On the Welfare Costs of Premature Deindustrialization

Roberto N. Fattal Jaef*

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Abstract

Developing countries are deindustrializing at earlier stages of development than experienced by advanced economies. Is this trend symptomatic of inefficiency? If so, what are the welfare costs? This paper proposes a definition of premature deindustrialization based on whether the pace of deindustrialization diverges from the one implied by a theoretical benchmark of efficient sectoral allocation. It identifies ten episodes of premature deindustrialization, carrying negligible welfare costs, below 1% of aggregate consumption.

1 Introduction

A widespread feature of economic development in advanced economies is the protracted reallocation of resources from agriculture into industry and ultimately the service sector. Among developing countries, however, industrialization is reaching lower levels and reversing at earlier stages of development, a pattern that Dasgupta and Singh (2007) and Rodrik (2016) coined *premature deindustrialization*. What are the causes underlying such a trend? Is it symptomatic of inefficiency or is it justified by fundamental drivers of structural change? If inefficient, how costly is it for welfare? We confront these questions in this paper. First, we propose an alternative definition

*Development Research Group, Macroeconomics and Growth, the World Bank. rfattaljaef@gmail.com. We are indebted to Guillermo Beylis and Rishabh Sinha for the helpful comments and suggestions. The views expressed here are solely the authors and do not represent the views of the World Bank Group, its affiliated organizations, or any of its member countries.

of premature deindustrialization based on whether the pace of deindustrialization diverges from the one implied by a theoretical benchmark of efficient sectoral allocation. In this way, deindustrialization will be premature only if it proceeds at a faster pace than dictated by fundamentals in the model. Then, equipped with a taxonomy of countries undergoing premature deindustrialization, we quantify its welfare cost. We identify ten episodes of premature deindustrialization with negligible welfare costs, below 1% of aggregate consumption.

The first step in our analysis is to propose a theory of structural transformation that provides the benchmark for efficient (de)industrialization. To this end, we appeal to the simplest framework that captures both demand and supply-side forces of structural change, namely a reallocation due to income effects under a non-homothetic demand system and unbalanced productivity growth across sectors under complementarities in expenditure. Our chosen framework is the one developed in Comin et al. (2021) abstracting from physical capital accumulation. We feed the model with a series of measured labor productivity across sectors and aggregate real consumption from the data. Then, we introduce wedges to the sectoral allocations of labor to reconcile the equilibrium employment shares with those observed in the data and back out the aggregate productivity path that sustains the observed real consumption as an equilibrium outcome. In this way, we recreate within the model the series of real consumption and the agricultural, industrial, and service shares observed in the data. Next, preserving the same dynamics of sectoral and aggregate productivity, we remove the wedges and solve for the efficient sectoral allocations and the efficient aggregate consumption.

Equipped with an efficient benchmark of structural transformation, we propose two empirical strategies to identify inefficient premature deindustrialization. In the first measure, which we refer to as *episodic*, we impose two conditions that each country's deindustrialization path must satisfy to be classified as inefficient: i) having undergone a period of industrialization within the time frame of our sample, and ii) having started deindustrialization which proceeds at a faster pace than the one predicted by the efficient benchmark for a decade or longer[1] The first requirement rules out advanced economies which have been deindustrializing throughout the entire sample period. The second requirement also rules out countries that are currently transiting the industrialization stage and thus are not deindustrializing. We are left

[1]Our episodic characterization of inefficient premature deindustrialization is similar in spirit to Hausmann et al. (2005)'s approach for identifying sustained growth acceleration episodes.

with ten episodes of premature deindustrialization satisfying our criteria, mostly in Latin America[2].

In the second approach, we follow Rodrik (2016) in proposing a regression-based assessment of premature deindustrialization. We regress the actual and the efficient industrial employment shares against a series of explanatory variables and decade dummies. We claim that premature deindustrialization has occurred if the point estimate for the decade dummies in the data decreases at a faster pace than the point estimates for the efficient model-based shares. Again, we find evidence of premature deindustrialization which is the most acute among Latin American countries. However, our comparison of the point estimates between the data and the efficient shares reveals premature deindustrialization that is less severe than inferred without any reference to efficient deindustrialization.

The second contribution of the paper is to quantify the welfare implications of premature deindustrialization. For each episode, we compute the welfare cost of premature deindustrialization as the difference between the present value of utility derived from the observed real consumption relative to the efficient one implied by the model. We find the welfare gains from reversing premature deindustrialization to be small, less than 1% of permanent consumption.

We offer two interpretations of our welfare results. First, we view them as supporting the arguments against the implementation of industrial policies aimed at relieving or reversing deindustrialization. Given the complex implementation of such policies and the discretion behind the choice of winners and losers, the magnitude of the gains does not justify the confrontation of these risks.[3] Rather, an efficient mechanism to ameliorate the pace of deindustrialization would be to identify channels to increase productivity growth in the service sector.

Alternatively, one could interpret the results as questioning the validity of our efficient benchmark. Skepticism concerning the model can push the welfare results in opposite directions, depending on the type of model miss-specification. One force that we abstract from in the model is international trade. As articulated in Rodrik (2016), trade could represent a plausible driver of faster deindustrialization. If trade

[2]As a preview, the episodes of premature deindustrialization are: Argentina, Bolivia, Brazil, Chile, Denmark, France, Peru, South Africa, The United Kingdom, the Philippines, and Venezuela

[3]While recent advocates of reviving industrial policy, for instance, Aiginger and Rodrik (2020), appeal to a fresher narrative that distinguishes the modern approach from the distortionary tools characterizing industrial policy in the past, we argue it is still useful for this dialogue to occur with concrete measures of what it is to be gained from implementing these policies, relative to its costs

indeed brings the efficient dynamics closer to the observed ones, it would further contribute to mitigating the already low welfare costs of premature deindustrialization. Conversely, if, as argued since Kaldor (1968), there are externalities in the production of manufacturing goods that are not accounted for in the model, the efficient path of (de)industrialization would be even further apart from the actual one and the welfare costs would be higher. Similarly, our model abstracts from physical capital accumulation which, as shown in García-Santana et al. (2021), interacts with the dynamics of industrialization. All caveats considered, we argue that our chosen benchmark, which stays close to the latest models in the structural transformation literature constitutes an adequate first approximation to the question of how much of the observed premature deindustrialization is inefficient and how big its welfare costs.

The rest of the paper is organized as follows. First, we review the related literature in section 2 and highlight our contributions. Next, section 3 introduces the theory, section 4 presents the data sources for the empirical and quantitative analysis, and section 5 discusses the calibration of parameter values and the determination of sectoral paths of relative productivity and real consumption expenditure. Then, in section 6, we characterize the inefficiency in premature deindustrialization based on episodic and regression-based approaches. In section 7 we quantify the welfare costs of premature deindustrialization and offer a discussion of our interpretation of the results in the context of the related literature and the ongoing debates around the role of industrial policies. Lastly, we conclude

2 Literature Review

Our work is heavily influenced by the premature deindustrialization trends identified in Dasgupta and Singh (2007) and Rodrik (2016). Our goal is to contribute to the discussion around the causes and consequences of premature deindustrialization endowing this concept with a notion of inefficiency. While, in the data, it is clear that developing countries are achieving lower rates of industrialization prior to reallocating labor towards the service sector, our view is that a proper discussion on the concerning nature of these patterns would be incomplete until the efficient and inefficient forces driving such reallocation are disentangled. Providing and implementing a strategy to achieve this goal is our main contribution to this empirical literature.

The theoretical framework guiding our identification of inefficient deindustrialization episodes builds upon the recent models of structural change encompassing both demand and supply-side forces. In particular, we adopt the combination of a Non-Homothetic Constant Elasticity of Substitution demand system and unbalanced sectoral productivity growth proposed in Comin et al. (2021), abstracting from physical capital accumulation. This framework provides a tractable and transparent characterization of structural transformation implementable across a broad set of countries while featuring the two main drivers of structural change: unbalanced productivity growth across sectors mediated by complementarity in expenditure (Ngai and Pissarides, 2007); and the reallocation of expenditure triggered by rising aggregate real income in a context of non-homothetic demand systems (Kongsamut et al., 2001).

In seeking to rationalize premature deindustrialization as an equilibrium outcome, our work relates to a recent but growing body of research. Sposi et al. (2021) build a model where supply and demand forces drive structural change in an open economy setting to study the role of these channels in explaining premature deindustrialization and industry polarization. In addition to remaining silent about industry polarization, we differ from this study in that we pursue a country-by-country exploration of the realized paths of deindustrialization against the efficient ones and identify the wedges that rationalize any divergence between the two. As a result, we are able to fulfill our objective of attaching a notion of inefficiency to a given path of deindustrialization and quantify its implications for economic welfare. We regard our small welfare costs as supporting the result in Sposi et al. (2021) that unbalanced productivity growth can account well, on average, for the premature deindustrialization in the data.

A similar contribution differentiates our work from Huneeus and Rogerson (2020) and Fujiwara and Matsuyama (2020). These papers identify the conditions under which differences in sectoral productivity growth or in countries' ability to catch up to frontier technologies can generate, as part of the equilibrium, industrialization and deindustrialization dynamics similar to those in the data. Our work shares the fundamental view that premature deindustrialization, despite being labeled as such suggesting an inefficiency, may indeed be merited by the standard forces of structural change. Our contribution, then, is to isolate the countries in which premature deindustrialization is inefficient and quantify its welfare costs. As said, our findings dictate that inefficient deindustrialization is less prevalent than otherwise concluded and carries minimal welfare costs.

3 Model

The theoretical framework underlying the efficient benchmark of structural transformation follows from Comin et al. (2021), abstracting from physical capital accumulation. The reasons that guided our choice were twofold. On the one hand, we sought to consider a model encompassing both of the primary forces of structural change considered in the literature: income effects due to non-homothetic demand and unbalanced sectoral productivity growth under complementarities in the demand for agriculture, industry, and services. The model in Comin et al. (2021) captures both forces in an empirically plausible fashion. On the other hand, we sought to consider a theoretical benchmark that provided a close fit to the structural transformation patterns of an advanced economy. By closely accounting for structural change in the U.S., Comin et al. (2021)'s model provides reassurance that any inferences of premature deindustrialization due to model misspecification are minimized.

In preparation for the forthcoming welfare cost calculation, we present the model introducing tax-like distortions to the production of manufacturing and services. As we explain in greater detail in section 5, these distortions are necessary to account for the observed pattern of employment shares in the model once we feed it with measured paths of sectoral relative productivity. The efficient allocation, then, is the one that results from shutting down the distortions. This efficient allocation provides the basis for the characterization of premature deindustrialization and the quantification of its welfare costs.

3.1 Non-Homothetic CES Demand System

We consider a representative household confronting a standard utility maximization problem subject to a budget constraint. Labor is supplied inelastically to the agricultural, manufacturing, and service sectors, and is perfectly mobile, thus compensated at a common wage. We abstract from physical capital accumulation and preclude the household from borrowing and saving technologies. Formally, the household solves:

$$max_{\{C_t\}} \Sigma_{t=0}^{\infty} \beta^t \frac{C_t^{1-\sigma}}{1-\sigma}$$

$$s.t.$$

$$C = w \left[L_A + L_M + L_S \right]$$

Notice we are adopting the final composite good as the numeraire.

Following the Non-Homothetic CES demand specification in Comin et al. (2021), the aggregate real consumption is defined implicitly as a function of the sectoral consumption according to the following constraint:

$$\Sigma_{i\epsilon\{A,M,S\}} \left[\Omega_i C^{\varepsilon_i} \right]^{\frac{1}{\sigma}} c_i^{\frac{\sigma-1}{\sigma}} = 1 \tag{1}$$

In order for this constraint to define a utility function, the parameter values must satisfy the following: 1) $\sigma > 0$ and $\sigma \neq 1$, 2) $\Omega_i > 0$ for all $i\epsilon\{A, M, S\}$,and 3) if $\sigma < 1$ $(\sigma > 0)$ then $\varepsilon_i > 0$ $(\varepsilon_i < 0)$. As shown in Comin et al. (2021), ε_i is the parameter controlling the strength of the income effects in each sector.

The objective of the household, then, is to minimize the cost of achieving a given level of real expenditure C, subject to the constraint 1. Taking the price vector as given, such cost minimization problem delivers the following demand function

$$c_i = \Omega_i \left(\frac{p_i}{E} \right)^{-\sigma} C^{\varepsilon_i} \tag{2}$$

where E is given by

$$E = \left[\Sigma_{i\epsilon\{A,M,S\}} \left(\Omega_i C^{\varepsilon_i} \right) \left(\frac{1}{p_i} \right)^{\sigma-1} \right]^{\frac{1}{1-\sigma}} \tag{3}$$

It can be readily shown that E stands for the aggregate cost of achieving real consumption C, $E = \Sigma_{i\epsilon\{A,M,S\}} p_i c_i$. Furthermore, it can be shown using equations 2 and 3 that the constraint that implicitly defines the measure of utility boils down to requiring that the sum of expenditure shares add up to 1. That is, denoting the expenditure share of good i as $\omega_i = \frac{p_i c_i}{E}$, satisfying equation 1 implies that $\Sigma_{i\epsilon\{A,M,S\}} \omega_i = 1$.

We can reformulate the demand function in equation 2 in terms of expenditure shares by defining $P \equiv \frac{E}{C}$ and rearranging, which yields

$$\omega_i = \Omega_i \left(\frac{p_i}{P}\right)^{1-\sigma} \left(\frac{E}{P}\right)^{\varepsilon_i-(1-\sigma)} \tag{4}$$

Taking the ratio of expenditure shares in any pair of sectors and expressing it in logs:

$$log\left(\frac{\omega_i}{\omega_j}\right) = log\left(\frac{\Omega_i}{\Omega_j}\right) + (1-\sigma)\, log\left(\frac{p_i}{p_j}\right) + \left(\varepsilon_i - \varepsilon_j\right) log\,(C) \tag{5}$$

Equation 5 shows transparently how the theory lends itself to decomposing the contributions of price and income effects. Price effects enter the equation as they would in the homothetic CES baseline. Assuming, as we shall in the quantitative analysis, that goods are more complementary than Cobb-Douglas (i.e. $\sigma < 1$), the expression establishes that as the relative price of a sector declines over time, its share of expenditure also falls in relation to the relatively more expensive good. The non-homothetic nature of the demand system manifests in the dependence of the relative expenditure shares on aggregate real consumption, a force that is captured in the last term of the right-hand side. Sectors with a higher income elasticity will experience a rise in expenditure share as the country becomes richer.

3.2 Production

We assume that production in each sector occurs in a representative competitive producer that operates a production function that is linear in labor (the sole input) and combines a sector-specific and an economy-wide productivity. Labor is freely mobile across sectors, and the labor market is also competitive. Formally, production technologies are

$$Y_i = \overline{A} A_i L_i$$

Economy-wide productivity is denoted with $\overline{A}$, while A_i stand for sector-specific productivity.

As said, we introduce a sequence of tax-like distortions to the production of manufacturing and services and a sequence of aggregate productivity so that the distorted allocation sustains the observed sectoral allocation and the aggregate real consumption in the data as equilibrium outcomes.

Concretely, let $\{\tau_{m,t}\}_{t=0}^{\infty}$, $\{\tau_{s,t}\}_{t=0}^{\infty}$, and $\left\{\overline{A}_t\right\}_{t=0}^{\infty}$ denote the sequences of revenue taxes in manufacturing and services, and the economy-wide sequence of aggregate productivity, the competitive representative producer in each sector solves[4]:

$$max_{L_i}\left\{(1-\tau_i)\,p_i\overline{A}A_iL_i - wL_i\right\}$$

Zero profit-making implies that

$$p_i\,(1-\tau_i)\,\overline{A}A_i = w$$

The above equation establishes that, under no distortions, the value of the marginal product of labor must be equalized across sectors. Distortions create a wedge in this optimal allocation rule.

The relative prices are given by

$$\frac{p_m}{p_s} = \frac{A_s}{A_m}\frac{(1-\tau_s)}{(1-\tau_m)} \tag{6}$$

$$\frac{p_m}{p_a} = \frac{A_a}{A_m}\frac{1}{(1-\tau_m)} \tag{7}$$

Again, distortions drive a wedge between the equalization of relative prices with the inverse ratio of relative productivity. Under no distortions, the relative price captures one of the fundamental drivers of structural change, the unbalanced productivity growth, thereby guiding the reallocation of expenditure and employment across sectors, mediated by the elasticity of substitution.

Market clearing in each sector implies

$$c_i = \overline{A}A_iL_i$$

Expressing in nominal terms and taking that ratio of market clearing conditions between any pair of goods, it follows that the ratio of expenditure shares and the ratio of employment shares are connected as follows:

$$\frac{\omega_i}{\omega_j} = \frac{p_i}{p_j}\frac{A_i}{A_j}\frac{L_i}{L_j}$$

[4]Given the static nature of the model, we omit the time subscripts to minimize the burden of notation and preserve simplicity.

Taking into account the relationship between relative prices and relative productivity in equations 6 and 7, we get

$$\frac{\omega_m}{\omega_s} = \frac{(1-\tau_s)}{(1-\tau_m)}\frac{L_m}{L_s}$$

$$\frac{\omega_m}{\omega_a} = \frac{1}{(1-\tau_m)}\frac{L_m}{L_a}$$

Given the ratio of expenditure shares derived in equation 5, we can solve for relative employment across sectors as a function of relative productivity, aggregate real consumption, and distortions, yielding:

$$log\left(\frac{L_m}{L_s}\right) = log\left(\frac{\Omega_m}{\Omega_s}\right) + (1-\sigma)\,log\left(\frac{A_s}{A_m}\right) + (\varepsilon_m - \varepsilon_s)\,log\,(C) + \sigma log\left(\frac{1-\tau_m}{1-\tau_s}\right) \tag{8}$$

$$log\left(\frac{L_m}{L_a}\right) = log\left(\frac{\Omega_m}{\Omega_a}\right) + (1-\sigma)\,log\left(\frac{A_a}{A_m}\right) + (\varepsilon_m - \varepsilon_a)\,log\,(C) + \sigma log\,(1-\tau_m) \tag{9}$$

Expressions 8 and 9 establish that in addition to the structural transformation forces of the undistorted economy, given by the relative productivity dynamics and the income effects, the relative employment across sectors in the distorted economy is also shaped by relative distortion.

A final step in the characterization of the equilibrium involves the determination of the aggregate real consumption. In the distorted economy, where we introduce distortions to replicate the sectoral allocations in the data, we feed the model with the actual real consumption observed in each country and back out the underlying path of aggregate productivity $\{\overline{A}_t\}_{t=0}^{\infty}$ that sustains such a consumption path as an equilibrium outcome. In the efficient allocation, where we shut down distortions, we take the sectoral and aggregate productivity paths as given, and solve for the optimal consumption.

To solve for the path of aggregate productivity consistent with observed aggregate real consumption, we appeal to the budget constraint of the household, which establishes that:

$$E = \Sigma_i p_i c_i = w\,(L_a + L_m + L_s) + T \tag{10}$$

where $T = \Sigma_i \tau_i p_i \overline{A} A_i L_i$ is a lump sum transfer to the household of the revenue collected through tax-like distortions. The purpose of the rebate is to ensure that the taxes affect the welfare only through their distortionary effect on allocations rather than through a transfer of resources to an outside agent.

Replacing wages from the firms' first-order conditions, recalling the identity $C = \frac{E}{P}$, we get

$$C = \overline{A}\left[\frac{p_a}{P}A_aL_a + \frac{p_m}{P}A_mL_m + \frac{p_s}{P}A_sL_s\right]$$

In the distorted economy, where we impute a sequence of values of C from the data, we can solve for the underlying aggregate productivity consistent with such value in equilibrium as:

$$\frac{C}{\left[\frac{p_a}{P}A_aL_a + \frac{p_m}{P}A_mL_m + \frac{p_s}{P}A_sL_s\right]} = \overline{A} \tag{11}$$

In the undistorted economy, where we impute the aggregate and sectoral productivity, we proceed in reverse and appeal to the same equation to solve for optimal consumption.

4 Data

Our sectoral data stems from the Groningen Growth and Development Centre's 10-sector database (Timmer et al. 2015). The data provides historically comparable information on sectoral nominal and real value-added, and employment for 10 broad sectors and 41 countries with varying degrees of economic development. We aggregate production into three broad sectors following the standard approach in the literature. The industrial sector comprises manufacturing, mining, and construction. The services sector is composed of Trade, Restaurants and Hotels; Transport, Storage, and Communications; Finance, Insurance, Real Estate and Business Services; Government Services; Community, Social, and Personal Services; and Utilities. The remainder is the Agricultural sector. We measure sectoral productivity in the model, A_i, as the Real Value Added per worker in the sector. We smooth the time series of sectoral employment shares by adopting the trend component of the Hodrick-Prescott filter with a smoothing parameter of 100

Aggregate real consumption per capita is drawn from the Penn World Table database, version 9.0. We work with the variable *rconna*, the real consumption in millions of U$S dollars of 2011, and divide it by the population. We focus on the trend component of the real consumption series resulting from applying the Hodrick-Prescott filter with a smoothing parameter of 100. We normalized real consumption to be equal to 1 in the first period of the sample[5].

While the broad stylized facts of structural transformation across countries have been documented in earlier literature (see, for instance, Herrendorf et al. 2014), we revisit the dynamics of the industrial employment share over time across the six regions covered in the data as a form of background to the systematic inquiry we pursue later. These dynamics are reported as deviations from the initial level of industrialization at the beginning of the sample period in figure 1.

Figure 1: Regional Industrial Employment Share Dynamics

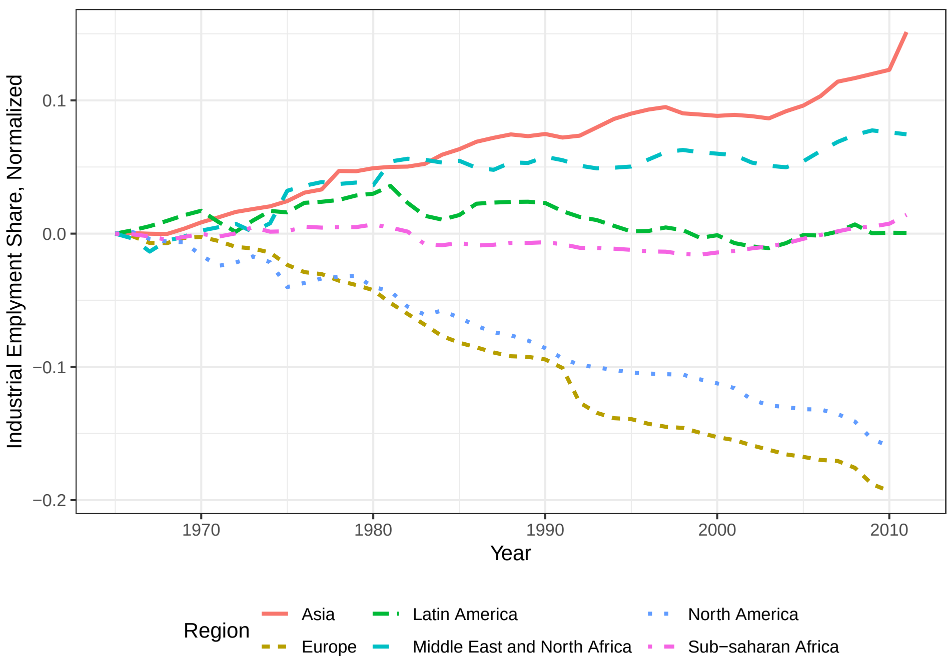


Figure 1 validates some of the established facts in the literature and hints at the regions of the world that may be prone to premature deindustrialization. The ad-

[5]Normalizing real consumption to 1 implies that we shall load the entire burden of matching the shares of labor in each sector at the beginning of the period on the scale parameters Ω_i. This assumption is innocuous for the patterns of structural change implied by the non-homothetic model. Adopting the actual value of real consumption per capita in period 1, and re-scaling the $\Omega_i's$ accordingly, is neutral for the dynamics. However, the normalization of real consumption to 1 implies that we can simply compare the behavior of the model with that of a homothetic CES utility function without having to re-calibrate the values of Ω_i.

vanced economies, mostly in Europe are North America, have long been undergoing the deindustrialization stage. While individual countries' dynamics may differ from the regional aggregate, when considered as a whole, these regions do not seem to qualify as candidates for premature deindustrialization because the industrial employment levels have already peaked. Aggregate dynamics in Asia are also suggestive of a low likelihood of premature deindustrialization given their still-rising industrial employment shares. However, as is the case in advanced economies, there may be heterogeneity within the region, which we shall explore later. Latin America, on the other hand, presents itself as a suitable candidate due to a reversal in trends taking place around the 1980s. Sub-Saharan Africa also shows deindustrialization after a mild industrialization stage, although a new industrialization stage ignited in the 2000s. The Middle East and North Africa region's degree of industrialization stabilizes around the 1980s, suggesting that when digging at the country level, premature deindustrialization episodes may emerge.

5 Calibration

Turning to the calibration of parameter values, we discuss first those governing the demand system. These are the elasticity of substitution across sectors, σ, the income elasticities ε_i, and the taste parameters Ω_i. We adopt the elasticity of substitution and the income elasticities reported in Comin et al. (2021) for the cross-country aggregate-level results. Among the many estimates reported in the article, we believe these are the most suitable ones for our country-level characterization of premature deindustrialization. The taste parameters, in turn, are calibrated so that, having normalized the sectoral productivity to one in each sector at the beginning of the period, the economy replicates the initial industrial employment share at the beginning of the period. The resulting parameter values are reported in table 5.

Parameter	Value	Strategy
σ	0.5	Comin et al. (2021), cross-country estimate
$\varepsilon_a - \varepsilon_m$	-0.89	(idem)
$\varepsilon_s - \varepsilon_m$	0.21	(idem)
Ω_i	country-specific	Match $\frac{L_m}{L}$ in $t = 0$

Table 1: Calibration

5.1 Construction of Distorted Allocations

This section discusses the calibration of the sectoral productivity dynamics and the distortions. Following the literature (for instance, Duarte and Restuccia 2010), the paths of relative sectoral labor productivity is measured directly from the data as real value-added per worker in each sector

$$\frac{A_i}{A_j} = \frac{\frac{Real-Value-Added_i}{Employment_i}}{\frac{Real-Value-Added_j}{Employment_j}}$$

We normalize the levels of productivity at the beginning of each country's sample to be equal to 1, letting the taste parameter Ω_i in each country be the adjustment variable to replicate the observed sectoral employment shares at the onset of the structural transformation.

The sectoral allocation of employment is also driven by the dynamics of aggregate real consumption. We read this directly from the Penn World Tables and normalize the initial level of consumption to be equal to 1 at the onset of the transformation period, as discussed in section 4.

The time series of manufacturing and service wedges are identified to match the evolution of sectoral employment shares. Given the estimated paths of relative productivity and aggregate real consumption, we identify the sequences of wedges by requiring that the equilibrium employment ratios across sectors match the employment ratios in the data for each country. This is achieved by solving for the pair of wedges in equations 8 and 9 imposing the observed values of the employment ratios in the left-hand sides of the equations. In addition to this baseline experiment, we shall also consider a distorted economy where we introduce a single wedge to match the industrial employment share without requiring us to replicate the service and agricultural employment ratios.

Finally, the replication of the observed sectoral employment and the aggregate real consumption as an equilibrium of a distorted economy implies an underlying path of economy-wide productivity, which we need to back out to be able to solve for efficient allocation. As explained earlier, $\overline{A}_t$ can be readily backed out from the economy's resource constraint in equation 11.[6]

[6] Notice that the sequence of aggregate productivity values will be specific to the composition of wedges under consideration. Thus, the aggregate productivity dynamics in the multiple wedge economy will differ from the one in the manufacturing wedge-only allocation

6 Characterizing the (In)Efficiency of Premature Deindustrialization

In this section, we assess the (in)efficiency of the observed deindustrialization in the data. As stated earlier, the core of the assessment relies on a comparison between the observed path of structural transformation and the one implied by the efficient benchmark. However, a challenge in pursuing such a comparison is that multiple points of divergence may emerge between the data and the theory. What if the divergence occurs in the industrialization phase? How many periods of excessive deindustrialization should we observe to label deindustrialization as premature? Here, where our goal is to attach a notion of inefficiency to the premature deindustrialization documented in the literature, we shall focus on protracted periods of deindustrialization. Later, when we focus on the welfare effects of premature deindustrialization, we will account for the entire departure between the observed and the efficient structural transformation path.

6.1 Episodic Characterization of Premature Deindustrialization

Our first approach for identifying inefficient episodes of premature deindustrialization resembles Rodrik (2016)'s selection of growth acceleration episodes. The idea is to filter the data through a number of criteria that countries should meet for their deindustrialization to be inefficiently premature. The first condition is that the country is deindustrializing after a rising period of industrial employment shares within the sample period. This is a natural requirement in light of how premature deindustrialization has been labeled in the existing literature. [7] The second condition, one of our contributions to the literature, is to require that the deindustrialization in the data is taking place at a faster pace than predicted by the efficient benchmark. [8]. It is the second condition that may lead to a narrower set of episodes of premature deindustrialization and the one that gives rise to welfare costs that may warrant remedial government policies.

In short, we define a premature deindustrialization episode as one where the

[7]Notice that this condition rules out advanced economies whose industrialization started earlier than the 1960s, the earliest years in our sample.

[8]Notice this condition covers a situation where the industrial employment share is still rising in the efficient allocation but declining in the data

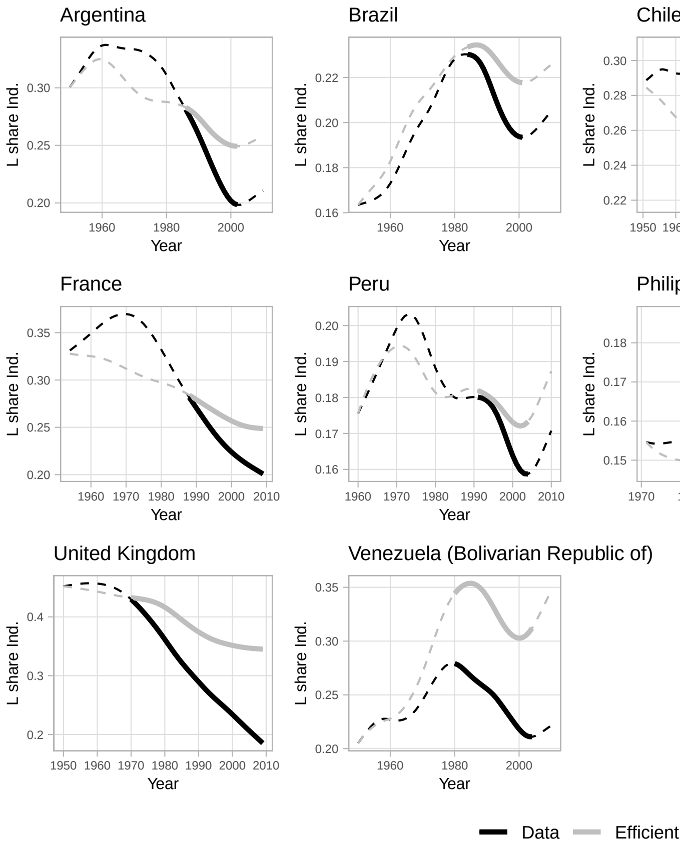
following conditions are met:

1. The economy underwent, during the sample period, a period of growing industrial employment shares prior to engaging in deindustrialization.

2. The industrial employment share in the data is declining and is lower than the efficient one for a period of a decade or longer

The countries that satisfy our criteria of premature deindustrialization are depicted in figure 2. The premature deindustrialization years are depicted in solid lines whereas, for reference, we accompany these with the preceding and succeeding years in dashed lines. We identify ten episodes of premature deindustrialization, the majority of these occurring in Latin America. Across the development spectrum, premature deindustrialization is most evident among late developers, although a few advanced economies are also captured by the methodology. Perhaps the most surprising one in the advanced economy group is the United Kingdom, usually considered the region with the longest industrial roots. The U.K. satisfies the criteria because industrial shares were still slightly rising between the 1950s and 1960s, and then started to decline inefficiently fast since 1970. Similarly, France, Denmark, and Sweden also qualify due to marginally satisfying the first criterion, and then deindustrializing prematurely.

Figure 2: Episodes of Premature Deindustrialization



Note: The figure shows the industrial employment shares, in the data and those implied by the efficient allocation, for the economies and periods that satisfy the criteria of premature deindustrialization.

A salient implication from Figure 2 is that the inefficiency in premature deindustrialization rests less on the level at which industrialization peaks but more on the pace at which it reverses. In the existing literature, premature deindustrialization is portrayed as a shift to the origin of the hump-shaped dynamics of the industrial employment shares.[9]. However, purely empirical in nature, this characterization does not allow to qualify such a shift as efficient or as a symptom of a distortion. Our analysis, which allows for such qualification, dictates that such a shift is, in most cases, warranted by efficient forces of structural transformation. This can be appreciated in figure 2 in that, with the exception of the Philippines, Venezuela, and (marginally)

[9]The shift to the origin is a visual conclusion inferred from the presentation of the industrial employment of a country against a measure of economic development. In our figures, industrialization is represented against time. The "shift to the origin" conclusion continues to apply in this context as it still captures a situation where industrialization should have persisted for longer, had late developers exhibited the structural transformation dynamics of currently advanced economies.

Brazil, the efficient industrial share does not peak at a higher level than observed in the data.

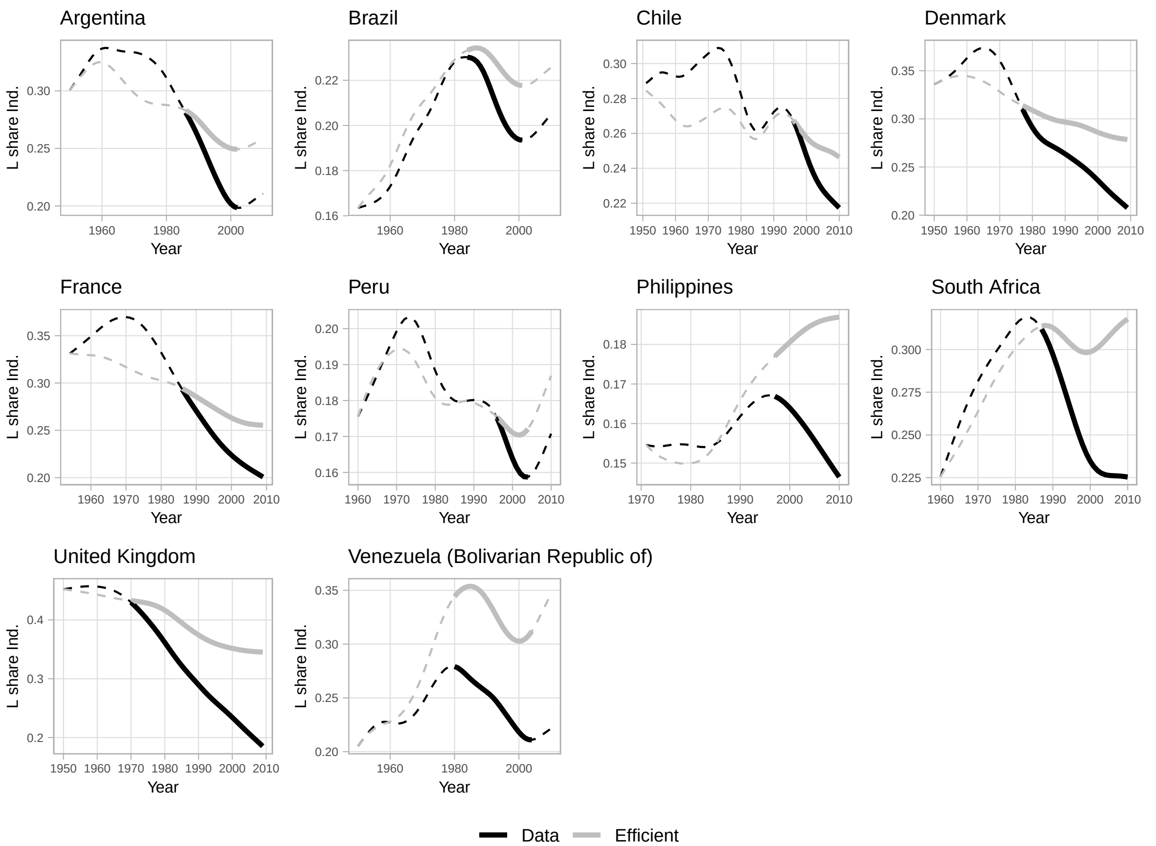
A final observation to be drawn from figure 2 concerns the dynamics outside premature deindustrialization. As shown in the figure, there also are sizable departures between data and efficiency in the run-up to the deindustrialization stage. While our goal of connecting with the existing literature led us to focus on deindustrialization, we take into account excessive industrialization when pursuing our welfare calculations. Since we find that the welfare gains of achieving efficient allocation along the entire path of structural transformation are negligible, constraining the welfare analysis to the premature deindustrialization periods would have yielded even less significant effects.

6.1.1 A Single-Wedge Economy

Our distorted economy features both a manufacturing and a service sector wedge to reconcile the model's sectoral and aggregate dynamics with the data. This choice ensured that not only the industrial but also the agricultural and the service sector employment shares were aligned with the empirical ones. However, since the paper focuses on understanding the efficiency properties of the observed patterns of deindustrialization, one could dispense from the service sector's wedge and seek to account for the manufacturing employment share only. How sensitive would the identification of premature deindustrialization episodes be to this choice? We address this question in this section.

To be precise, we solve for the sequence of manufacturing wedges and aggregate productivity, $\{\tau_{m,t}, \overline{A}_t\}$, that sustains the aggregate real consumption and the industrial employment share in the data as part of the distorted competitive equilibrium. The paths of relative sectoral productivity dynamics were determined straight from the data and hence are unaffected by the choice of wedges. Then, keeping the paths of sectoral and aggregate productivity, we solve for the efficient allocation shutting down the manufacturing wedge. Finally, we apply the same identification criteria from the previous section to characterize an economy as deindustrializing prematurely.

Figure 3: Episodes of Premature Deindustrialization with a Manufacturing Wedge Only



Note: The figure shows the industrial employment shares, in the data and those implied by the efficient allocation, for the economies and periods that satisfy the criteria of premature deindustrialization. The distorted economy comprises a manufacturing wedge but abstracts from wedges to the service sector.

Figure 3 shows that the selection of episodes is unchanged between the one and two wedge economies. In a subsequent section, we also show that the welfare gains from achieving efficiency are marginally affected.

6.2 Econometric Characterization of Premature Deindustrialization

In this section, we present a regression-based approach for assessing the efficiency properties of premature deindustrialization. In Rodrik (2016), premature deindustrialization is assessed by regressing the industrial employment shares against decade dummies and a series of controls, and by documenting a secular decline in the point estimate for the time dummies. To connect to this empirical strategy, we follow the same regression-based approach as in Rodrik (2016) but implement it not only on the empirical industrial employment shares but also on the efficient ones implied by the model. With this approach, we seek to account for a secular decline in deindustrialization that may exist even under the efficient allocation when controlling for the same variables in a regression setting. In this context, we shall define premature deindustrialization as the difference between the point estimate for the decade dummies in the data and the model's regression.

Concretely, we estimate the following panel regression:

$$\left(\frac{L_m}{L}\right)_{c,t} = \begin{array}{c} \alpha_0 + \beta_1 log\left(pop_{c,t}\right) + \beta_2\left[log\left(pop_{c,t}\right)\right]^2 + \theta_1 log\left(GDPpc_{c,t}\right) \\ +\theta_2\left[log\left(GDPpc_{c,t}\right)\right]^2 + \Sigma_{c=}^{N}\gamma_c\Gamma_c + \Sigma_{t=1}^{T}\phi_t D_t + \varepsilon_{c,t} \end{array} \tag{12}$$

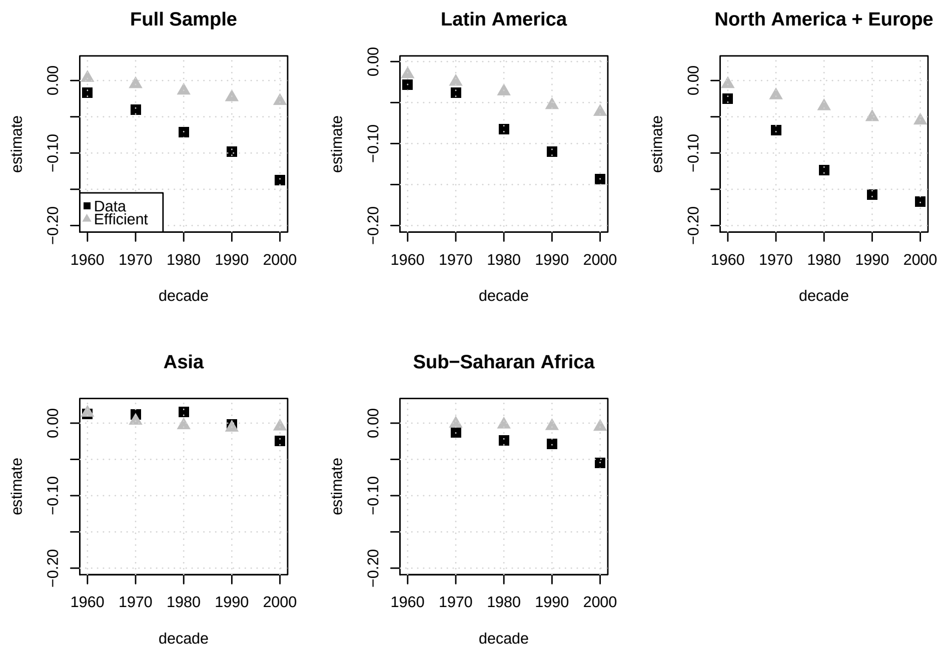
where $\left(\frac{L_m}{L}\right)_{c,t}$ is the industrial employment share of country c at time t, $log\left(pop_{c,t}\right)$ is the logarithm of population, $log\left(GDPpc_{c,t}\right)$ the logarithm of GDP per capita, Γ_c collects the country's fixed effects, and D_t denotes the decade dummies. We estimate this regression for the entire set of countries and then separately by region[10]. Given the time span of the data, the decade dummies are for the 1960s, 1970s, 1980s, 1990s, and 2000s, except for Sub-Saharan Africa, where data is lacking for the 1950s, thus forcing us to estimate a decade's dummy starting in the 1970s

As said, we define premature deindustrialization in this regression-based context as the difference between the declining time trend of industrial employment shares in the data relative to the ones in the efficient allocation. By bringing into consideration a model of structural transformation, we can assess if the fundamental drivers of structural change mostly acknowledged in the literature are also trending down over time as observed in the data. If so, and in the same spirit as the episodic characterization, we shall consider premature deindustrialization to be given by the difference between the declining time trend in the data relative to the efficient paths.

We present the estimates for the decade dummies in figure 4 and leave a complete report of estimates of all variables in the table 3 in appendix B.

[10]Please see appendix A for the list of countries covered in each region

Figure 4: Regression-Based Measure of Premature Deindustrialization.



Note: The figure shows the estimates for decade dummies resulting from the estimation of equation 12. The top left panel reports the estimate for the full sample of countries, whereas the remaining panels reproduce the results for countries within the specified regions. The composition of countries in each region can be found in appendix A.

Figure 4 validates the declining trend of the industrial employment shares documented earlier in the literature and shows that such a trend extends, albeit less markedly, to the efficient allocations. This last observation implies that the fundamental drivers of structural change can account for a fraction of the deindustrialization in the data, thereby mitigating the welfare losses presumed to be associated with such a trend. Across regions, the declining inefficient deindustrialization is most acute in Latin America and Developed Economies. As shown in the episodic characterization, a few European countries in the Developed Economies group exhibited evidence of premature deindustrialization despite the advanced nature of their economies. This pattern manifests also in the context of panel regressions. Latin America, again, stands as the region with the most pervasive premature deindustrialization among the late industrializers, whereas Asia and Sub-Saharan Africa show no significant trends.

6.3 Discussion

Summarizing, the purpose of this section was to appeal to theory to aid in the characterization of premature deindustrialization as a sign of inefficient allocation of resources meriting policy interventions. We narrowed down the number of inefficient episodes to 10 economies, occurring most prominently in Latin America. We validated this last result in the context of panel regressions, documenting divergences between point estimates of the industrial employment shares on decade dummies both for the data and the efficient allocation. The objective now is to turn this visual characterization of premature deindustrialization into an actual quantification of its associated welfare losses.

Prior to engaging in the quantitative analysis, however, it is important to acknowledge two caveats concerning our analysis. The first caveat relates to the efficient theoretical benchmark against which observed industrialization is assessed. While the theory encompasses two of the acknowledged drivers of structural change, namely unbalanced productivity growth across sectors and non-homothetic demand systems, it abstracts from features that may have affected the shape of the efficient dynamics. The first abstraction relates to the lack of physical capital investment in the model. As eloquently shown in García-Santana et al. (2021), the investment dynamics is an important driver of the dynamics of the industrial employment share over the development path. If the investment rate in developing countries had been increasing alongside a decline in industrialization, a concern would emerge that countries should have been industrializing or deindustrializing at a lower pace in the efficient benchmark, thereby magnifying the welfare costs of the inefficiency. Alternatively, if deindustrialization had been accompanied by declining investment rates, efficient deindustrialization would have been steeper and closer to the data. A similar concern emerges with the lack of consideration for international trade in the model. If, as articulated in Rodrik (2016), international trade efficiently led to deindustrialization, then the observed trends would carry smaller welfare losses. Conversely, if, as argued since Kaldor (1968), there are externalities in the production of manufacturing goods that are not accounted for in the model, the efficient path of deindustrialization would be even further apart from the actual one, leading to higher welfare costs. All in all, given the counteracting nature of these forces, we argue that our proposed benchmark constitutes an adequate first approximation to the question of how much of the observed deindustrialization is efficient. However, we shall come back to these caveats when interpreting the results from the quantitative analysis.

7 Quantifying the Welfare Costs of Premature Deindustrialization

In this section, we conduct the quantification of the welfare implications of premature deindustrialization. Focusing on the economies satisfying our episodic characterization, we compute the welfare gains that would have accrued to a representative household if the distortions underlying premature deindustrialization had been dismantled and the household would have transited the efficient path. As shown in figure 2, the observed sectoral dynamics differed from the efficient one not only during the premature deindustrialization episode but also before and after. For this reason, we calculate the welfare gain assuming that the entire path of structural transformation becomes the efficient one.

Let V^* and V^D denote the net present value of aggregate real consumption in the efficient allocation and in the data. These are given by:

$$\begin{aligned} V^* &= \Sigma_{t=t_0}^{T} \beta^{t-t_0} \frac{\left(C_t^*\right)^{1-\rho}}{1-\rho} \\ V^D &= \Sigma_{t=t_0}^{T} \beta^{t-t_0} \frac{\left(C_t^D\right)^{1-\rho}}{1-\rho} \end{aligned} \tag{13}$$

where C_t^* and C_t^D stand for the observed and the actual sequence of aggregate real consumption, and t_0 and T denote the first and last period in a country's sample.[11]. In our baseline quantification, C_t^* refers to the sequence of efficient consumption resulting from having dismantled both the manufacturing and service sector wedges. To complement the analysis of the role of the mix of wedges in the characterization of

[11]Notice that we are measuring utility flows for a finite period of time, which in the quantitative exercise is given by the length of the time period in the data. An alternative approach would have been to estimate constant growth rates of sectoral and aggregate productivity and construct aggregate consumption growth according to the Balanced Growth Path in the model so that the welfare measures are based on infinite utility streams. Given the still highly fluctuating pattern of sectoral productivity in the data, we decided to constrain the welfare calculation to the life cycle of the household implied by the data. Notice that, for the purpose of the welfare gain calculation, this is akin to assuming that the observed allocation converges to the efficient one immediately after the sample period finishes.

premature deindustrialization episodes, we also compute the welfare effects that result from attaining efficient allocation after shutting down the manufacturing wedge in the single-wedge economy.

We measure the welfare gain of having attained the efficient path of structural transformation as the permanent consumption compensation that the households in each country must have received for having remained indifferent between staying in the distorted economy or transitioning to the efficient one. [12] Letting this compensation be given by Λ, it is determined by:

$$V^D(\Lambda) = \Sigma_{t=t_0}^{T} \beta^{t-t_0} \frac{\left(\Lambda C_t^D\right)^{1-\rho}}{1-\rho} \equiv V^* \\ \iff \\ \Lambda = \left(\frac{V^*}{V^D}\right)^{\left(\frac{1}{(1-\rho)}\right)} \tag{14}$$

We report the results in table 7. The first column, which focuses on the reversal of both the manufacturing and the service sector wedges, shows that the welfare gains would have been small, below for 1% for the majority of the countries, with the exception of Peru, where the welfare gains reach 1.2%. While the visual and regression-based representation of premature deindustrialization may convey a striking and concerning picture regarding the pattern of structural change in developing economies, our results show that once the efficient forces of structural change are properly accounted for, the inefficient component of premature deindustrialization does not represent a significant drag on welfare.[13]

The second column of table 7 reports the results for the case where only a manufacturing sector wedge is at play. This case allows us to decompose the source of the total gains into those stemming from reversing premature deindustrialization only and those arising also from achieving also efficient agriculture and service sec-

[12]Given the retrospective definition of welfare comparing realized and counterfactual deindustrialization dynamics, we interchangeably refer to the welfare gains and welfare losses of premature deindustrialization, understanding that the former refers to what would have been gained under the counterfactual path, and the latter refers to what was foregone but not having attained it.

[13]Recall that the results reported in table 7 correspond to the welfare gains from a complete reversal of wedges in every period, not just in those where the premature deindustrialization takes place. Having narrowed the analysis just to the premature deindustrialization years would have naturally led to even lower gains.

tor shares.[14] The results show that premature deindustrialization accounts for more than half of the total welfare gains in Argentina, Chile, Denmark, France, the United Kingdom, and Venezuela; while it constitutes an insignificant source of foregone welfare in Brazil, Peru, the Philippines, and South Africa.

Table 2: Welfare Gains of Dismantling Distortions

Country	Welfare Gain Both Wedges	Welfare Gain Manufacturing Wedge
Argentina	0.18	0.1
Brazil	0.52	0.03
Chile	0.23	0.15
Denmark	0.11	0.1
France	0.31	0.2
Peru	1.19	0.02
Philippines	0.31	0.05
South Africa	0.69	0.17
United Kingdom	0.24	0.22
Venezuela (Bolivarian Republic of)	0.36	0.31

Table 7 illustrates the welfare gains from dismantling the sectoral distortions in episodes of premature deindustrialization identified in section 6.1. The welfare gain is computed as the permanent consumption compensation that equalizes the present value of utility derived from the efficient consumption paths and the one observed in the data. The gains are reported as percentages.

7.1 Discussion

We close the quantitative analysis by providing an interpretation of our results in the context of the caveats highlighted in section 6.3. The model's abstraction from physical capital accumulation, international trade, and externalities in the manufacturing sector may raise questions about the accuracy of our welfare calculations. As stated earlier, accounting for these elements may contribute to either expanding or mitigating the welfare effects, depending on the direction in which they operate and on how the data disciplines their strength in the model, making it difficult to establish

[14] As a reminder, in the single-wedge economy, only a manufacturing wedge ensures that the distorted economy replicates the industrial employment share, but there is no requirement that the agriculture and service sector shares are inefficient. Therefore, its dismantlement captures the welfare gains from resolving the industrial inefficiency

whether our results represent a lower or an upper bound. Our view is that a transparent assessment of the inefficiency associated with premature deindustrialization in a simple and tractable framework that encompassed the main drivers of structural change would be of value to researchers and policymakers for updating their priors about the concerning nature of premature deindustrialization in the data.

8 Conclusion

Since the work of Dasgupta and Singh (2007) and Rodrik (2016), structural transformation in developing countries has been characterized as undergoing premature deindustrialization. That is a reallocation of employment away from the industrial sector and towards services occurring earlier in the development stage and at lower levels of industrialization than experienced by currently advanced economies. Moreover, hinting at an underlying inefficiency that needs policy intervention, premature deindustrialization contributed to fueling a revived interest in industrial policy as an attempt to ameliorate or even revert this trend. However, a formal assessment of whether premature deindustrialization denotes an inefficient allocation of resources is absent in the literature. The main purpose of this paper was to fill this gap.

We began proposing a simple theoretical framework to characterize the inefficiency of premature deindustrialization. Albeit simple, the model featured both of the most acknowledged drivers of structural change in the literature, unbalanced productivity growth across sectors and income effects in aggregate expenditure. Endowing this benchmark with the observed paths of relative productivity and aggregate productivity, we backed out manufacturing and service sector wedges that rationalized the premature deindustrialization in the data as an equilibrium outcome. Then, removing these wedges, we solved the efficient dynamics of sectoral employment shares and aggregate expenditure.

Comparing the efficient and realized paths of deindustrialization, we identified ten episodes of inefficient deindustrialization. We imposed two criteria for a country's path of deindustrialization to be defined as inefficiently premature. The first requirement was that the economy's industrial share peaked within the time frame of our sample. This ensured that we ruled out advanced economies like the United States, where deindustrialization has been underway throughout all of the years in the sample. The second, and more constraining one, is that deindustrialization in the data occurred at a faster pace than in the efficient benchmark. This requirement allowed for some economies' premature deindustrialization to be efficient and narrowed the concerning component of premature deindustrialization to only the countries and years where the trend is stronger in the data than in the model. It was this requirement, then, that endowed the resulting periods of premature deindustrialization with a well-defined sense of inefficiency.

A second approach for assessing the inefficiency of premature deindustrialization involved doing it in the context of the same panel regressions where such a trend was established in the literature. In Rodrik (2016), premature deindustrialization was established as a declining point estimate of the industrial employment shares when regressed against decade dummies and income and population controls. In our analysis, we connected with this approach by performing the same regressions with the model-based industrial employment shares as dependent variables. The idea was to allow for the possibility that even the efficient shares exhibited a declining trend, and hence the premature deindustrialization in the data would be inefficient only in so far as it exceeded the trend in the model. We showed that, indeed, the efficient share exhibited a secular decline in industrial employment. However, it was still the case that the strength of the secular decline in the data exceeded the model, and, hence, inefficient deindustrialization was at play.

The final contribution of the paper converted the visual and regression-based observation of inefficient premature deindustrialization into a meaningful quantification of its welfare costs. Not only did the existing literature lack a well-defined sense of inefficiency, but it also did not convey a strategy to convert the observation of premature deindustrialization into a quantitative measure of its economic costs. Without such a strategy, any policy response that would be considered to revert this trend would be impeded from a proper cost-benefit analysis. Given our theory-based assessment of premature deindustrialization, we appealed to the same theoretical framework to provide a consistent quantitative measure of its welfare costs. We found that these costs are insignificant.

While we highlighted the simplicity and tractability of our theoretical framework as a virtue in providing a first step in assessing the inefficiency of premature deindustrialization, we incurred a number of abstractions that may affect the results. As stated throughout the text, having accounted for physical capital accumulation, international trade, and externalities, may have strengthened or weakened the severity of premature deindustrialization. We leave the consideration of these compounding forces as an objective for future research

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A Data Description

B Regression Estimates

The estimates from the implementation of the regression described in equation 12 are reported in table 3.

Table 3: Panel Regressions for Industrial Employment Shares

	Employment Share Industry, Data					Employment Share Industry, Efficient				
	All Countries	Developed	Asia	Latam	Africa	All Countries	Developed	Asia	Latam	Africa
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ln_pop	0.100***	−0.098*	0.013	0.154***	0.060***	0.047***	−0.361***	0.029*	0.084***	0.015**
	(0.007)	(0.059)	(0.030)	(0.012)	(0.014)	(0.004)	(0.034)	(0.017)	(0.009)	(0.007)
ln_pop2	0.003***	0.022***	−0.002	0.001	−0.001	0.001***	0.033***	0.001	0.002*	0.001*
	(0.001)	(0.005)	(0.003)	(0.001)	(0.002)	(0.000)	(0.003)	(0.002)	(0.001)	(0.001)
ln_rgdppc	0.334***	1.746***	0.694***	0.332***	0.026	0.320***	0.649***	0.319***	0.494***	0.035
	(0.019)	(0.100)	(0.049)	(0.067)	(0.038)	(0.013)	(0.080)	(0.035)	(0.046)	(0.030)
ln_rgdppc2	−0.017***	−0.088***	−0.036***	−0.020***	0.001	−0.018***	−0.031***	−0.018***	−0.028***	−0.001
	(0.001)	(0.005)	(0.003)	(0.004)	(0.002)	(0.001)	(0.004)	(0.002)	(0.003)	(0.002)
dummy60	−0.017***	−0.025***	0.013	−0.028***		0.004*	−0.005	0.014	−0.015***	
	(0.004)	(0.005)	(0.019)	(0.005)		(0.002)	(0.003)	(0.011)	(0.003)	
dummy70	−0.041***	−0.069***	0.012	−0.038***	−0.013**	−0.005**	−0.020***	0.003	−0.025***	−0.001
	(0.005)	(0.008)	(0.020)	(0.008)	(0.005)	(0.003)	(0.005)	(0.011)	(0.005)	(0.003)
dummy80	−0.071***	−0.124***	0.016	−0.083***	−0.024***	−0.014***	−0.036***	−0.003	−0.036***	−0.002
	(0.006)	(0.009)	(0.023)	(0.010)	(0.007)	(0.003)	(0.006)	(0.013)	(0.006)	(0.004)
dummy90	−0.098***	−0.157***	−0.001	−0.110***	−0.029***	−0.023***	−0.050***	−0.006	−0.053***	−0.004
	(0.007)	(0.011)	(0.026)	(0.012)	(0.011)	(0.004)	(0.007)	(0.015)	(0.008)	(0.005)
dummy00	−0.137***	−0.167***	−0.025	−0.143***	−0.055***	−0.028***	−0.055***	−0.005	−0.061***	−0.005
	(0.009)	(0.014)	(0.030)	(0.014)	(0.013)	(0.005)	(0.009)	(0.017)	(0.009)	(0.007)
Country F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	
Observations	2,105	453	496	538	516	2,105	453	496	538	516
R^2	0.978	0.995	0.975	0.988	0.975	0.994	0.998	0.988	0.995	0.993

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.