, in a second phase, these economies fell behind and were unable to keep catching up with the U.S. economy (Costa, Kehoe, and Raveendranathan, 2016).

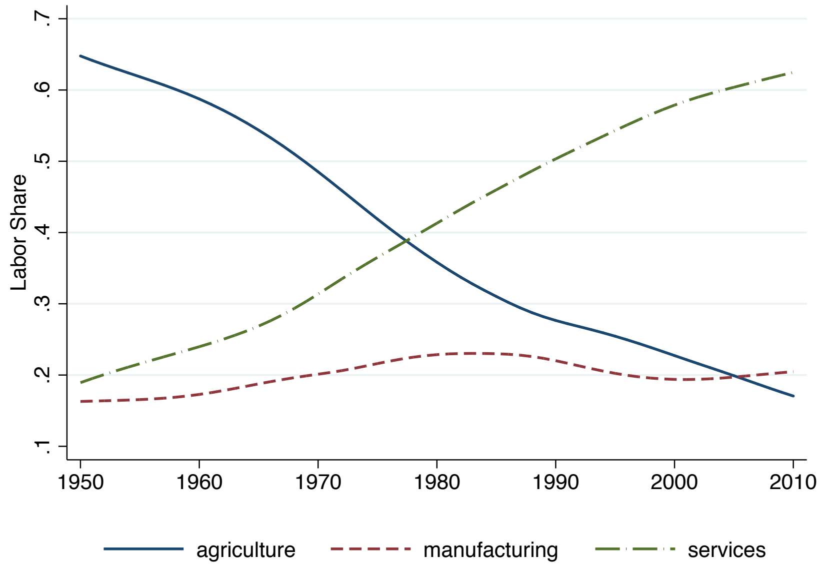
3.2.2 Structural Transformation

The reallocation of economic activity across sectors that accompanies economic growth characterizes the process of structural transformation. Two common measures of economic activity at sectoral level are employment shares or value-added shares. The stylized facts of structural transformation are the decline in agriculture employment share, a hump shape in manufacturing and an increase in services through time. At initial development stages, labor is reallocated from agriculture towards manufacturing and services. Then, as the economy develops, from agriculture and manufacturing towards services[11]. Figure (3.2) exhibits the evolution of the labor reallocation process in Brazil.

In 1950, 65% of the Brazilian labor force worked in the agriculture sector, 16% in the manufacturing sector, and the remaining 19% in the services sector. The share of employment in manufacturing reached its peak of 23% in 1983, and then it started to decline,

[11]For a further discussion on the stylized facts, see Maddison (1980) and Herrendorf, Rogerson and Valentinyi (2014).

Figure 3.2: Share of Employment by Sector in Brazil



granting its characteristic hump-shaped pattern. Notice that, in 1983, the employment share in services was already above that of agriculture, 42% and 35%, respectively. In the last year of our data series, 2010, Brazil had 17% of its labor force in agriculture, 20% in manufacturing, and 63% in services.

Although Brazil presents the main characteristics of structural transformation processes common to many other countries, it has its peculiarities. Herrendorf *et al.* (2014) document that the employment share in manufacturing peaks at a GDP per capita of around $8,100 (1990 international dollars)[12] for both rich and poor countries, a level that Brazil has yet to achieve. As a comparison Table (II) shows the characteristics of Brazil and the United States in the year that each country reached their manufacturing employment share peak. We also include Herrendorf *et al.* (2014) estimates for a pool of 103 countries in the last column as a proxy for the rest of the world (RoW).

Throughout the structural transformation process, value-added paths mimic the behavior of sectoral labor shares–a sharp decrease in agriculture, a hump shape in manufacturing, and an increase in services. Herrendorf *et al.* (2014) also show that services value-added share accelerates once GDP per capita reaches the $ 8,100 (1990 international dollars) level and the share of manufacturing value-added peaks. But another striking characteristic of the Brazilian structural transformation process are the nearly constant shares of value-added by sector, depicted in Figure (3.3).

[12] Also known as Geary-Kahmis dollar, which reflects the current year's exchange rate with current PPP adjustments.

Figure 3.3: Share of Real Value-Added by Sector in Brazil

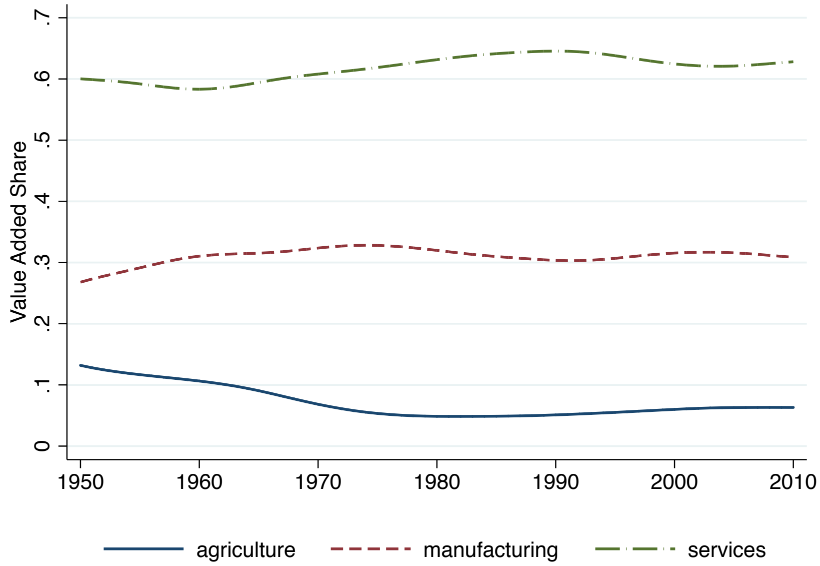


Figure (3.4) shows labor productivity level by sector. Until mid-1980s, labor in the services sector was the most productive of the economy. Manufacturing labor productivity caught up with services' productivity in 1987, five years after the manufacturing employment share peak. Note that this change is mostly due to the falling services labor productivity, rather than an improvement performance of manufacturing productivity. In fact, in 1987, manufacturing productivity was declining when it first became more productive than services. And after a good performance of the 1990s, manufacturing productivity was mostly constant during the 2000s.

Figure (3.5) compares labor productivity growth by sector for Brazil and the U.S.. In both countries, agriculture was the fastest growing sector, with manufacturing following in second and services having the slowest growth. This pattern is also observed in most

Table II: Manufacturing Employment Share Peak

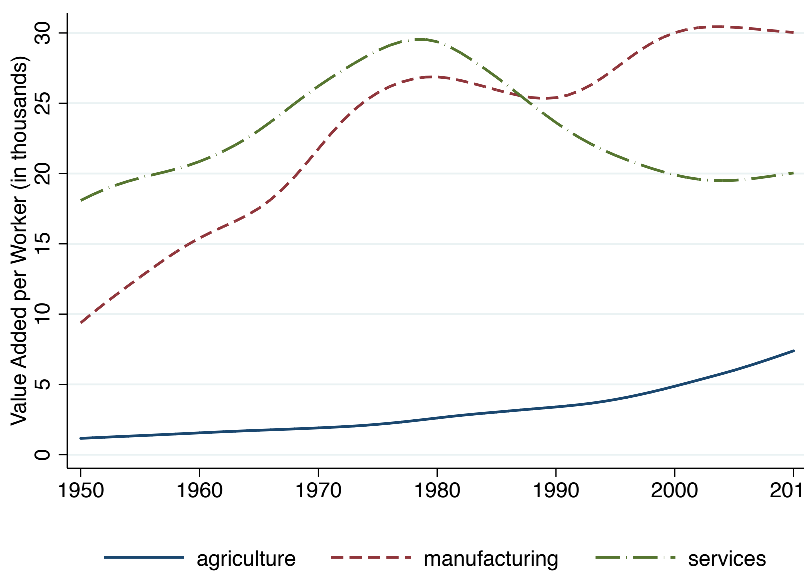
Summary statistic	Brazil	Unites States	RoW average
Peak year	1983	1950	–
GDP per capita (Int'l$)	4,908	9,809	8,100
Manufacturing employment share	23.0%	33.4%	30.0%
Manufacturing value-added share	31.3%	30.5%	37.0%

Note: Table (II) shows Manufacturing employment share peak. The American manufacturing employment share peaks in the first year of our sample and decreases in all years of the analysis. RoW average refers to fitted curves results from Herrendorf *et al.* (2014) for 103 countries.

countries [13]. Labor productivity in agriculture grew 6.3 times in Brazil and 9.4 times in the U.S. from 1950 to 2010. Labor productivity of manufacturing grew about the same in both countries from 1950 to 2010, 3.2 times in Brazil and 3.1 in the U.S.. Manufacturing in the U.S., although stagnated for most of the 1960s and the 1970s, grew at a fast pace for the remaining of the period. Meanwhile, manufacturing in Brazil grew steadily until the 1980s, displayed a stagnation period, recovered for a while after the liberalizing economic reforms of the early 1990s, and finally entered a new stagnation phase. For the 1950-1980 period, manufacturing productivity actually grew faster than in agriculture. Services is the sector that had the most diverging behavior in terms of labor productivity for the two countries. While services productivity in the U.S. grew steadily throughout the period, in Brazil it displayed a more erratic behavior. Services labor productivity in Brazil peaked in 1979[14], after growing by 1.6-fold, but then declined steadily and ended the analyzed period at roughly the same level as in 1950.

Jointly analyzing figures (3.2) and (3.4), it is possible to explain the movements of aggregate productivity depicted in figure (3.1a). Because aggregate labor productivity is the sum of labor productivity across sectors weighted by the share of employment in each sector, reallocation of labor affects aggregate productivity. As the productivity in agriculture increased, more and more of the labor force in that sector was reallocated towards the other two sectors. While the manufacturing sector was absorbing some of these workers,

Figure 3.4: Labor Productivity by Sector



[13] See Duarte and Restuccia (2010) and Herrendorf et al (2014).

[14] The peak in the data before using the HP filter actually happened in 1980.

Figure 3.5: Normalized Sectoral Productivity - Brazil and U.S.

(a) Brazil (b) U.S.

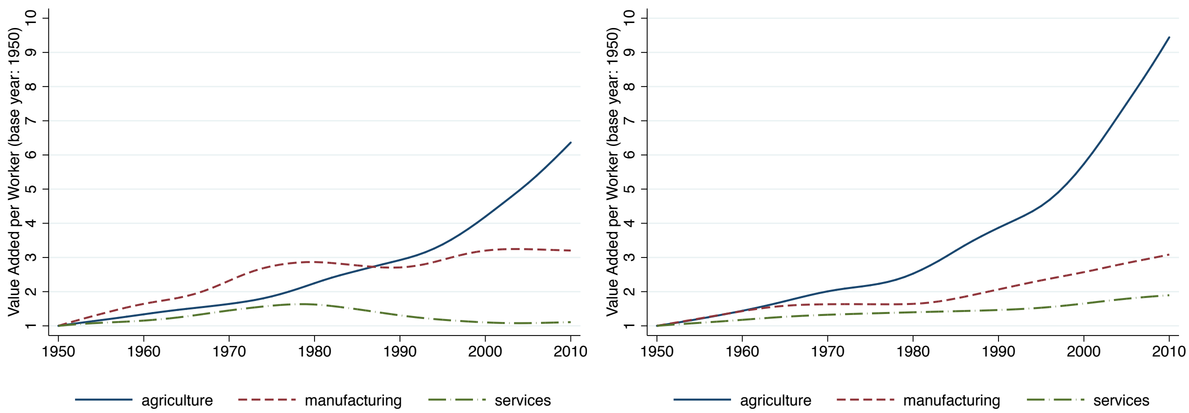


Table III: Average Productivity Growth Rates

	Brazil			United States		
	Ag	Mfg	Srvcs	Ag	Mfg	Srvcs
1950-2010	3.08	1.95	0.18	3.76	1.87	1.06
1950-1980	2.65	3.47	1.58	3.04	1.63	1.09
1980-2010	3.55	0.37	-1.24	4.48	2.07	1.01

Note: Table (III) shows the average percentage growth rates of labor productivity in agriculture (Ag), manufacturing (Mfg), and services (Srvcs) for Brazil and U.S. for three different periods. The catching up period of 1950-1980 is characterized by the fast growth in manufacturing labor productivity. The stagnation period of 1980-2010 is characterized by the slow growth of manufacturing productivity and the decline in services productivity.

the overall Brazilian productivity grew quickly as productivity in the manufacturing sector was larger than in agriculture both in terms of level and growth rate. The deceleration of manufacturing productivity growth coincides with the peak of its labor force share. At this time, the services sector was absorbing labor from both agriculture and manufacturing. However, services productivity was declining and, together with the sluggish behavior of manufacturing productivity, total productivity in the Brazilian economy declined.

3.3 Model

In this section, we present the model that guides our analysis of the sectoral reallocations of labor and aggregate labor productivity in the Brazilian economy. We build on the structural transformation literature that uses both demand and supply drivers of labor reallocation. On the supply side, our model closely follows Duarte and Restuccia (2010) in the use of sector-specific productivity growth that generates different price paths across sectors. On the demand side, we assume a representative household has preferences represented by the implicit nonhomothetic CES utility function, introduced in the structural transformation literature by Comin *et al.* (2015). This utility function is particularly suitable in the context of this paper because it generates nonhomothetic demand for every level of income. In addition, the implicit nonhomothetic CES has the property that substitution and income elasticities are independent of each other, allowing us to identify each elasticity separately.

Our model economy has three sectors: agriculture (a), manufacturing (m) and services (s). The representative firm of each sector uses labor as sole input of production and the production function is assumed to be linear in labor. The representative household consumes agricultural, manufacturing, and services goods, and supplies labor inelastically. Because there is no capital in the economy, all the output produced is consumed.

3.3.1 Firms

The representative firm of sector $i \in \{a, m, s\}$ produces according to the following linear production function:

$$Y_i = A_i L_i \tag{3.1}$$

where Y_i is output, L_i is labor input, and A_i is a sector-specific productivity. The labor input, L_i, is defined as total employment in sector i.

The representative firm of each sector behaves competitively in markets for both goods and labor. In each period, firm i takes price p_i and wage w as given to solve its static profit maximization problem:

$$\max_{L_i > 0} \{p_i A_i L_i - w L_i\}. \tag{3.2}$$

3.3.2 Households

The representative household lives for infinite periods. She is endowed with L units of time each period which are supplied inelastically in the labor market. Her preferences over consumption are represented by:

$$\sum_{t=0}^{\infty} \beta^t \log(C_t), \tag{3.3}$$

where $\beta \in (0,1)$ is the discount factor and C_t is the aggregate consumption at time t. The aggregate consumption combines sectoral goods, c_{it} for $i \in \{a,m,s\}$, according to the implicit nonhomothetic CES aggregator as in Comin et al. (2015):

$$\sum_i \Omega_i^{\frac{1}{\sigma}} C_t^{\frac{\epsilon_i - \sigma}{\sigma}} c_{it}^{\frac{\sigma-1}{\sigma}} = 1, \tag{3.4}$$

where $\sigma \in (0,1)$ is the elasticity of substitution, $\Omega_i > 0$ is a constant weight for each sector $i \in \{a,m,s\}$, and ϵ_i is a measure of the income elasticity of demand for good i. Notice that the standard CES aggregator is the special case of equation (3.4) when $\epsilon_i = 1$ for all i. When $\epsilon_i \neq 1$, for at least one i, this parameter drives the weight of consumption of good i as aggregate consumption C_t increases. Even though there is no closed-form solution for aggregate consumption as a function of the sectoral consumption goods, the demand functions are still tractable.

Notice that because we abstract from intertemporal decisions, the household problem is a sequence of static problems. Given prices, the representative household chooses consumption of each good to maximize the period-by-period utility subject to a budget constraint and standard non-negativity constraints[15]:

$$\begin{aligned} \max_{c_i \geq 0} \quad & \log(C) \\ \text{s.t.} \quad & p_a c_a + p_m c_m + p_s c_s = wL \\ & \sum_i \Omega_i^{\frac{1}{\sigma}} C^{\frac{\epsilon_i - \sigma}{\sigma}} c_i^{\frac{\sigma-1}{\sigma}} = 1. \end{aligned} \tag{3.5}$$

[15]We removed the time index for ease of notation.

3.3.3 Equilibrium

A competitive equilibrium for this economy is a set of prices $\{p_a, p_m, p_s\}$, allocations $\{c_a, c_m, c_s\}$ for the household, and allocations $\{L_a, L_m, L_s\}$ for the firms such that, for every period:

1. Given prices, household's allocations solve the maximization problem in (3.5).

2. Given prices and wages (here, normalized to 1), firms' allocations solve the maximization problem in (3.2).

3. Labor and goods markets clear, that is

$$L = L_a + L_m + L_s \tag{3.6}$$

$$c_i = Y_i, \quad \forall i \in \{a, m, s\}. \tag{3.7}$$

3.3.4 Characterization of Equilibrium

Firm's optimal choice implies that the price in each sector $i \in \{a, m, s\}$ is the inverse of the sector productivity[16]:

$$p_i = \frac{1}{A_i}. \tag{3.8}$$

As a consequence, more productive sectors have lower prices. For any two sectors $i, j \in \{a, m, s\}$, their relative price is given by the ratio of their productivities:

$$\frac{p_i}{p_j} = \frac{A_j}{A_i}. \tag{3.9}$$

Now, we turn to household choice. Household demand for good i is given by:

$$c_i = \Omega_i \left(\frac{p_i}{P}\right)^{-\sigma} C^{\epsilon_i}, \tag{3.10}$$

where P is the aggregate price index is:

$$P \equiv \frac{\sum_i p_i c_i}{C} = \frac{1}{C}\left[\sum_i \Omega_i C^{\epsilon_i - \sigma} p_i^{1-\sigma}\right]^{\frac{1}{1-\sigma}}. \tag{3.11}$$

Define expenditure share on good i as $\omega_i = (p_i c_i)/(PC)$. Using household demand from equation (3.10), expenditure share may be rewritten as:

$$\omega_i = \Omega_i \left(\frac{p_i}{P}\right)^{1-\sigma} C^{\epsilon_i - 1}. \tag{3.12}$$

[16] Notice that wage, w, is normalized to one.

From the definition of expenditure share and equation (3.8), it is easy to see that $L_i = \omega_i PC$. From household budget constraint and equation (3.11), we have that $PC = L$. So, we find that the labor share in sector i is equal to the expenditure share:

$$\omega_i = \frac{L_i}{L}. \tag{3.13}$$

Intuitively, as the expenditure share on good i increases, labor allocated for sector production also increases to meet demand. Using the fact that the sum of expenditure shares equals one, we may characterize labor share as a function of productivities and aggregate consumption:

$$\frac{L_i}{L} = \frac{\Omega_i C^{\epsilon_i} A_i^{\sigma-1}}{\sum_i \Omega_i C^{\epsilon_i} A_i^{\sigma-1}}. \tag{3.14}$$

From equation (3.10), relative consumption can be written as a function of relative prices and aggregate consumption:

$$\frac{c_i}{c_j} = \frac{\Omega_i}{\Omega_j} \left(\frac{p_i}{p_j}\right)^{-\sigma} C^{\epsilon_i - \epsilon_j}. \tag{3.15}$$

From this equation, we can see two properties of the nonhomethetic CES utility function. First, the income elasticity is constant and heterogeneous across sectors:

$$\frac{\partial \ln(c_i/c_j)}{\partial \ln(C)} = \epsilon_i - \epsilon_j. \tag{3.16}$$

This property ensures that the nonhomotheticity does not vary as income grows; that is, the degree of nonhomotheticity is the same for all levels of income. Second, the elasticity of substitution between goods is constant:

$$\frac{\partial \ln(c_i/c_j)}{\partial \ln(p_j/p_i)} = \sigma. \tag{3.17}$$

Notice that this functional form delivers a perfect separation of the price and the income effects. While the price effect always generates a negative correlation between relative real sectoral consumption and relative sectoral prices, the income effect makes both aggregates co-move in aggregate consumption.

3.3.5 Parameter Selection

The estimation of preference parameters is based on the intratemporal choice of relative consumption and equilibrium prices, given by equations (3.15) and (3.8), respectively. We identify σ and ϵ_i using the natural log of the relative labor allocation, equation (3.13), that can be written as:

$$\ln\left(\frac{L_m}{L_a}\right) = (1-\sigma)\ln\left(\frac{A_a}{A_m}\right) + (\epsilon_m - \epsilon_a)\ln(C) + \ln\left(\frac{\Omega_m}{\Omega_a}\right) \tag{3.18}$$

$$\ln\left(\frac{L_s}{L_a}\right) = (1-\sigma)\ln\left(\frac{A_a}{A_s}\right) + (\epsilon_s - \epsilon_a)\ln(C) + \ln\left(\frac{\Omega_s}{\Omega_a}\right) \tag{3.19}$$

Conditional on the observed sectoral productivities A_i and aggregate consumption C, we use the demand system to estimate the elasticity of substitution σ and the income elasticities ϵ_i. The estimated coefficient with respect to relative productivities, $(1-\sigma)$, must be equal in both equations, imposing a cross-equation restriction in the estimation. Also, note that we are only able to pin down the difference between the income elasticities, not its specific value[17].

Our point estimate of the elasticity of substitution, σ, is 0.536 with standard deviation of 0.012, which is within the one standard-deviation interval of confidence of world estimates performed by Comin et al (2015). The difference in income elasticities between agriculture and manufacturing, $\epsilon_m - \epsilon_a$ is positive and equal to 0.455. The difference in income elasticities between services and agriculture, $\epsilon_s - \epsilon_a$ is positive and equal to 0.638. Those numbers imply that manufacturing is more income elastic than agriculture and that services is more income elastic than manufacturing, as expected. Table (IV) summarizes the results of our estimates.

As in Comin *et al.* (2015), we also find that the elasticity of substitution, σ, is statistically different from zero. This result contrasts with previous estimations that have commonly relied on Stone-Geary utility functions[18]. Because in the Stone-Geary utility function the income effect becomes less important as consumption grows, its estimated substitution parameter σ asymptotically goes to zero[19]. This implies that the estimation based

Table IV: Estimated Parameter Values

σ	$\epsilon_m - \epsilon_a$	$\epsilon_s - \epsilon_a$	OBS	R^2
0.536 (0.012)	0.455 (0.007)	0.638 (0.009)	61	0.992

[17]For the simulations in the next sections, we will assume $\epsilon_a = 1$.

[18]The generalized Stone-Geary utility has the functional form:

$$u(c_a, c_m, c_s) = \log(C)$$

such that

$$C = \left[\sum_i \Omega_i^{\frac{1}{\sigma}} (c_i + \bar{c}_i)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}},$$

where $\bar{c}_a < 0$, $\bar{c}_m = 0$, and $\bar{c}_s > 0$.

[19]Notice that the nonhomotheticity effects are generated by parameters $\bar{c}_i$ and these effects decrease as

on Stone-Geary preferences relies more on the price effects and the complementarity of consumption. The usual example of the literature is the increase in the relative consumption of services while services relative price also increase. Due to the vanishing income effects of the Stone-Geary preferences, increases in the relative consumption of services require that the goods have very low substitutability. In the limit, the elasticity parameter σ goes to zero. For example, Buera and Kaboski (2009), Herrendorf, Rogerson and Valentinyi (2013) and Moro, Moslehi and Tanaka (2017) find that the substitution parameter σ is not statistically different from zero. [20]. For Brazil, Ferreira and da Silva (2015) calibrate the elasticity parameter σ to be fairly inelastic, but different from zero though.

Now we turn to the calibration of the sectoral preference weight, Ω_i. The preference weighting Ω_i is calculated so that labor share of each sector in the model matches the data in 1950. Because 1950 is the start of our sample period, we normalize $A_{i,1950} = 1$ for all sectors and the aggregate consumption C also equals one in 1950. Given these normalizations, we use equation (3.14) to determine Ω_i as:

$$\Omega_i = \frac{L_{i,1950}}{L_{1950}}.$$

That is, the preference weighting equals the labor share in 1950.

3.4 Quantitative Results

In this section, we analyze the fit of model to the data. We feed the model with the observed labor productivities and aggregate output[21], and see how well the model captures the behavior of the labor shares and aggregate productivity.

3.4.1 Results for Benchmark Economy

Overall, our simulated economy successfully matches the data. Figure (3.6) plots the labor share for our benchmark economy and from the data. For the entire period, the model predicts a share of labor in agriculture lower than the share observed in the data. On the other hand, it predicts a higher services labor share than observed. Also, for most of the 1950-1990 period, simulated manufacturing labor share grows slower than in the data.

The model is able to generate an increase of the relative demand of services at the same time that its relative price increases. This increase in relative demand concomitant with the increase of relative price is only possible because of the nonhomotheticity assumption.

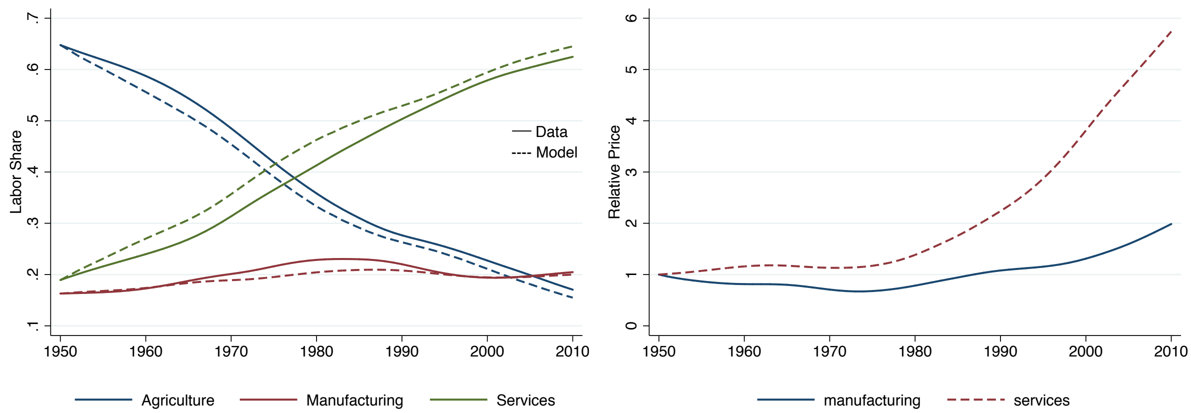
consumption c_i increases.

[20]See Comin, Mestieri and Lashkari (2015) for further discussion.

[21]Since there is no capital in the economy, aggregate consumption equals aggregate output.

Figure 3.6: Labor Shares and Relative Prices

(a) Labor Share (b) Relative Prices



Note: Manufacturing relative price is p_m/p_a and services relative price is p_s/p_a.

To see why, consider the case in which household preferences are homothetic, that is, $\epsilon_i = 1, \forall i \in \{a, m, s\}$. Given that the elasticity of substitution is lower than one, $\sigma < 1$, demand falls relatively less than the price increase. For example, consider an increase in the relative price of services. Because the household has a preference for balanced consumption, there is an increase in the expenditure on services relative to agriculture and manufacturing, whereas the consumption of services decreases. So, homothetic preferences are not able to match the data. On the other hand, if preferences are nonohomothetic, for given relative prices, an increase in aggregate income results in a larger increase in the demand for the income elastic good; that is, the one with higher ϵ_i value. This implies that as income grows, the increase in the demand for services is larger than for agriculture and manufacturing. In our specification, both substitution and income effects are present. If income effect is large enough to offset substitution effect, the model generates an increase in the demand for the sector with rising relative price.

Labor allocation in the model is the result of the interaction of substitution and income effects. Because estimated elasticity of substitution, σ, is less than one, the goods are complementary in consumption and the household has a preference for balanced consumption. The expenditure share increases with the price of the good and labor moves towards the sector with increasing relative price, as characterized by equation (3.13). In the model, the sector price equals the inverse of productivity[22] and, because the services sector has the lowest productivity growth rate, it also has the highest price. Therefore, the substitution effect induces labor towards the services sector. Our estimation results indicate that services

[22] Recall that sectoral productivities have been normalized to one in the initial period.

demand is more income elastic than manufacturing, which is more income elastic than agriculture[23]. Notice that both effects cause an increase in the labor share towards the services sector.

Figure (3.6b) plots the relative prices in the model p_i/p_a, $i \in \{m, s\}$. We see that the relative price of manufacturing to agriculture declines gradually until the mid 1970s. Because of the preferences for consumption complementarity, $\sigma < 1$, this price dynamics would actually induce a decline in the manufacturing labor share. Hence, the observed reallocation of labor towards manufacturing during this period is entirely due to the income increase. Likewise, income effect plays a predominant role in the services sector because, until mid 1980s, there is only a small increase in the relative price of services with respect to agriculture.

In our model, aggregate productivity equals the average of sectoral labor productivities weighted by their labor shares:

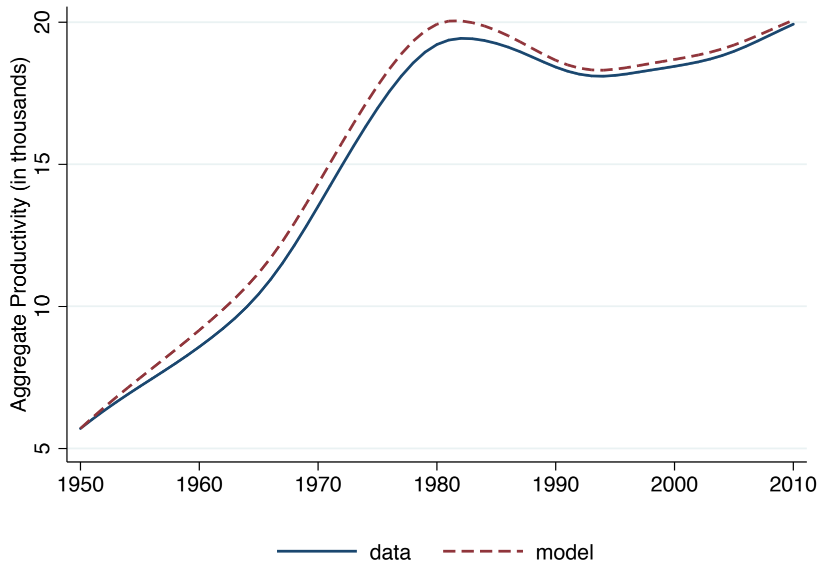
$$\frac{Y}{L} = \sum_{i \in \{a,m,s\}} \frac{Y_i}{L_i} \frac{L_i}{L}.$$

Therefore, the behavior of aggregate productivity depends on the behavior of sectoral productivities A_i and of the labor shares L_i/L through time. Because labor productivity is exogenous and the model is able to reproduce salient features of the labor allocation across sectors, the simulated economy closely reproduces the aggregate productivity. The results are plotted in Figure (3.7).

Recall from Figure (3.4) that labor productivity in agriculture is lower than in the other sectors, even though it grows at a fast pace through the entire period. Taking into account that the simulated economy reallocates more labor away from agriculture towards manufacturing and services than observed in the data, aggregate labor productivity generated by the model is actually higher than in the data despite the higher share of labor in services.

[23] This result is standard in the literature. See Herrendorf, Rogerson and Valentinyi (2014) for further discussion.

Figure 3.7: Aggregate Productivity



Note: Aggregate productivity equals the weighted average of sectoral productivities. Changes in the labor share affects aggregate productivity even if sector productivities are constant.

3.5 Wedges: Distortions in the Brazilian Economy

Even though our framework is able to capture the long run behavior of the sector labor shares, there are still some discrepancies between model and data. Following the methodology of Chari, Kehoe and McGrattan (2007), we use the benchmark model[24] to compute sectoral wedges that account for the differences between model allocation and data. These wedges reflect distortions in the economy that are not captured by the benchmark model. Here they are represented by labor demand costs and are calculated such that, given income and productivity paths, the model labor shares equal the data labor shares. Consider the modified problem of a firm in sector $i \in \{a, m, s\}$:

$$\max_{L_i > 0} \; \{p_i A_i L_i - (1 + \tau_i) w L_i\} \tag{3.20}$$

where $(1 + \tau_i)$ represents the wedge on labor demand in sector i. In the presence of wedges, the equilibrium price is[25]:

$$p_i = \frac{1 + \tau_i}{A_i}. \tag{3.21}$$

[24] We will call the model developed in section 3.3 as 'benchmark model' through the rest of the paper.

[25] As in the benchmark model, wage w is normalized to one.

Plugging the new price equation into the relative consumption equation (3.15), we find that:

$$\frac{c_i}{c_j} = \frac{\Omega_i}{\Omega_j}\left(\frac{(1+\tau_i)}{(1+\tau_j)}\frac{A_j}{A_i}\right)^{-\sigma} C^{\epsilon_i-\epsilon_j} \tag{3.22}$$

Because only the relative wedges matter for the allocation, we assume that there is no wedge in the agricultural sector, $\tau_a = 0$. The manufacturing and services wedges can now be computed analytically:

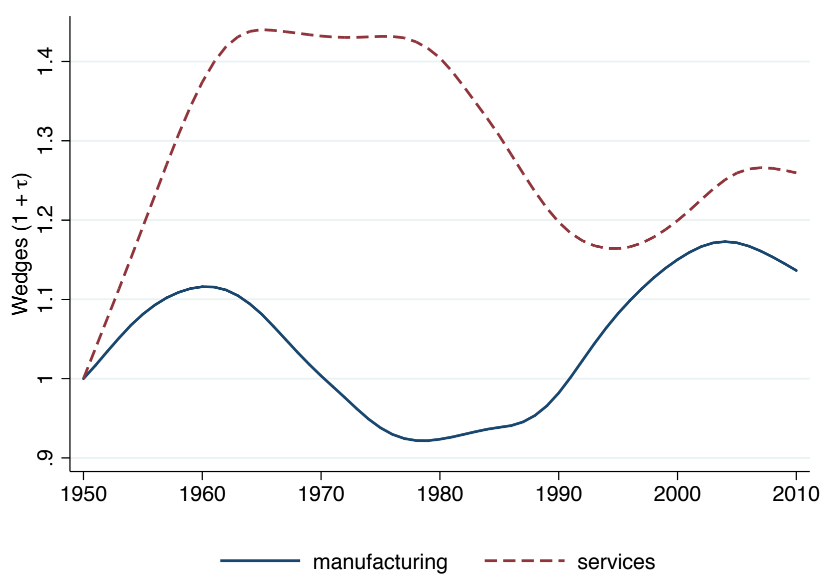
$$1+\tau_m = \left[\frac{\Omega_m}{\Omega_a}\frac{L_a}{L_m}\left(\frac{A_a}{A_m}\right)^{1-\sigma} C^{\epsilon_m-\epsilon_a}\right]^{\frac{1}{\sigma}} \tag{3.23}$$

$$1+\tau_s = \left[\frac{\Omega_s}{\Omega_a}\frac{L_a}{L_s}\left(\frac{A_a}{A_s}\right)^{1-\sigma} C^{\epsilon_s-\epsilon_a}\right]^{\frac{1}{\sigma}}. \tag{3.24}$$

Using the data on employment shares, sectoral productivities and aggregate income, we compute the manufacturing and services wedges. Figure (3.8) plots the results.

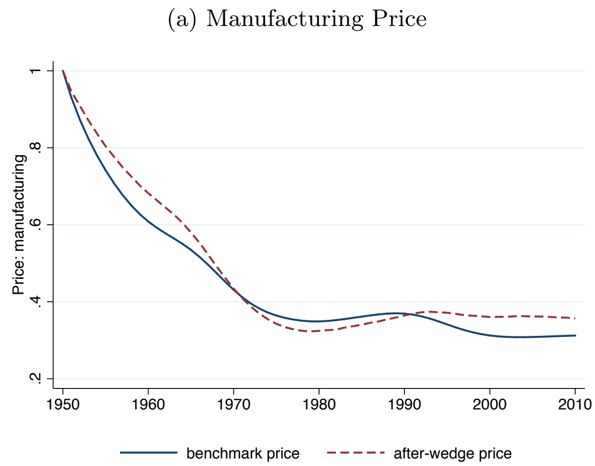
If wedge $1+\tau_i < 1$, labor demand in sector i is as if the labor cost was lower than the market cost and the labor allocation is higher in the data than predicted by the model. For example, we observe in figure (3.8) that, between 1970 and 1990, $1+\tau_m < 1$ and, in figure (3.6a), that manufacturing labor share in the model is lower than in the data. We interpret

Figure 3.8: Wedges



Note: The wedges are $1+\tau_m$ and $1+\tau_s$ distortions not explained by the benchmark model. Manufacturing wedge $1+\tau_m$ has a more erratic behavior. Services wedge $1+\tau_s > 1$ throughout all the periods.

Figure 3.9: Benchmark Price and After-Wedge Price



Note: Panel (a) plots manufacturing price without and with wedge and Panel (b) plots for services. Manufacturing wedge has little impact on after-wedge price and, as consequence, in the allocation of labor. After-wedge services price is very different from its price. It captures most of the differences between benchmark model and data.

a wedge less than one to be a distortion/subsidy that incentivizes allocation towards sector i. On the other hand, if $1 + \tau_i > 1$, labor demand is as if the labor cost was higher than the market cost. Then, allocation is lower in the data than predicted by the model. Consider the wedges and labor shares for the services sector. The model predicts a higher labor allocation than observed in the data and its wedge is positive for the entire 1950-2010 period.

Figure (3.9) plots prices with and without wedges. Through the rest of the paper, we will call the price with wedges as the 'after-wedge price' and the price without wedges as the 'benchmark price'. First, notice that the after-wedge price of manufacturing is close to the benchmark price. Thus, the manufacturing wedge will have relatively small impact on the allocation of labor. On the other hand, after-wedge price of services behaves very differently from the benchmark price. For the initial periods, the increase of the services wedge is so large that the after-wedge price goes in the opposite direction of the benchmark price.

Wedges may reflect economic policies or institutional constraints that are not captured by our benchmark model. In the following subsections, we discuss policies of the period and how they could be captured by our model or translated into the wedges. Later, in section (3.7.3), we discuss the quantitative effects of each wedge in the economy by removing one at a time.

3.5.1 Capital Accumulation

It is important to emphasize that, if policies translate themselves into capital accumulation, then they are already captured by our productivity series. To see why, notice that if we assumed Cobb-Douglas production functions in each sector of the form $Y_i = A_i k_i^{\alpha} l_i^{1-\alpha}$, where k_i is capital stock in sector i, we could rewrite it as $Y_i = A_i(k_i/l_i)^{\alpha} l_i$. A standard result in the structural transformation literature is that if capital share α is constant across sectors, then sectoral capital-labor ratio equals aggregate capital-labor ratio, $k_i/l_i = K/L$. Between 1950 and 1980, aggregate capital-labor ratio increased more than 4-fold[26]. We conjecture that the increase in capital stock, as consequence of the policies of the period, explains the small impact of manufacturing wedge, at least until the early 1990s[27].

There were many different policies implemented between 1950 and 1964 with the goal of increasing capital accumulation in Brazil. A first example is the Sumoc Instruction number 70 (*Instrução Sumoc 70*)[28] from 1953 that implemented the regime of multiple exchange rates. This policy created an auction process for the purchase of foreign currency at different price brackets. For example, an overvalued exchange rate would be applied for the imports of capital goods (making them cheaper for Brazilian producers) or for the exporting sectors. At the same time, an undervalued exchange rate would be applied for the import of consumption goods. A second example is the Sumoc Instruction number 113 (*Instrução Sumoc 113*) that allowed the imports of industrials equipments and machines without international reserves use requirements. Throughout President Juscelino Kubitschek's term, from 1956-1960, an ambitious Plan of Goals (*Plano de Metas*) was implemented with its motto "fifty years in five". The plan gave priority to major investments in energy, cement, steel, mining, and the automotive industries, and the construction of the new capital, Brasília. Assuming these policies translate into higher capital accumulation, then they are already accounted for by higher sectoral productivities.

Between 1964 and 1967, many institutional changes were implemented in the context of the PAEG (*Plano de Ação Econômica do Governo*). Among these changes was the creation of housing financing instruments such as the National Housing Bank (*Banco Nacional de Habitação*) and Mortgage Backed Bonds (*Letras Imobiliárias*). These financing instruments allowed a boom in the housing sector (Frieden, 1987) and, because housing is computed as part of the services sector, these institutional changes are already captured in our series of services productivity.

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[26] See Ellery (2013).

[27] To better understand the distortions associated with capital accumulation, a model with inter-temporal choice is required.

[28] Sumoc stands for *Superintendência da Moeda e do Crédito*.

3.5.2 Capital Goods Production

In the context of the import substitution development strategy, the government implemented policies with the goal of furthering the production of capital goods domestically. These policies were particularly important during the 1970s and 1980s period. In 1975, the government implemented the II PND (*II Plano Nacional de Desenvolvimento*) as an answer to the oil shock. This plan aimed to foster the domestic production of capital goods, electronics, and oil (Carneiro, 2014). As most of the capital goods are produced in the manufacturing sector[29], the stimulus to capital production would show up mainly as labor demand in the manufacturing sector, which would translate into a negative τ_m in our wedge economy. From figure (3.8), we can see that τ_m was indeed negative in this period.

3.5.3 Costly Reallocation and Non-Market Compensation

The benchmark agriculture labor share is always lower than in the data. This low agriculture labor allocation could be the result of major rural-urban reallocation costs that aren't captured in the model. In the early years of our analysis the largest share of population was in the rural areas and migration cost likely plays a major barrier for labor reallocation. Another important aspect is the existence of non-market in-kind compensation to rural workers, such as housing and the possibility of subsistence food production. The non-existence of these compensations for urban workers resulted in a wage premium in the manufacturing and services sectors. In 1963, the rural worker statute (*Estatuto do Trabalhador Rural*) was approved and extended to rural workers many of the labor laws ensured by the CLT (*Consolidação das Leis do Trabalho*) that were already granted to urban workers. This extension of rights increased the costs of hiring agricultural workers. However, we don't see a major change in the reallocation of agricultural labor neither in the data nor in the model. This could be a consequence of informal labor relations.

3.5.4 Limited Competition

During the early years of our analysis, successive governments had the explicit goal of industrializing the country. A major government policy known as import substitution was widely implemented[30]. It advocates for the reduction of imports and the policy of 'national similar' was widely implemented aiming to protect the infant industry. Under this policy, the import of goods that were already produced domestically faced many restrictions, sometimes essentially prohibited. This severe barrier on competition generated monopolies and oligopolies in the production of many tradable manufacturing goods. As is well known,

[29] A common assumption in the structural transformation literature is to assume that all capital goods are produced in the manufacturing sector. See Herrendorf, Rogerson and Valentinyi (2014).

[30] It became an official government policy in 1947, during the presidency of Eurico Gaspar Dutra.

a firm that exercises market power produces less than competitive firms, generating a lower demand for workers. If the manufacturing sector is more monopolized than the agricultural sector, the manufacturing wedge, $1 + \tau_m$, should be greater than one.

3.5.5 International Trade

In the benchmark model, we consider a closed economy in which consumption equals domestic production. In an open economy, production and demand may differ. Let NX_i be net exports for sector $i \in \{a, m, s\}$ and $c_i = Y_i - NX_i$. For a given level of consumption, if net export is negative, $NX_i < 0$, a lower domestic production is required to satisfy demand and less workers would be observed in the data. Therefore, negative net exports would be translated into positive wedge, $\tau_i > 0$. On the other hand, if $NX_i > 0$, total quantity demanded of the good is higher than domestic demand. This implies that the level of employment observed in the data would be higher than computed by the benchmark model and it would be translated into a negative wedge $\tau_i < 0$. In short, trade induces a higher labor share in the net exporting sector.

Opening the Brazilian economy was a central economic policy objective during the early 1990s. Tradable manufacturing goods whose imports were previously prohibited started being imported. The opening to competition is often associated with the decline of manufacturing labor share in the Brazilian economic literature debate. Bonelli, Pessôa and Matos (2013) and Cosar (2013) study the impact of international trade on labor reallocation.

3.6 Decomposition

In this section, we use the model (with wedges) to decompose the change of manufacturing and services labor allocations relative to agriculture, L_m/L_a and L_s/L_a, respectively. We compute how much of the change was due to the price effect, to the income effect, and to the wedges. We use the logarithm of equation (3.15) to decompose these different sources. Ignoring the constant weighting terms Ω_i, we get the following:

$$\ln\left(\frac{L_m}{L_a}\right) = (1-\sigma)\ln\left(\frac{A_a}{A_m}\right) + (\epsilon_m - \epsilon_a)\ln(C) - \sigma\ln(1+\tau_m) \tag{3.25}$$

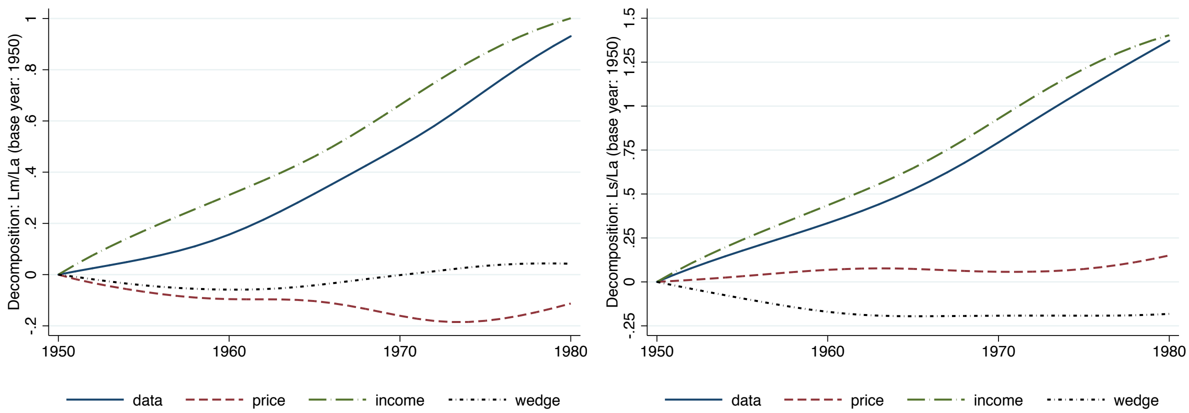
$$\ln\left(\frac{L_s}{L_a}\right) = (1-\sigma)\ln\left(\frac{A_a}{A_s}\right) + (\epsilon_s - \epsilon_a)\ln(C) - \sigma\ln(1+\tau_s) \tag{3.26}$$

The sources of relative labor allocation are given by (3.25) and (3.26). We call price effect the term $(1-\sigma)\ln(A_a/A_i)$, income effect the term $(\epsilon_i - \epsilon_a)\ln(C)$ and wedge effect $(-\sigma)(1-\tau_i)$. Because the economy behaves so differently before and after 1980, we decompose the sources of relative labor changes in these two sub-periods separately.

Figure 3.10: Decomposition: 1950-1980

(a) Manufacturing

(b) Services



Note: Panel (a) plots decomposition of manufacturing relative labor L_m/L_a. Panel (b) plots decomposition of services L_s/L_a. For both sectors, increase in income is the main force to explain relative labor allocation.

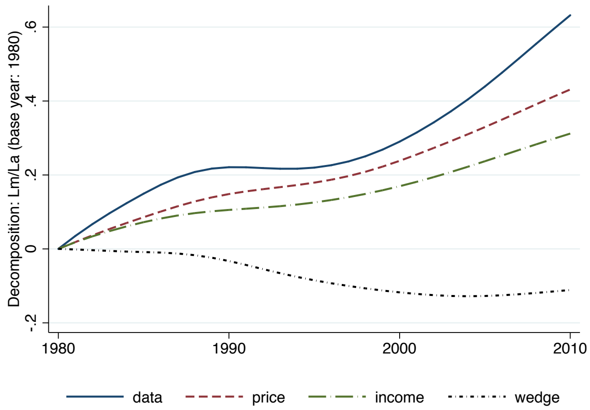
From Figure (3.6b), we see that the manufacturing price relative to agriculture declines until the mid 1970s and its level is below the 1950 level until the mid 1980s. If household preferences were homothetic, $\epsilon_i = 1 \; \forall i \in \{a, m, s\}$, labor should actually be allocated towards agriculture, due to the decrease in price of manufacturing relative to agriculture. Until the mid 1970s, the price effect is inducing labor to the opposite direction of what is observed in the data. This effect is illustrated in Figure (3.10a) by the decrease in the price effect (red dash line). The income effect (green dash-dot line) is the main driver of the increase in L_m/L_a. In the absence of price effects or distortions, the relative labor would actually be higher than in the data. From Figure (3.10a), we also see that the wedge has a minor role on labor allocation.

Now we turn to the decomposition of labor towards the services sector. During the first sub-period, there is only a small increase in the relative price of services with respect to agriculture, see Figure (3.6b). Even though the price effect induces labor towards services, the effect is quantitatively small. As in the manufacturing sector, income effect plays the major role. From Figure (3.10b), we see the importance of the income effect and the minor role of the price effect. For the entire period, the wedge effect would induce a decline in the services labor. In Figure (3.8), one can see that $\tau_s > 0$ for every period, acting as a tax on labor demand in the services sector.

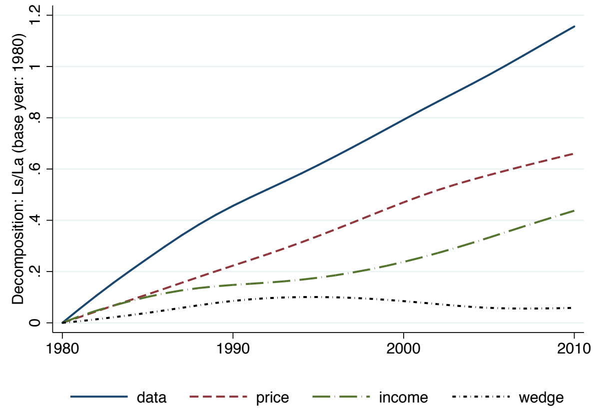
Figure (3.11) plots the decomposition of labor in manufacturing and services relative to agriculture for the following sub-period, 1980-2010, where the variables are now normalized to their 1980 levels (including the wedges). During the second sub-period, we see large changes in relative prices, as illustrated in Figure (3.6). The price effect is now the main

Figure 3.11: Decomposition: 1980-2010

(a) Manufacturing



(b) Services



Note: Panel (a) plots decomposition of manufacturing relative labor L_m/L_a. Panel (b) plots decomposition of services L_s/L_a. For both sectors, price effect is the main force to explain relative labor allocation, but income is also important.

source of labor reallocation for both sectors, even though income effect is still quantitatively important. As before, the wedges play a minor role in the allocation of labor.

Consider Figure (3.11b) plotting the services sector decomposition. The increase of the wedge effect captures the decrease of the wedge relative to its level in 1980, although it is positive, $\tau_s > 0$, throughout the entire 1950-2010. The positive wedge effect means the size of the wedge decreased, not necessarily that its value is now negative $\tau_s < 0$. In the Figure (3.11b), we observe that the decomposition captures as if the wedge effect actually contributes to an increase of the relative labor $\ln(L_s/L_a)$.

In Table (V), we present the decomposition of manufacturing labor relative to agriculture

Table V: Decomposition: Manufacturing

	Labor	Price	Income	Wedge
1950-2010	0.0256	0.0052	0.0215	-0.0011
		(0.2031)	(0.8398)	(-0.0429)
1950-1980	0.0300	-0.0036	0.0323	0.0014
		(-0.12)	(1.0766)	(0.0466)
1980-2010	0.0204	0.0139	0.0101	-0.0036
		(0.6813)	(0.4950)	(-0.1764)

Note: Table (V) shows the average growth of manufacturing labor relative to agriculture. It decomposes the quantitative importance of price, income and wedge effects in the allocation of labor for different period intervals. Price effect is $(1-\sigma)\ln(A_a/A_m)$. Income effect is $(\epsilon_m - \epsilon_a)\ln(C)$. Wedge effect is $(-\sigma)\ln(1+\tau_m)$. The values in parenthesis indicate the relative contribution of each effect.

Table VI: Decomposition: Services

	Labor	Price	Income	Wedge
1950-2010	0.0415	0.0102	0.0302	-0.0020
		(0.2458)	(0.7277)	(-0.0482)
1950-1980	0.0443	0.0049	0.0453	-0.0059
		(0.1106)	(1.0226)	(-0.1332)
1980-2010	0.0373	0.0213	0.0141	0.0019
		(0.5710)	(0.3780)	(0.0509)

Note: Table (VI) shows the average growth of manufacturing labor relative to agriculture. It decomposes the quantitative importance of price, income and wedge effects in the allocation of labor for different period intervals. Price effect is $(1-\sigma)\ln(A_a/A_s)$. Income effect is $(\epsilon_s - \epsilon_a)\ln(C)$. Wedge effect is $(-\sigma)\ln(1+\tau_s)$. The values in parenthesis indicate the relative contribution of each effect.

averaged over different periods and the results represent the average growth rate[31]. The income effect is the most important force for the allocation of labor between manufacturing and agriculture for the entire 1950-2010 period. The income effect is responsible for 83.98% of the increase in relative labor. For the first sub-period, the income effect is actually higher than one and equal to 107.66%; that is, if there was no decrease in relative price of manufacturing with respect to agriculture, relative labor $\ln(L_m/L_a)$ would be higher than observed. In the second sub-period 1980-2010, the importance of the income effect is actually lower than the price effect. In this sub-period, income effect is responsible for 49.50%, whilst price effect for 68.13%.

Table (VI) presents the decomposition results for the services sector. As in the manufacturing sector, income effect is responsible for most of the allocation of labor with 72.77%. In the first sub-period from 1950 to 1980 its contribution is equal to 102.26%. In the second sub-period, income effect is also lower than price effect. Income effect is responsible for 37.80% and price effect for 57.10%. Again, the wedge effect has a small impact.

3.7 Counterfactuals

In this section, we use the model (with wedges) for computational experiments to gain insights about the different factors driving the process of structural transformation in Brazil.

[31] The average for each subperiod of size T is:

$$\frac{\ln(L_{m,t+T}/L_{a,t+T}) - \ln(L_{m,t}/L_{a,t})}{T} = (1-\sigma)\frac{\ln(A_{a,t+T}/A_{m,t+T}) - \ln(A_{a,t}/A_{m,t})}{T} + (\epsilon_m - \epsilon_a)\frac{C_{t+T} - C_t}{T} - \sigma\frac{\ln(1+\tau_{m,t+T}) - \ln(1+\tau_{m,t})}{T}.$$

If we compute the labor allocation paths of the model when all exogenous variables (including wedges, sectoral productivities and income[32]) are set to the values observed in the data, the model matches the data exactly. In the counterfactual exercises, we quantify the contributions of productivities and wedges by removing one at a time, and checking their effects in the relevant variables such as aggregate productivity and manufacturing labor share[33]. We focus on the manufacturing labor share because matching model to data in this sector is particularly challenging due to its non-monotonic behavior. Moreover, many of the Brazilian policies implemented during the period studied have aimed at stimulating the production in this sector.

To perform the counterfactuals, we first calculate the total labor L such that the model with wedges matches the data. Then, we compute the counterfactuals in two steps. First, we calculate aggregate consumption C, taking as given aggregate labor L. We then compute labor shares using the relative consumption equation (3.22) in equilibrium. In the first counterfactual, we explore the effects of manufacturing productivity A_m in the economy. We find that the fast growth of manufacturing productivity in Brazil compared to the U.S. accounts for aggregate productivity being 15% higher in 1980. In the second counterfactual, we discuss the importance of manufacturing and services productivities after 1980. Our main finding is that the low productivity in the services sector is the main driver of the decline in the labor share of the manufacturing sector and for the stagnation of aggregate productivity. In the third counterfactual, we study the importance of the sectoral wedges.

3.7.1 Counterfactual 1: The Role of Manufacturing Productivity

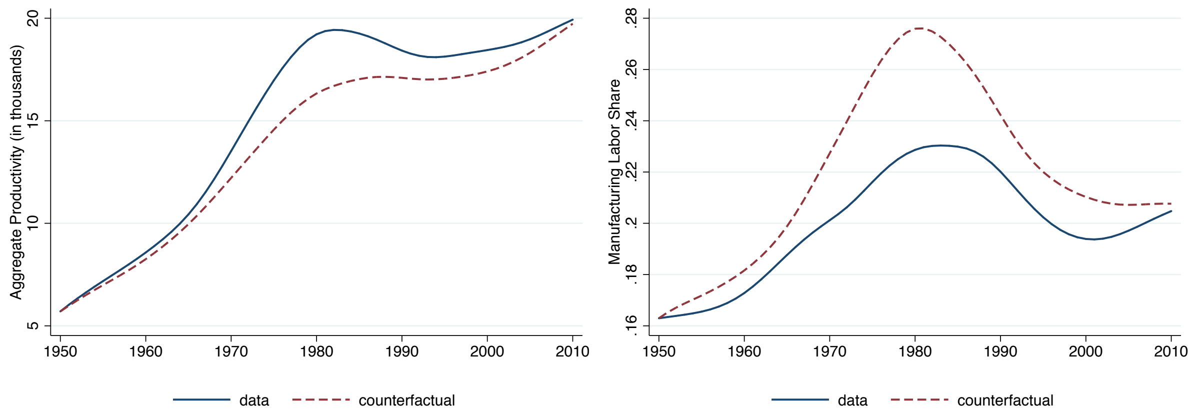
The first counterfactual exercise evaluates the impacts of the manufacturing productivity A_m on labor allocation and aggregate productivity. The main motivation for this counterfactual is the fast growth of the manufacturing productivity in Brazil from 1950 to 1980. Recall from Table (III) that in this period, the average manufacturing productivity growth rate in Brazil was 3.47% while in the U.S. it was 1.63%. In the second sub-period, we actually observe that the average growth rate in Brazil was just 0.37% while in the U.S. it was 2.07%. In this counterfactual, we evaluate how the fast paced manufacturing productivity growth in Brazil relative to the U.S. affected the economy. We feed the model with the wedges computed in the previous section, aggregate labor and observed productivities in agriculture and services for Brazil. To determine the effect of the growth of the Brazilian manufacturing productivity, we replace it with the productivity growth rates observed in

[32]Given the normalization of wages w equal to one in every period, aggregate income equals total labor L.

[33]In the Appendix, we also plot the labor shares for the other sectors, aggregate consumption and price level.

Figure 3.12: Counterfactual 1

(a) Aggregate Prodcutivity (b) Manufacturing Labor Share



Note: Panel (a) plots aggregate productivity if manufacturing labor productivity behaved as in the U.S. Panel (b) plots the manufacturing labor share in the data and the counterfactual. A lower than observed growth in manufacturing productivity implies a higher share of labor in the manufacturing sector.

the U.S..

In 1980, the aggregate productivity in the counterfactual economy is equal to 85% of the level observed in the data. That is, of the observed aggregate productivity level in 1980, 15% comes from the fast growth in manufacturing productivity. The lower productivity in the counterfactual also induces a higher allocation of labor towards manufacturing. Since a lower productivity is associated with a higher sector price, p_m, the preference for balanced consumption ($\sigma < 1$) generates a higher allocation of labor in the manufacturing sector as a way to meet demand. We see in Figure (3.12) that the labor share in manufacturing would be significantly higher than observed in the data. In particular, in the counterfactual economy, manufacturing labor share peaks in 1981 at a level of 27.6%, whereas in the data the peak happens in 1983 at 23%. Finally, the fast growth results on an aggregate consumption, C, 5.9% larger in the data than in the counterfactual in 1980.

In the second sub-period, aggregate productivity in the counterfactual economy catches up to the observed in the data due to the sluggish behavior of manufacturing productivity in Brazil after 1980. Also, in 2010, the manufacturing labor share would be 20.76%, close to 20.48 observed in the data. Lastly, aggregate consumption is at the same level for both the data and the counterfactual.

3.7.2 Counterfactual 2: Stagnation and the Role of Productivities

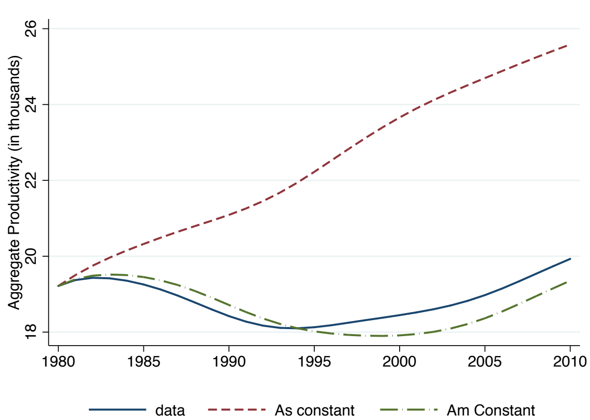
The second counterfactual concentrates on the stagnation of the second sub-period. As previously discussed, between 1980 and 2010, manufacturing productivity stood almost still and services productivity declined, see Figures (3.4) and (3.5). We conjecture that the decline in services productivity was particularly detrimental to the Brazilian economy and, to evaluate its importance, we assume it was constant at its 1980 level for the rest of the period. For completeness, in the end of this section, we also discuss the results for this counterfactual fixing manufacturing productivity instead.

The results show that the deterioration of services productivity had major repercussions for the Brazilian economy. Labor share in manufacturing would be higher than in the data throughout the entire period. As an illustration, the counterfactual economy manufacturing labor share in 2010 equals 22.7% whilst it equals 20.4% in the data. Likewise, by 2010, aggregate productivity would be 28.8% higher than observed in the data[34]. This large effect on aggregate productivity is observed because the drop of productivity occurred in a large and growing sector of the economy. Furthermore, aggregate consumption in 2010 would be 12.5% higher than in the data. By simply not declining, services productivity has large effects in the economy.

On the other hand, if manufacturing productivity had been constant at its 1980 level, manufacturing labor share and aggregate productivity would have had a behavior very similar to the observed in the data. In 2010, aggregate productivity productivity would had been only 3% lower; that is, 97% of the data level. The impact on manufacturing labor would also be small, reaching 21.3% in the counterfactual. This confirms our conjecture

Figure 3.13: Counterfactual 2

(a) Aggregate Productivity (b) Manufacturing Labor Share



Note: Panels (a) and (b) plots the data and two counterfactuals. One counterfactual assume services productivity A_s constant at 1979 level (red dash line) and the other assume manufacturing productivity A_m at 1979 level (green dash-dot line).

[34] Labor productivity observed in 2010 equals \$19,931 (2005 local prices). In the counterfactual, it reaches \$25,585 (2005 local prices).

that the services productivity behavior was crucial in determining the observed aggregate productivity path while manufacturing productivity had a secondary role.

Premature Deindustrialization

The U.S. and other developed countries have experienced the process of deindustrialization for decades. The shares of labor and value-added in the U.S. manufacturing sector have steadly declined since the 1950s. Labor share in manufacturing declined from 33.4% in 1950 to 15.1% in 2010 and value-added share declined from 30.5% to 18.5%.

In contrast, Brazil experienced a monotonic increase in manufacturing labor share from 1950 to 1983. This period is also characterized by the implementation of protective policies such as import substitution which advocates replacing imports for domestic production and prohibiting the imports of goods for which there were a 'national similar'. These policies had the explicit goal of increasing activity in the domestic manufacturing sector. After its peak in 1983, labor share in manufacturing decreased until the early 2000s, followed by a mild increase. A well documented structural transformation fact is the inverted U-shaped path of manufacturing labor share over the course of development[35]. Even though such pattern can be observed in developing countries, including Brazil, the Brazilian manufacturing labor share turning point happens at a much lower level of income than observed at countries that industrialized earlier such as the U.S. and some European countries. This turning point at lower levels of income is the so called premature deindustrialization[36].

In our model, a decline in services productivity, A_s, reallocates labor away from agriculture and manufacturing – and towards services – due to complementarity of consumption. With a larger labor share in the services sector, services labor productivity then has more influence over aggregate productivity levels. As the counterfactual indicates, services productivity is crucial in explaining the manufacturing labor share and aggregate productivity after 1980. From the lens of our model, the premature deindustrialization in the Brazilian economy is mostly due to the low productivity in the services sector as firms in this sector require much more labor as a way to meet demand.

An increase in manufacturing productivity, A_m, has two enforcing effects that pushes labor away the manufacturing sector towards services. Higher manufacturing productivity reallocates labor towards services due to the preference for balanced consumption, $\sigma < 1$, and due to the high income elasticity, $\epsilon_s > \epsilon_m$. In the counterfactual exercise with A_m constant, the impacts on manufacturing labor share were very limited. Based on our model,

[35]See Herrendorf, Rogerson and Valentinyi (2014) for a thorough discussion of the structural transformation facts.

[36]Rodrick (2016).

manufacturing productivity A_m is not the major cause of the drop of manufacturing labor share observed.

3.7.3 Counterfactual: Wedges

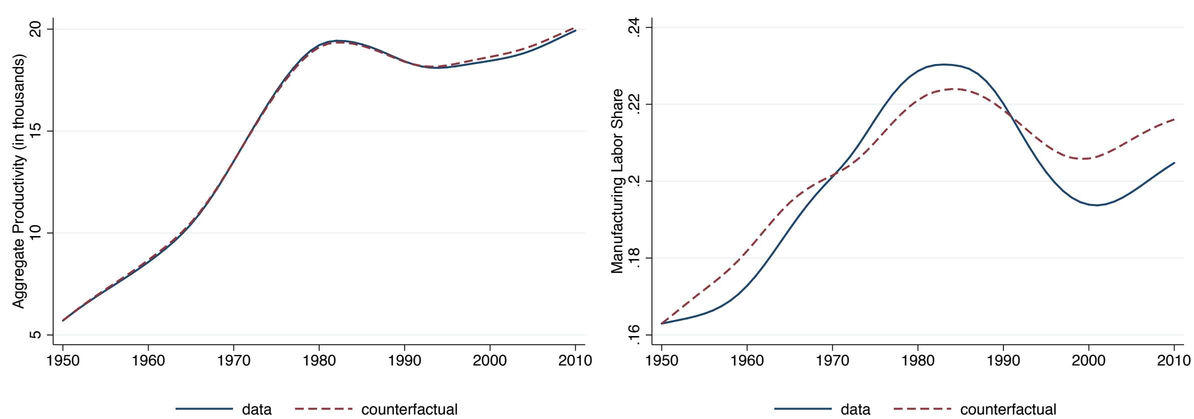
This counterfactual exercise assesses the quantitative importance of the distortions in the economy captured by the wedges. First, consider the case without manufacturing wedge, $\tau_m = 0$. Figure (3.9) shows that manufacturing after-wedge price is close to its benchmark price. Therefore, the manufacturing wedge will not have a large impact on labor allocation. Overall, the impact of the manufacturing wedge is very limited. This result is surprising given all the implemented policies with the clear goal of stimulating production in the manufacturing sector.

Figure (3.14) plots aggregate productivity and manufacturing labor share in the data and in the model without the wedge[37]. From the plots, we can see that the model without wedges captures well the data, leaving little room for wedges to have a big impact on aggregate productivity. Nevertheless, the addition of wedges would have a significant impact on manufacturing labor share. Without such wedge, manufacturing labor share would actually had grown faster until late 1960s. This result suggests that market frictions that caused a low demand for labor in the manufacturing sector were important, which is consistent with the view that monopolies and oligopolies were constraining the demand for labor in the sector. Therefore, given all the increase of manufacturing productivity, including the effects

Figure 3.14: Wedge: Manufacturing

(a) Aggregate Productivity

(b) Manufacturing Labor Share



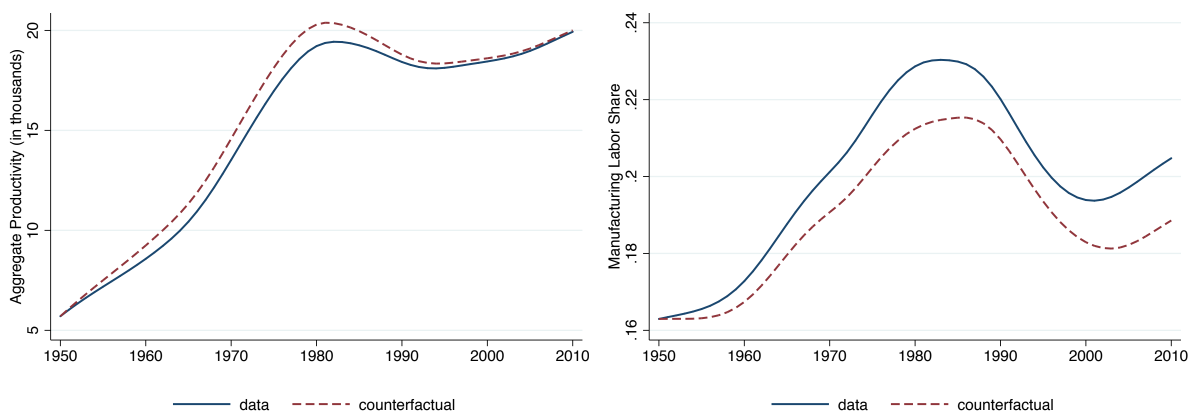
Note: Panel (a) plots aggregate productivity if there was no wedge on manufacturing $\tau_m = 0$. Panel (b) plots the manufacturing labor share. Notice that the impact on aggregate productivity is negligible. The effect on manufacturing labor share is relatively small.

[37] Appendix (C.4) shows the graphs for the other variables.

Figure 3.15: Wedge: Services

(a) Aggregate Productivity

(b) Manufacturing Labor Share



Note: Panel (a) plots aggregate productivity if there was no wedge on manufacturing $\tau_s = 0$. Panel (b) plots the manufacturing labor share.

associated with higher capital stock, we should had observed an even higher allocation of labor on manufacturing. From 1970 to 1990, manufacturing labor share of the counterfactual is below the data. This behavior is consistent with a government policy that stimulated the domestic production of capital goods. During the 1990-2010 period, the manufacturing wedge captures a larger difference between model and data. Manufacturing labor share is higher than the data for most of the period and this is consistent with the view that opening the economy has reduced the manufacturing labor share.

We now turn to the effects of the services wedge. From Figure (3.9), we see that services after-wedge price is considerably different from benchmark price. This distortion in a large and growing sector of the economy has bigger impacts in the overall economy than the manufacturing wedge. It captures almost all the gap between data and benchmark model of aggregate productivity. As in the benchmark, agriculture labor would be lower than observed, whereas services labor would be higher[38]. In addition, manufacturing labor share would be lower than the data throughout the entire period. Quantitatively, services wedge has a larger impact on manufacturing labor share than the manufacturing wedge itself.

3.8 Conclusion

This paper studies the Brazilian process of structural transformation process between 1950 and 2010. We use a framework that accommodates both long-run demand and supply drivers of labor reallocation. We decompose the sources of structural transformation and

[38] See Appendix (C.5)

find that income effect is the most important driver for the 1950-2010 period. However, if we focus only in the 1980-2010 period, price effect is now the most important driver even though income effect is still quantitatively important. For the entire period, the distortions captured by the wedge effect had minor impact on relative labor allocation. During the catching up period, we find that the fast manufacturing productivity growth was responsible for 15% of the aggregate productivity level in 1980. We also find that the decline in services productivity is the crucial determinant for the stagnation period after 1980. If services productivity has simply stayed constant at its 1980 level, aggregate productivity would be 28% higher in 2010.

The model used in this paper considers labor as the only input of production and ignores capital stock. However, many of the policies observed had the clear objective of increasing the capital accumulation in the country. Our next research step is to consider a model with endogenous inter-temporal choice that allows us to compute the effects of policies that distorted the increase of capital stock.

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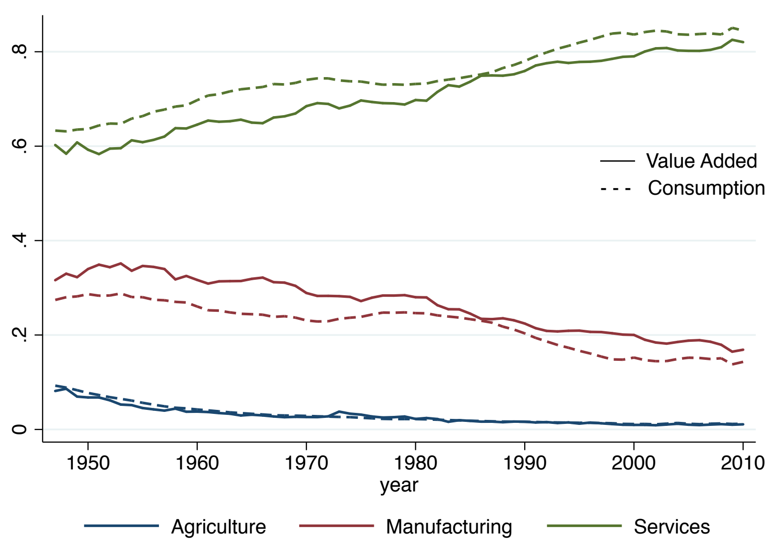
Appendix A

Appendix to Chapter 1

A.1 Extra Figures

Figure A.1: Consumption and Value-Added Shares



Note: Figure plots the consumption and value-added shares. Notice that both series follow the patterns. A decline of agriculture and manufacturing shares, and a continuous increase of services.

A.2 Income Elasticity of Consumption Demand

In the subsection (1.4.2), I discussed the income elasticity of expenditure share. Usually, the income elasticity is computed for consumption demand c_i. In this section, I calculate the income elasticity for consumption and show that it has the very same behavior as ξ_i.

Define the income elasticity of demand as $\hat{\xi}_i$:

$$\hat{\xi}_i = \frac{\partial c_i/\partial e}{c_i/e} \tag{A.1}$$

Using the consumption demand equation (1.3):

$$\frac{\partial c_i}{\partial e} = \frac{\mathbf{B}_i}{\mathbf{B}} + \mathbf{D}_i(1-\epsilon)\left[\frac{e}{\mathbf{B}} - \mathbf{A}\right]^{-\epsilon} \tag{A.2}$$

Therefore, the income elasticity of demand is:

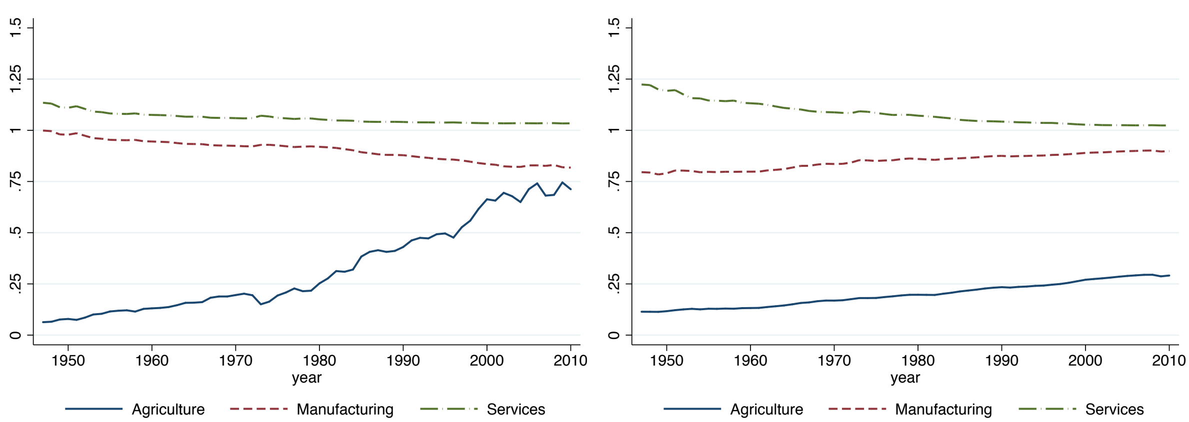
$$\hat{\xi}_i = \frac{\frac{\mathbf{B}_i}{\mathbf{B}} + \mathbf{D}_i(1-\epsilon)\left[\frac{e}{\mathbf{B}} - \mathbf{A}\right]^{-\epsilon}}{c_i/e} \tag{A.3}$$

The income elasticities $\hat{\xi}_i$ for both specifications are depicted in Figure (A.2). Notice that $\hat{\xi}_i$ has the same behavior as ξ_i. Now the good is a luxury if $\hat{\xi}_i$ is larger than one and a necessity if it is lower.

Figure A.2: Income Elasticity

(a) Generalized Stone-Geary

(b) Stone-Geary



Note: The income elasticity is ξ_i. The elasticity for the Stone-Geary specification is monotone and becomes weaker over time, converging towards zero.

A.3 Expenditure Share Algebra

In this section, I show the calculations to get the expenditure share used for estimation. Consider the CES functional form of $\mathbf{B}$:

$$\mathbf{B} = \left[\sum_{i\in\{a,m,s\}} \phi_i p_i^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$$

The derivative wrt to good j is:

$$\begin{aligned}\mathbf{B}_j &= \frac{1}{1-\sigma}\left[\sum_{i\in\{a,m,s\}} \phi_i p_i^{1-\sigma}\right]^{\frac{1}{1-\sigma}-1} (1-\sigma)\phi_j p_j^{-\sigma} \\ &= \left[\sum_{i\in\{a,m,s\}} \phi_i p_i^{1-\sigma}\right]^{\frac{1}{1-\sigma}-1} \phi_j p_j^{-\sigma}\end{aligned}$$

Notice that:

$$\sum_{i\in\{a,m,s\}} \phi_i p_i^{1-\sigma} = \mathbf{B}^{1-\sigma}$$

Rewriting $\mathbf{B}_j$:

$$\mathbf{B}_j = \frac{\left[\sum_i \phi_i p_i^{1-\sigma}\right]^{\frac{1}{1-\sigma}}}{\sum_i \phi_i p_i^{1-\sigma}} \phi_j p_j^{-\sigma} = \frac{\mathbf{B}}{\mathbf{B}^{1-\sigma}}\phi_j p_j^{-\sigma} = \frac{1}{\mathbf{B}^{-\sigma}}\phi_j p_j^{-\sigma} = \mathbf{B}^{\sigma}\phi_j p_j^{-\sigma}$$

Now, consider the functional form of $\mathbf{D}$:

$$\mathbf{D} = \bar{D}\sum_{i\in\{m,s\}} \nu_i \ln\left(\frac{p_i}{p_a}\right)$$

So, the derivatives for $j \in \{m, s\}$:

$$\begin{aligned}\mathbf{D}_j &= \bar{D}\nu_j \frac{1}{p_j/p_a}\frac{1}{p_a} \\ &= \bar{D}\nu_j \frac{1}{p_j}\end{aligned}$$

The derivative for $j = a$:

$$\begin{aligned}\mathbf{D}_a &= \bar{D}\sum_i \nu_i \frac{1}{p_i/p_a} p_i(-1)p_a^{-2} \\ &= -\bar{D}\sum_i \nu_i \frac{1}{p_a}\end{aligned}$$

Finally, the functional form of $\mathbf{A}$ is:

$$\mathbf{A} = \mathbf{B}^{-1} \sum_i p_i \bar{c}_i$$

The derivative wrt p_j:

$$\mathbf{A}_j = \mathbf{B}^{-1} \bar{c}_j + (-1)\mathbf{B}^{-2}\mathbf{B}_j \sum_i p_i \bar{c}_i$$

We have that

$$\mathbf{A}_j \mathbf{B} = \bar{c}_j - \mathbf{B}^{-1}\mathbf{B}_j \sum_i p_i \bar{c}_i$$

The expenditure share equation can be written as:

$$\begin{aligned}
\omega_j = \frac{p_j c_j}{e} &= \left[p_j \bar{c}_j - \mathbf{B}^{\sigma-1} \phi_j p_j^{1-\sigma} \sum_i p_i \bar{c}_i \right] \left(\frac{1}{e} \right) + \mathbf{B}^{\sigma-1} \phi_j p_j^{1-\sigma} + \mathbf{D}_j \, p_j \left(\frac{e}{\mathbf{B}} - \mathbf{A} \right)^{1-\epsilon} \left(\frac{\mathbf{B}}{e} \right) \\
&= \frac{\phi_j p_j^{1-\sigma}}{\sum_i \phi_i p_i^{1-\sigma}} + \left[p_j \bar{c}_j - \frac{\phi_j p_j^{1-\sigma}}{\sum_i \phi_i p_i^{1-\sigma}} \sum_i p_i \bar{c}_i \right] \left(\frac{1}{e} \right) + \mathbf{D}_j \, p_j \left(\frac{e}{\mathbf{B}} - \mathbf{A} \right)^{1-\epsilon} \left(\frac{\mathbf{B}}{e} \right) \\
&= \frac{p_j \bar{c}_j}{e} + \frac{\phi_j p_j^{1-\sigma}}{\sum_i \phi_i p_i^{1-\sigma}} \left[1 - \left(\sum_i p_i \bar{c}_i \right) \frac{1}{e} \right] + \bar{D} \nu_j \left(\frac{e}{\mathbf{B}} - \mathbf{A} \right)^{1-\epsilon} \left(\frac{\mathbf{B}}{e} \right)
\end{aligned}$$

The functional form of expenditure share equation (1.5) used for estimation is:

$$\omega_j = \frac{p_j \bar{c}_j}{e} + \frac{\phi_j p_j^{1-\sigma}}{\sum_i \phi_i p_i^{1-\sigma}} \left[1 - \left(\sum_i p_i \bar{c}_i \right) \frac{1}{e} \right] + \bar{D} \nu_j \left(\frac{e}{\mathbf{B}} - \mathbf{A} \right)^{1-\epsilon} \left(\frac{\mathbf{B}}{e} \right)$$

where the Stone-Geary formulation considers the case with $\bar{D} = 0$.

Appendix B

Appendix to Chapter 2

B.1 Data Sources

- Data sources:

  1. Value added:

     - value added is from BEA's 'GDP-by-Industry' tables

  2. Employment and hours worked:

     - employment is full-time and part-time employees reported in BEA's 'GDP-by-Industry' tables
     - I assume average hours worked is the same across the sectors and use the series 'Average Annual Hours Worked by Persons Engaged' from St Louis FRED database.

  4. Energy use:

     - energy data is energy consumption of end users from 'Montlhy Energy Review' provided by the Energy Information Agency (EIA). EIA divides end use sectors in Industrial, Commercial, Residential and Transportation and has limited mapping to NAICS classification.
     - Industrial sector energy use encompasses NAICS Agriculture (11), Construction(23), Mining (21) and Manufacturing (31-33).

- Sector assignment:

  1. I assume the value added of the coal, petroleum, natural gas and electricity sectors equal the US Bureau of Economics (BEA) Mining (21) and Utilities (22)

value added from "GDP-by-Industry" tables. Since in the model all energy use is imported, I subtract these two sectors from the value added and employment data.

2. EIA Industrial energy use data includes Mining. To subtract the energy use by this sector I make use of the KLEMS database provided by the BEA. I assume the share of expenditure on energy by the Mining sector equals its share of energy use in the Industrial data.
3. Commercial, Residential and Transportation energy use were considered services use
4. Goods sector corresponds to NAICS sectors Agriculture (11), Construction (23) and Manufacturing (31-33).
5. Services sector corresponds to all the other sectors, excluding Utilities (22).
6. BEA does not publish quantity of value added at the level of the two broad sectors used in this paper, so these quantities need to be constructed. The real quantities were constructed using the chain-weighted method. I followed the methodology described in Herrendorf, Herrington and Valentinyi (2015).

- Energy prices:

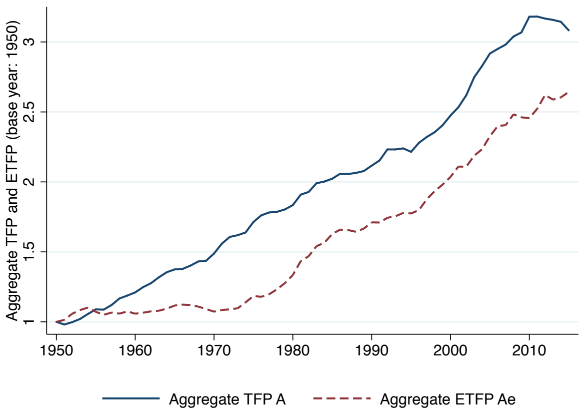
1. Prices for coal, natural gas and oil are 'production price' series from 'Annual Energy Review' and 'Monthly Energy Review'. Prices are in dollars per million Btu.
2. Prices for electricity is 'retail price of electricity' sold by electric utilities. The price is in cents per kilowatthour. EIA conversion factor is $3,412$ Btu per kilowatthour.
3. Data serie for electricity price starts only in 1960. I assumed the prices from 1950 to 1959 were equal to 1960. Given that the energy price is roughly constant throughout the 1960s, this assumption is unlikely to affect the results.
4. Energy price index was also constructed using the chain-weighted method.

- Carbon emission:

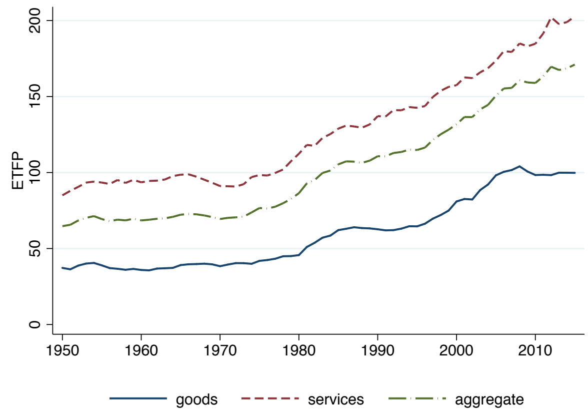
1. Carbon emission series from EIA. Total sum of end-use sectors.
2. Carbon Emission was adjusted by the energy use in the Mining sector.
3. Data from 1950 to 2011 is from 'Annual Energy Review'. From 2012 to 2015 from 'Monthly Energy Review'.

B.2 Aggregate Productivity

In this section I simply plot aggregate productivity and aggregate energy-saving productivity.



(a) Aggregate TFP and ETFP (base year:1950)



(b) ETFP Level

Figure 19: Aggregate TFP and ETFP

Note: Panel (a) plots aggregate TFP and ETFP normalized for 1950. Panel (b) plots ETFP levels. Energy-saving productivity is also roughly constant up to mid 1970s. Afterwards, there is a fast increase.

B.3 Estimation

For the quantitative exercises I calibrated the model parameters (b, σ, η) that better matched the data. The estimation of the model may also be based on household consumption allocation. Preference parameter b is determined after σ and η are estimated. More specifically, given σ and η, b is chosen to match labor share in the goods sector in 1950. I have chosen not to do so because I am considering all production is consumed, and in the data a share of production is used for investment. So, it is possible to find parameter that better matches the data than the estimated ones.

The estimation of σ and η relies on the household allocation of consumption given by equation (10) in its log-linear form:

$$\ln(c_{gt}) = \sigma \ln\left(\frac{p_{st}}{p_{gt}}\right) + \eta \ln(c_{st}) - \sigma \ln\left(\frac{1-b}{b}\frac{\sigma-\eta}{\sigma-1}\right) \tag{11}$$

In the model, consumption equals value-added of production in each each sector. To estimate equation (11) I just use value-added per capita series for each sector. The prices for each sector were also calculated using the chain-weighted method Table (1) reports the

σ	η	R^2	Obs
0.263*	0.603*	0.981	61
(0.06)	(0.048)		

Table 2: Parameter Estimation

Note: The table shows the estimation results of household allocation using consumption in value-added. Robust standard errors are in parentheses. Obs stands for number of observations.
p-value: * $p < 0.01$.

results of the estimation:

The estimated value of σ is 0.263 with (robust) standard deviation of 0.06. Notice that the estimated value of σ is statistically different from zero. The relative income elasticity η is equal to 0.603. This value of η equals the ratio of the income elasticity of goods over the income elasticity of services and it makes sense because an η less than one indicates that goods are income inelastic and services are income elastic. Given the values of σ and η, I calibrate $b = 0.02$ to match total energy (per hour) in the model with the data.

The economic literature has not found conclusive results for the value of the elasticity of substitution across the sectors. Herrendorf *et al.* (2013) estimate the elasticity of substitution using a Stone-Geary utility with three consumption goods (agriculture, manufacturing and services). They find a value of σ that is not statistically different from zero. Using a similar utility function, Buera and Kaboski (2009) finds a similar result for the 1870-2000 period (as discussed on footnote 3 of their paper). On the other hand, using an utility function with constant income effects, Comin *et al.* (2015) find the elasticity of substitution to be statistically different from zero [1]. As in Comin et al. I also consider an utility function with constant income effects, and I also find a significant value for σ. During the period, both the share of expenditure in services and the relative price of services with respect to goods grow. The utility used in this paper both the income effect and the price effect cause an increase in the share of spending on services.

[1] Comin *et al.* (2015) estimated the value of σ is 0.57 with standard deviation of 0.1.

Appendix C

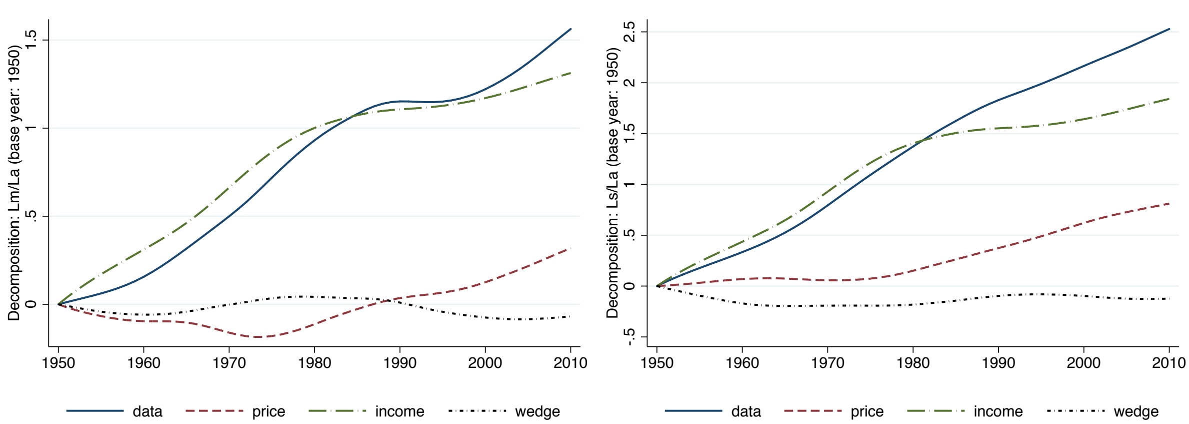
Appendix to Chapter 3

C.1 Decomposition

Figure (C.1) plots the decomposition for the entire 1950-2010 period. Between 1950-1980 income effect follows very closely the data. After 1980, its slope is much smaller and it doesn't follow the data so closely anymore. This change motivates our decision of making the decomposition exercise in two different sub-periods. It is also clear that the manufacturing wedge has just a small effect on labor allocation. Services sector wedge is only quantitatively important from 1950 to 1980. Table (I) shows the average importance of each effect for the entire 1950-2010 period. Notice that, if analyzed for the entire period, income is the most

Figure C.1: Decomposition: 1950-2010

(a) Manufacturing (b) Services



Note: Panel (a) plots decomposition of manufacturing relative labor L_m/L_a. Panel (b) plots decomposition of services L_s/L_a. Income is the most important force between 1950 and 1980. After 1980, price becomes the most important, even though income effect is still relevant.

important force for both sectors.

Table I: Decomposition: Manufacturing

	Labor	Price	Income	Wedge
1950-2010	0.0256	0.0052	0.0215	-0.0011
		(0.2031)	(0.8398)	(-0.0429)
1950-1980	0.0300	-0.0036	0.0323	0.0014
		(-0.12)	(1.0766)	(0.0466)
1980-2010	0.0204	0.0139	0.0101	-0.0036
		(0.6813)	(0.4950)	(-0.1764)
1950-1960	0.0156	-0.0096	0.0311	-0.0059
		(-0.6153)	(1.9935)	(-0.3782)
1960-1970	0.0343	-0.0065	0.0351	0.0057
		(-0.1895)	(1.0233)	(0.1661)
1970-1980	0.0431	0.0048	0.0339	0.0044
		(0.1113)	(0.7865)	(0.1020)
1980-1990	0.0221	0.0148	0.0105	-0.0033
		(0.6696)	(0.4751)	(0.1493)
1990-2000	0.0069	0.0090	0.0064	-0.0085
		(1.3043)	(0.9275)	(-1.2318)
2000-2010	0.0342	0.0193	0.0142	0.0007
		(0.5643)	(0.4152)	(0.0204)

Note: Table (I) shows the average growth of manufacturing labor relative to agriculture. It decomposes the quantitative importance of price, income and wedge effects in the allocation of labor for different period intervals. Price effect is $(1-\sigma)\ln(A_a/A_m)$. Income effect is $(\epsilon_m-\epsilon_a)\ln(C)$. Wedge effect is $(-\sigma)\ln(1+\tau_m)$. The values in parenthesis indicate the relative contribution of each effect.

Table II: Decomposition: Services

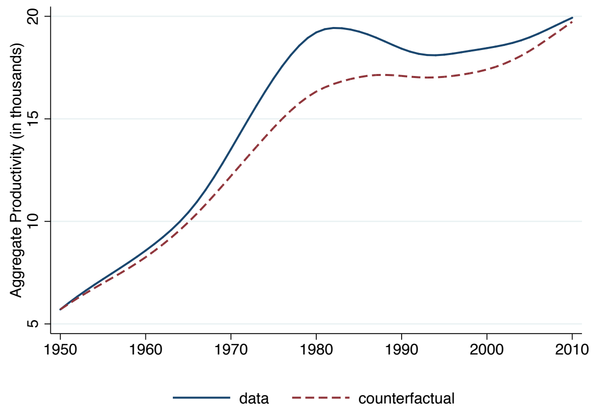
	Labor	Price	Income	Wedge
1950-2010	0.0415	0.0102	0.0302	-0.0020
		(0.2458)	(0.7277)	(-0.0482)
1950-1980	0.0443	0.0049	0.0453	-0.0059
		(0.1106)	(1.0226)	(-0.1332)
1980-2010	0.0373	0.0213	0.0141	0.0019
		(0.5710)	(0.3780)	(0.0509)
1950-1960	0.0334	0.0068	0.0436	-0.0170
		(0.2036)	(1.3054)	(-0.5090)
1960-1970	0.0459	-0.0011	0.0493	-0.0022
		(-0.0240)	(1.0741)	(-0.0479)
1970-1980	0.0579	0.0093	0.0475	0.0010
		(0.1606)	(0.8204)	(0.0173)
1980-1990	0.0456	0.0223	0.0148	0.0086
		(0.4890)	(0.3246)	(0.1886)
1990-2000	0.0336	0.0247	0.0090	-0.0001
		(0.7351)	(0.2679)	(0.0030)
2000-2010	0.0364	0.0190	0.0200	-0.0026
		(0.5220)	(0.5495)	(-0.0714)

Note: Table (II) shows the average growth of manufacturing labor relative to agriculture. It decomposes the quantitative importance of price, income and wedge effects in the allocation of labor for different period intervals. Price effect is $(1-\sigma)\ln(A_a/A_s)$. Income effect is $(\epsilon_s - \epsilon_a)\ln(C)$. Wedge effect is $(-\sigma)\ln(1+\tau_s)$. The values in parenthesis indicate the relative contribution of each effect.

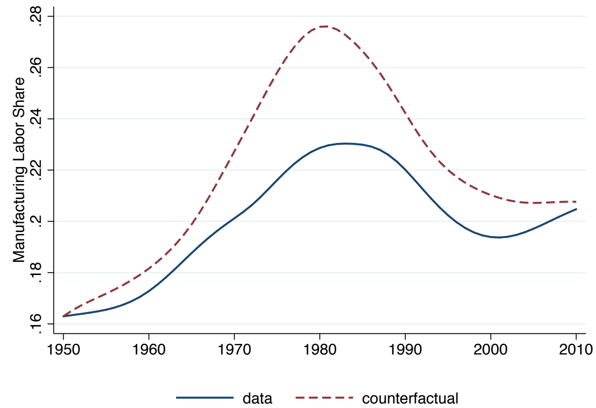
C.2 Counterfactual 1

Figure C.2: Counterfactual 1

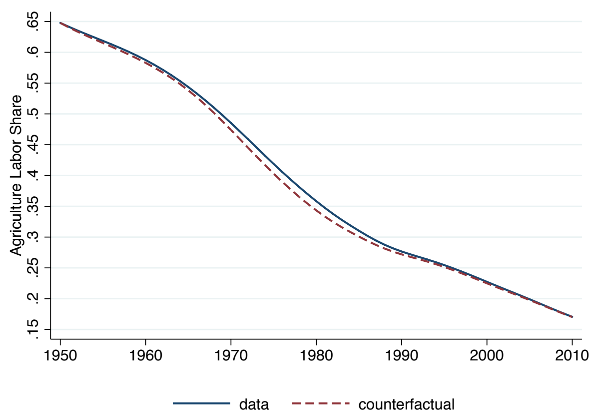
(a) Aggregate Prodcutivity



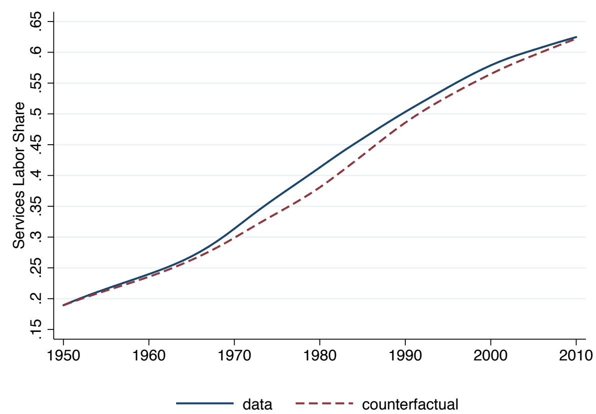
(b) Manufacturing Labor Share



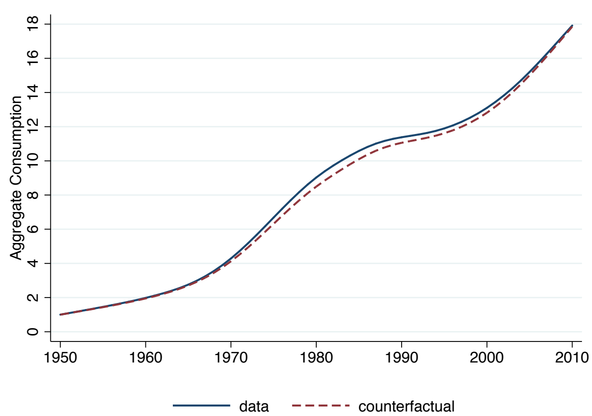
(c) Agriculture Labor Share



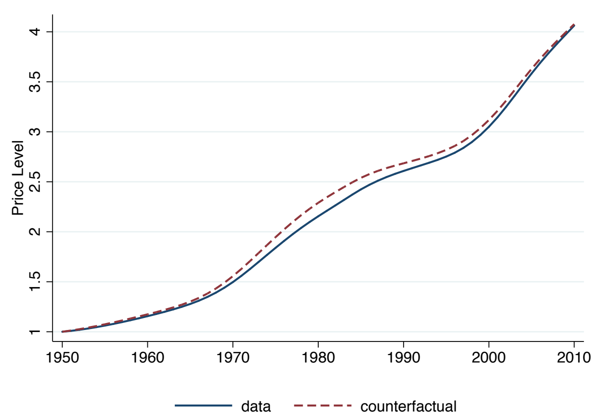
(d) Services Labor Share



(e) Aggregate Consumption



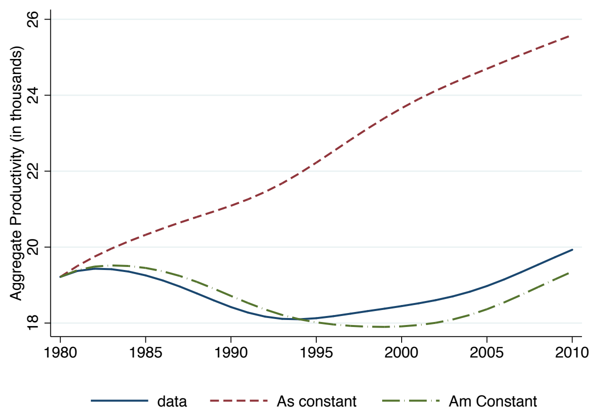
(f) Price Index



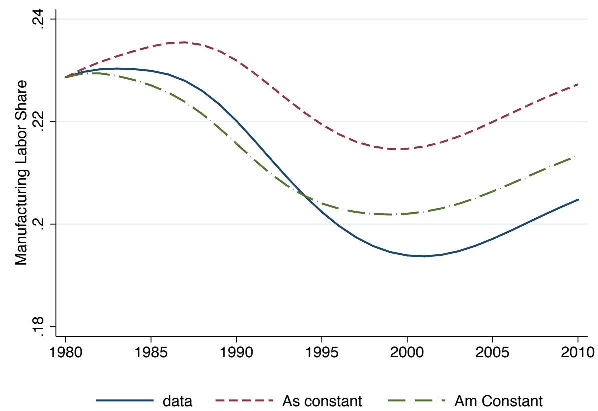
C.3 Counterfactual 2

Figure C.3: Counterfactual 2

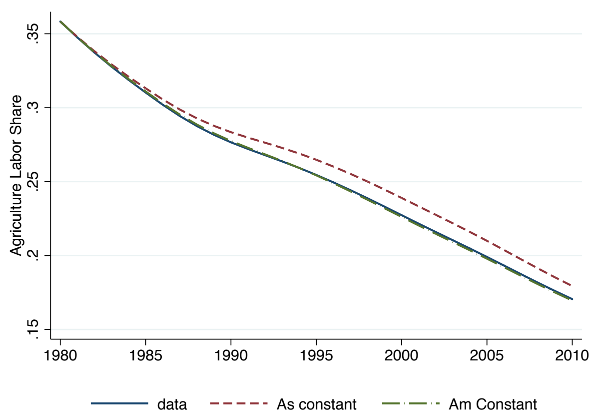
(a) Aggregate Prodcutivity



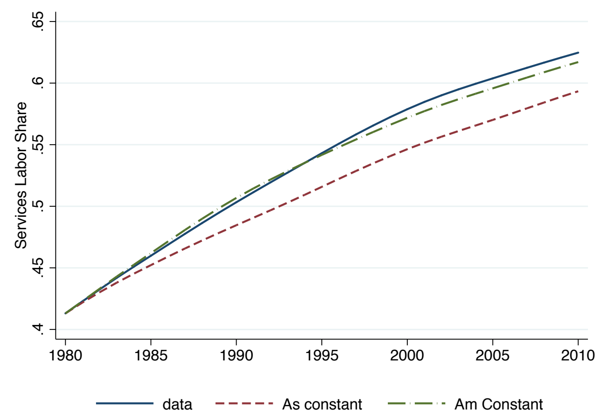
(b) Manufacturing Labor Share



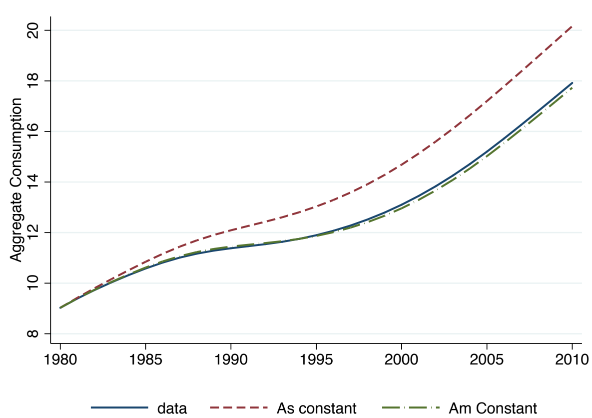
(c) Agriculture Labor Share



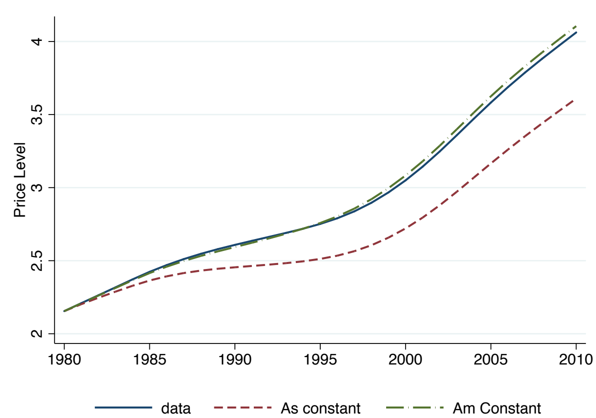
(d) Services Labor Share



(e) Aggregate Consumption



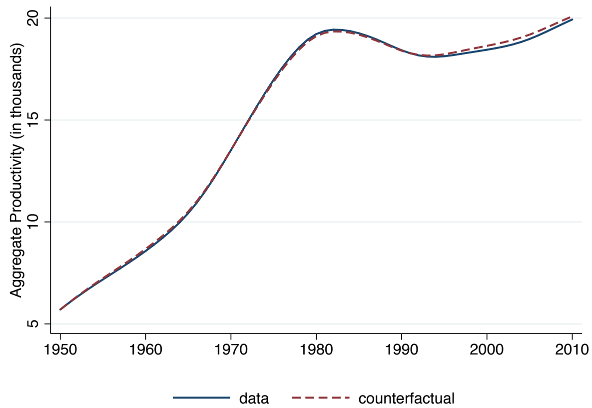
(f) Price Index



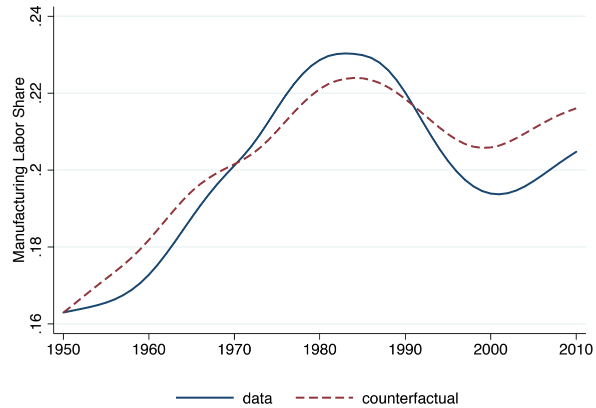
C.4 Counterfactual - Manufacturing Wedge $\tau_m = 0$

Figure C.4: Counterfactual - No Manufacturing Wedge

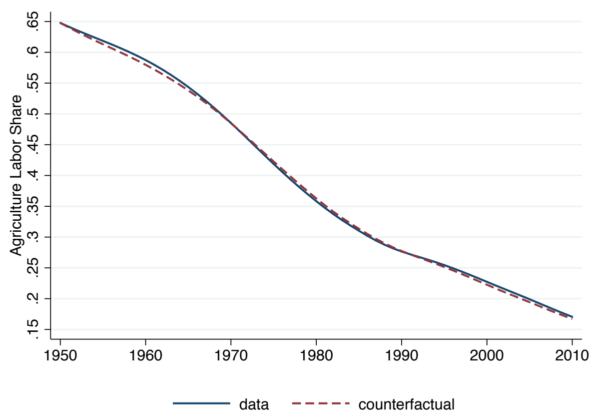
(a) Aggregate Prodcutivity



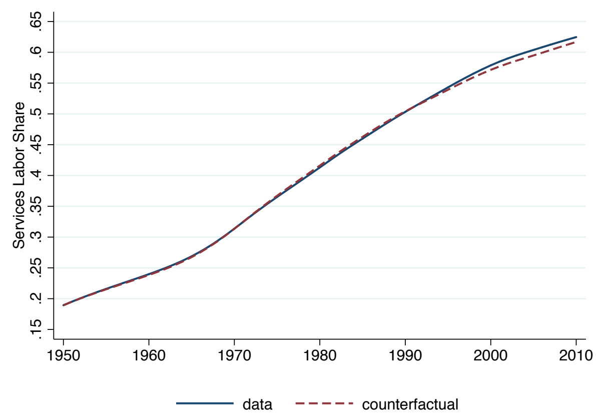
(b) Manufacturing Labor Share



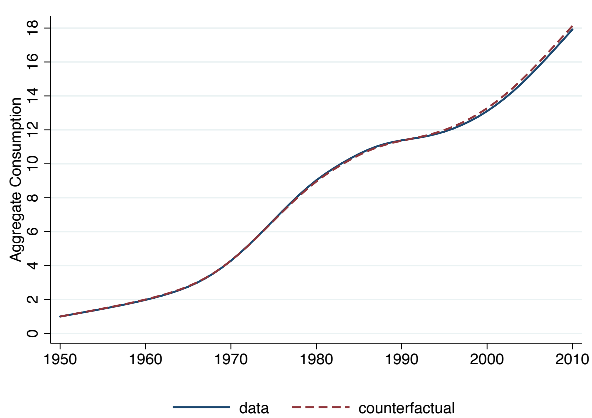
(c) Agriculture Labor Share



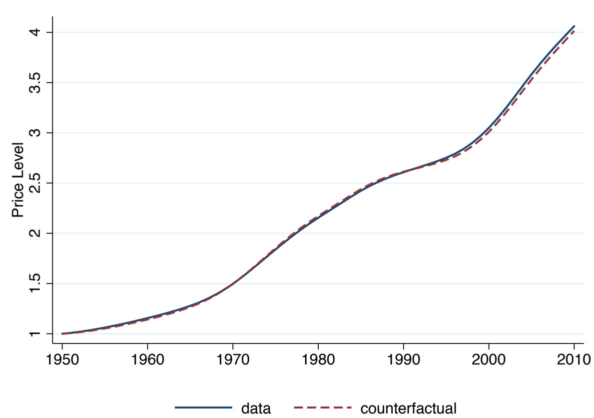
(d) Services Labor Share



(e) Aggregate Consumption



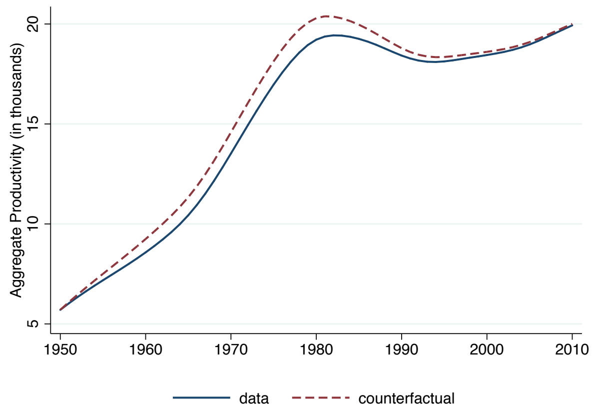
(f) Price Index



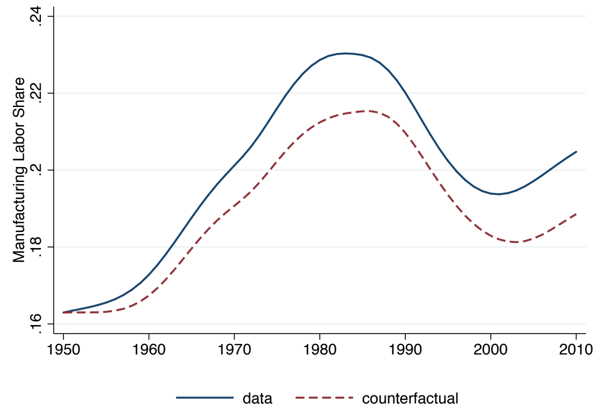
C.5 Counterfactual - Services Wedge $\tau_s = 0$

Figure C.5: Counterfactual - No Services Wedge

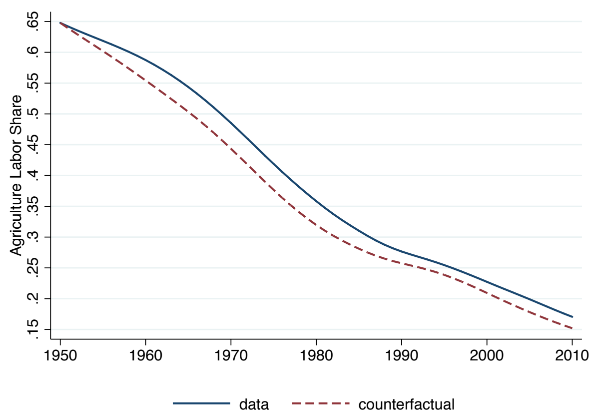
(a) Aggregate Prodcutivity



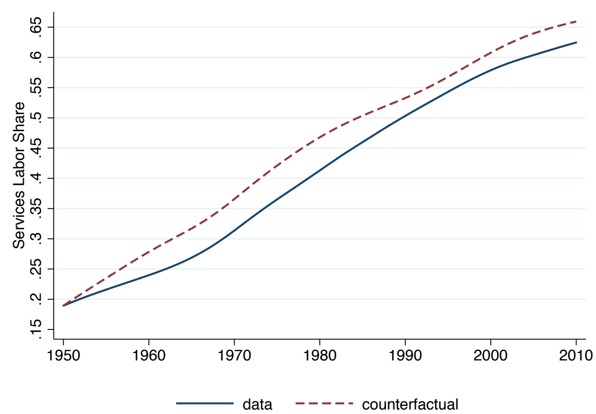
(b) Manufacturing Labor Share



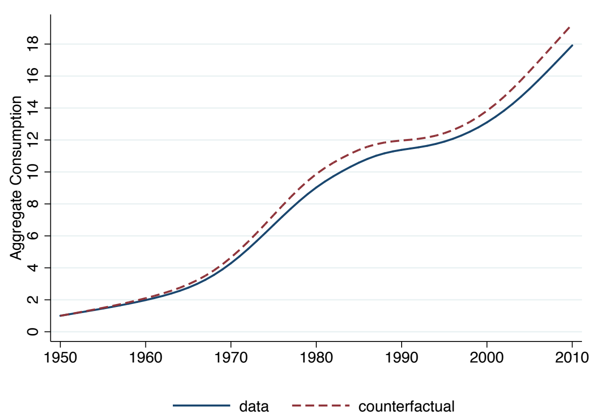
(c) Agriculture Labor Share



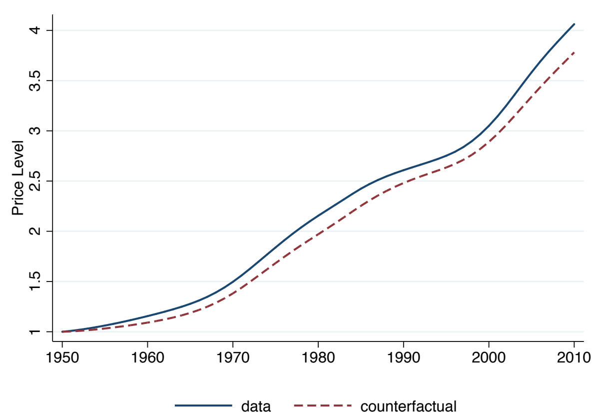
(d) Services Labor Share



(e) Aggregate Consumption



(f) Price Index



C.6 Another Analysis on the Contribution of Relative Prices and Consumption

Table (III) below presents the results for different regression specifications of the regression.

Table III: Contribution of Relative Prices and Consumption

Specification	Coefficient	χ^2	p-value	AIC	BIC
Relative Price	1.10	1403.85	0.00	-141.44	-131.11
Consumption	0.54	2173.54	0.00	-249.89	-241.44
	0.87	1003.17	0.00		
Full		8005.08	0.00	-399.14	-388.58
		17364.68	0.00		

Note: Table (III) shows different estimations of the demand functions (3.18). The specification 'Relative Price' considers the model with usual homothetic CES aggregator. The specification 'Consumption' considers only the nonhomotheticity terms without substitutability between the consumption goods. The first coefficient equal to 0.54 refers to $(\epsilon_m - \epsilon_a)$ and the second equal to 0.87 to $(\epsilon_s - \epsilon_a)$. The 'Full' refers to the case with both effects discussed in the text. AIC refers to Akaike Information Criterion, BIC to Bayesian Information Criterion.

Table (6) compares different specifications of the demand equations (18) and (19). Model with only relative prices is estimated considering the cross-equation coefficient value restriction and corresponds to the usual homothetic CES aggregator. The estimated elasticity of substitution would actually be negative because the coefficient term is $1 - \sigma = 1.10$. If we constraint the coefficient to be less than one (i.e., $1 - \sigma < 1$), estimated elasticity of substitution is statistically equal to zero. Model 'Consumption' has a better fit than 'Relative Price' based on its lower AIC and BIC. Also, as expected, the full model has the highest explanatory power.

Now we discuss the partial correlations in the model. Assume that y is determined by $x_1, x_2, ..., x_N$. The squared semipartial correlation between y and x_1 represents the proportion of variance in y that is explained by x_1 only. That is, the proportion of all variance in y that is associated with x_1, but not with any other predictor. The squared partial correlation between y and x_1 represents the proportion of variance in y not associated with any other x's that is explained by x_1.

Table IV: Partial Correlations

	Consumption $\ln(C)$		Relative Prices $\ln(A_a/A_i)$	
	Partial Corr^2	SemiPartial Corr^2	Partial Corr^2	SemiPartial Corr^2
$\ln(L_m/L_a)$	0.993	0.504	0.886	0.024
$\ln(L_s/L_a)$	0.983	0.150	0.955	0.054

Note: Table (IV) shows the squared partial correlations and the squared semipartial correlations of equation (3.18).