Federal Reserve Bank of Dallas

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Globalization Institute Working Paper 428 **August 2024**

Research Department

https://doi.org/10.24149/gwp428

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March 15, 2024

Abstract

We add to recent evidence on deindustrialization and document a new pattern: increasing industry polarization over time. We assess whether these new features of structural change can be explained by a dynamic open economy model with two primary driving forces, sector-biased productivity growth and sectoral trade integration. We calibrate the model to the same countries used to document our patterns. We find that sector-biased productivity growth is important for deindustrialization by reducing the relative price of manufacturing to services, and sectoral trade integration is important for industry polarization through increased specialization. The interaction of these two driving forces is also essential as increased trade openness transmits global technological change to each country's relative prices, sectoral specialization, and sectoral trade imbalances.

JEL Classifications: F11, F43, O41, O11

Keywords: structural change; international trade; sector-biased productivity growth

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*We thank Satyajit Chatterjee, Josep Pijoan-Mas, Klaus Desmet, and seminar and conference participants at the SED conference, Singapore Management University, INSEAD, Ryerson University, University of British Columbia, Clemson University, Midwest Macro Conference, Sogang University, Indiana University, Chicago Fed, UC Santa Cruz, the Bank of Chile, the Bank of Spain, GGDC/U. of Groningen, CEMFI, Southern Economics Association Meetings, Texas Tech University, University of Missouri, University of Southern California, York University, World Bank Workshop on Services and Structural Transformation, and Conference in honor of Tim Kehoe for their comments. We also thank Jackson Crawford, Valerie Grossman, and Valentina Palmiotti for outstanding research assistance. The views expressed here are those of the authors and do not necessarily reflect those of the Federal Reserve Banks of Chicago and Dallas, and the Federal Reserve System.

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1 Introduction

Other than per capita income growth, probably the most important feature of countries' long-run development is structural change, a phenomenon well-documented since the pioneering work of Kuznets. As countries develop, the agriculture share of value-added decreases, the services share increases, and the industry or manufacturing share follows a "hump" pattern. These patterns have long been considered immutable, but recent research challenges this perception. Rodrik (2016) and subsequent studies indicate that countries are undergoing deindustrialization. Countries today, at the same level of GDP per capita, allocate a smaller share of total value-added to manufacturing than their counterparts did several decades ago, suggesting diminished opportunities for industrialization.

Moreover, our paper introduces a new facet of structural change: industry polarization. In contrast to prior decades, there is now a widened cross-country dispersion in the manufacturing share of value-added. While, on average, countries exhibit a declining trend in the industry share, signaling deindustrialization, the variance in these shares has increased over time, showcasing a phenomenon we call "industry polarization." These new facts demonstrate that the process of structural change itself is evolving over decades. The two facts are intrinsically related – they are both about the manufacturing value-added share – with one about the first moment and the other about the second moment.

Can these new patterns be explained by the same driving forces and mechanisms that are important for structural change? We seek to address this question in a parsimonious and quantitative way. We already know from the existing literature that sector-biased productivity growth operating through non-unitary elasticities of income (non-homothetic preferences) and of substitution (the "Baumol" disease) are important. In addition, international trade is a plausible driving force. The period we examine is known as the "third era of globalization"; existing research supports international trade's role in structural change, and, as our two facts are global facts, considering a global force is appealing. Hence, our approach is to embed two driving forces for structural change—sector-biased productivity growth and trade integration—in a dynamic open economy model featuring the essential mechanisms of relative price effects, income and scale effects, comparative advantage, and investment. Taking a global approach with more than two dozen countries, our calibration generates implications commensurate with the data.

We find that sector-biased productivity growth and trade integration together quantitatively explain the majority of deindustrialization and industry polarization. Specifically, sector-biased productivity growth is important for deindustrialization by reducing the relative price of manufacturing to services, and trade integration is important for industry polarization through increasing specialization across countries. Also essential is the interaction of these two driving forces. Finally, non-homothetic mechanisms in intermediate input demand, in addition to final demand, are an important channel through which productivity growth and trade integration generate deindustrialization.

Our main data analysis uses a balanced panel of 28 countries covering 1971–2011. We run a panel regression of the sectoral value-added share on per-capita income and per-capita income squared, each interacted with pre-and post-1990 dummies, together with country fixed effects. We find that, as in Rodrik (2016), the estimated hump-shaped relationship between the manufacturing value-added share and per-capita income shifts down over time. The peak of the manufacturing hump in the post-1990 period is 3.5 percentage points lower than in the pre-1990 period. Hence, our findings illustrate that countries increasingly "graduate" from agriculture to services directly, bypassing industrialization. In addition, we document that the cross-country dispersion of manufacturing valued-added shares increases substantially between the two periods. The variance of the log-shares almost doubles between the pre-1990 and post-1990 periods, with most of the increase stemming from a number of countries whose manufacturing value-added shares declined in the post-1990 period.

Our open economy model of structural change features two key driving forces: sector-biased productivity growth and sectoral trade integration. Moreover, the model embodies four structural-change mechanisms induced by both driving forces: (i) income effects on sectoral consumption and investment demand, generated by non-homothetic preferences; (ii) scale effects in intermediate demand, generated by non-homothetic production functions; (iii) relative price effects on sectoral final and intermediate input demand, enabled by non-unitary elasticities of substitution; and (iv) comparative advantage-based international trade and specialization, which generates sectoral reallocation directly through sectoral trade imbalances and indirectly through its impact on relative prices and income effects. All of the effects on sectoral demands ultimately affect sectoral value-added shares mediated through endogenous input-output linkages. Our model also features endogenous capital accumulation to account for the long-run nature of these patterns, and because recent research has shown that evolving investment patterns is also a key feature of structural change.[1]

To facilitate a careful comparison with our empirical findings, we calibrate our model to the same set of countries and time frame as in our main data analysis. This global approach is needed because, at a narrow level, industry polarization is a second-moment fact, and thus we need a large sample of countries, and at a broader level, the two data patterns we seek to explain are global patterns. We estimate the substitution, income, and scale elasticities. Our estimated substitution elasticities between sectoral goods in consumption, investment,

[1] See García-Santana, Pijoan-Mas, and Villacorta (2021) and Herrendorf, Rogerson, and Valentinyi (2021).

and intermediate input demand are all less than one. Our estimated income elasticities for agriculture and services are, as expected, less than one and greater than one, respectively. Finally, our scale elasticities are a little more nuanced. An expansion in scale in a sector increases intermediate input demand from its own sector the most. Furthermore, the scale effects in production imply that the expansion of a given sector, all else equal, induces an increase in that sector's relative price due to upward sloping supply curves.

We calibrate the time series of sectoral fundamental TFP and trade costs for each country to match data on sectoral prices and trade flows. In the data, the relative price of manufactured goods to services declines with income, and manufacturing net exports as a share of GDP rises with income. The median growth rate of fundamental TFP is the highest in agriculture, followed by manufacturing, and then services. The rate of decline of trade costs is the highest for manufacturing, followed by agriculture, and then services.

We reiterate that there is no *a priori* reason to expect our model, with its limited number of driving forces, to generate deindustrialization and industry polarization, as well as the basic patterns of structural change. With our model-implied outcomes, we run the same regression as we did with the actual data. The model predicted paths for manufacturing value added shares over income are close to those in the data. In particular, the model implies a decline in the peak manufacturing value-added share of 3.0 percentage points from the pre-1990 period to the post-1990 period, 86% of that in the data. In addition, the model can explain about three-fourths of the increase in the variance from the pre-1990 period to the post-1990 period. Thus, our calibrated model explains most of deindustrialization and industry polarization over time.

To assess the role of each driving force in generating deindustrialization and industry polarization, we conduct three counterfactual exercises. In one exercise, we remove international trade and implement autarky. In another exercise, we remove sector-biased productivity growth and implement constant relative productivity across sectors in each country, while allowing aggregate productivity growth to vary across countries. In a third exercise, both driving forces are removed. For each exercise, we solve the model and then fit the relationship between sector value-added shares and income using the model-implied "data".

Our counterfactual exercises reveal that sector-biased productivity growth alone explains almost 60 percent of deindustrialization produced by our model, but is insignificant for industry polarization. In contrast, trade integration alone explains more than all of industry polarization, but is not significant for deindustrialization. The exercises also imply that explaining these two facts requires strong interaction effects between the two driving forces.

The key channel driving deindustrialization is the declining relative price of manufacturing to services over time. In turn, these declining relative prices stem from a confluence of driving forces and model features, especially, high productivity growth in manufacturing relative to services across a large swath of countries and scale effects in production. The scale effects propagate increases in services production into shifts in the composition of demand for intermediate sectoral goods away from manufacturing and towards services. In addition, the scale effects perpetuate the decline in the manufacturing relative price as the cost of services production increases at a faster rate than that of manufacturing as a by-product of faster expansion of the services sector. To a lesser extent, trade integration has also contributed to the declining manufacturing relative price, because trade costs have fallen more quickly in manufacturing than in services. The cumulative effect of these forces was a substantially lower relative price of manufacturing in the post-1990 period than in the pre-1990 period. Consequently, under the "Baumol" elasticities (less than one), global manufacturing expenditure as a share of global GDP has fallen in recent decades by about five percentage points. Thus, at the same level of per capita income, later industrializers have fewer opportunities to reach the industrial heights of economies like Taiwan and S. Korea in the pre-1990 period; they are more likely to bypass manufacturing and join services.

The remaining 40 percent of deindustrialization is encompassed by non-linear interaction between sector-biased productivity growth and trade integration affecting relative prices and sectoral trade imbalances. Three forces underlie this interaction. First, openness to trade leads to lower relative prices of manufactured goods owing to the fact that manufactured goods trade costs are lower than services trade costs. Related, openness facilitates the transmission of sector-biased productivity growth in other countries to the home country. Finally, increases in openness amplify this transmission. These forces also yield sectoral trade imbalances, e.g., net export deficits in manufacturing. Moreover, these forces are more pronounced post-1990, owing to the cumulative effect of the trade integration and sector-biased productivity growth. Through an additional counterfactual involving trade costs held constant at their 1970 values, we confirm the importance of the non-linear interaction for deindustrialization. To summarize, trade integration allows countries to, in effect, "import" sector-biased TFP growth from other countries through both prices and quantities.

Regarding industry polarization, particularly post 1990, countries with a comparative disadvantage in manufacturing increasingly rely on imports for their manufactured goods and have lower manufacturing value added shares over time. The opposite is true for countries with a comparative advantage in manufacturing. Trade integration alone generates industry polarization stronger than what we observe since 1990. Sector-biased TFP growth plays a key role in mitigating the effects of increased specialization. Hence, while the interaction between our two driving forces has an amplifying effect to explain deindustrialization, it has a mitigating effect to explain industry polarization.

To further ascertain the importance of key features of our model, we also study a closed economy version of our model and a version with homothetic intermediate goods production. We find that the closed economy model, calibrated to replicate the data as closely as possible, can generate a little more than half of the deindustrialization of our baseline model, and explain very little of industry polarization. The key reason for the weaker performance of the closed economy model is that trade integration exerts both price effects and quantity effects (via specialization). The former can be captured to a large extent in a closed economy, but the latter cannot be captured in a closed economy. The model with homothetic production can explain about two-thirds of the deindustrialization implied by our baseline model. This suggests that non-homothetic intermediate input demand plays a role, but not the majority role, for deindustrialization.

The starting point for our paper is Rodrik (2016), which was the first to document deindustrialization in a wide swath of countries. Recently, Felipe, Mehta, and Rhee (2019) and Haraguchi, Cheng, and Smeets (2017) provide further evidence for deindustrialization in a large sample of countries.[2] The two papers most closely related to ours are Huneeus and Rogerson (2020) and Fujiwara and Matsuyama (2020). Huneeus and Rogerson (2020) show that heterogeneous paths of agricultural productivity across countries are a key driver of both structural change and deindustrialization. Fujiwara and Matsuyama (2020) explain deindustrialization in terms of heterogeneous technology gaps between sectors and across countries. Their model can qualitatively generate the declining "hump" pattern for the later industrializers, as well as lower per capita income at that hump. Like these two papers, our paper emphasizes sectoral productivity growth, but in an integrated, open economy setting where we also examine industry polarization.

In addition, our paper relates to several strands of the structural change literature. The first strand is the workhorse models of structural change that feature non-homothetic consumption demand and/or relative price effects. Key papers in this literature include Kongsamut, Rebelo, and Xie (2001), Ngai and Pissarides (2007), and Herrendorf, Rogerson, and Valentinyi (2013). We add to this literature by using an open economy framework with capital accumulation and input-output linkages. The second strand is the research on assessing the importance of the open economy in structural change. This research includes Matsuyama (2009), Sposi (2012), Uy, Yi, and Zhang (2013), Świecki (2017), Betts, Giri, and Verma (2017), Teignier (2018), Cravino and Sotelo (2019), and Matsuyama (2019). Cravino and Sotelo (2019) also emphasize the declining relative price of manufactured goods in their

[2]Haraguchi, Cheng, and Smeets (2017) provide evidence of deindustrialization in manufacturing employment shares; they argue there is no deindustrialization in manufacturing value-added shares, but they examine real shares – this is consistent with deindustrialization in the nominal shares, because the relative price of manufactured goods has declined over time.

explanation of how trade-induced structural change can lead to an increased skill premium. Lewis et al. (2021) address the feedback from structural change to trade openness. The third is the research on investment and structural change, and includes Kehoe, Ruhl, and Steinberg (2018), Herrendorf, Rogerson, and Valentinyi (2021), and García-Santana, Pijoan-Mas, and Villacorta (2021). The final strand is research on input-output linkages and structural change, and includes Sinha (2019) and Sposi (2019). The papers from these three strands of research do not examine deindustrialization or industry polarization.

There is a growing literature that employs non-homothetic functional forms for production, in addition to preferences. These papers draw from Sato (1977) and include Bauer, Boussard, and Lashkari (2023) and Trottner (2022). Finally, our paper also relates to the literature on multi-country Ricardian trade models with capital accumulation, and includes Eaton et al. (2016), Alvarez (2017), Ravikumar, Santacreu, and Sposi (2019). These papers do not study structural change. Our paper unifies all of the features from the structural change literature and the multi-country models with capital accumulation.

The paper is organized as follows. Section 2 presents the established and new stylized facts about structural change. Section 3 lays out our model, and section 4 describes the model calibration. Section 5 presents our results, and the final section concludes.

2 Evidence on Deindustrialization and Polarization

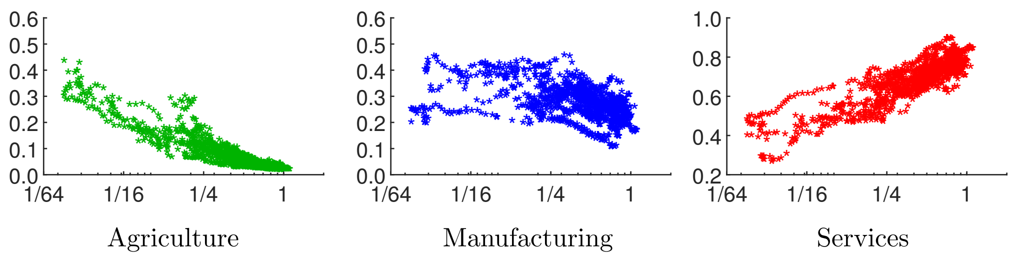
We document two interrelated facts of global structural change. We first add to the body of evidence on deindustrialization: countries that have developed more recently have tended to experience a greater share of resources effectively "bypassing" manufacturing and going directly from agriculture to services. We then show an increasing cross-country dispersion of the manufacturing value added shares over time, a feature we call *industry polarization*.

Data We construct a balanced panel of 28 countries over period 1970–2011: Australia, Austria, Belgium-Luxembourg, Brazil, Canada, China, Cyprus, Germany, Denmark, Spain, Finland, France, United Kingdom, Greece, Hungary, Indonesia, India, Ireland, Italy, Japan, South Korea, Mexico, Netherlands, Portugal, Sweden, Turkey, Taiwan, and United States. Using the International Standard Industrial Classification of All Economic Activities, Revision 4, we construct three broad sectors. Agriculture includes Agriculture, forestry and fishing (A). Manufacturing includes: Mining and quarrying (B); Manufacturing (C); Electricity, gas, steam and air conditioning supply (D); Water supply, sewerage, waste management and remediation activities (E). Services includes the remaining sectors from F to S.

We use two data series in the empirical analysis. The first is income per capita, sourced from version 9.0 of the Penn World Table (Feenstra, Inklaar, and Timmer, 2015, PWT), defined as expenditure-side real GDP at chained PPP prices divided by the population. The other is sectoral value added shares. From 1995 to 2011, data are from the World Input-Output Database (Timmer, 2012, WIOD). Prior to 1995, we use data from United Nations Industrial Development Organization (UNIDO), the Groningen Growth and Development Centre (Timmer, de Vries, and de Vries, 2014, GGDC), and EU KLEMS.

Deindustrialization Figure 1 plots the sectoral value added share against real income per capita in PPP terms (normalized by the 2011 US income per capita). The figure shows the well known fact that as countries develop agriculture's share declines, service's value added share increases, and manufacturing's share follows a "hump" pattern.

Figure 1: Sectoral Value Added Shares: 1971–2011



Notes: The x-axes are real income per capita at PPP prices, relative to United States in 2011, and the y-axes are HP trends of sectoral value added shares. The data is a balanced panel covering 28 countries from 1971–2011.

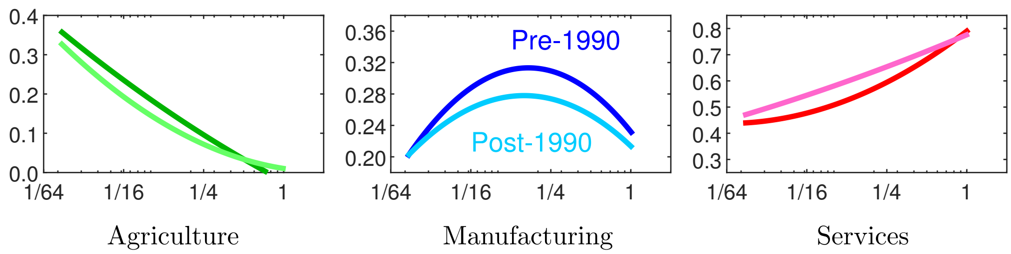
In order to gauge how the relationship between the sectoral value added shares and income change over time, we estimate the relationships for the pre-1990 and post-1990 periods using an OLS regressions of a quadratic specification using country fixed effects along with time period dummies. We separate the sample at the year 1990 because it is the mid-point of our sample, and also because trade integration has accelerated since 1990. The quadratic specification accommodates a nonlinear relationship with respect to income per capita, particularly the hump-shaped relationship in the manufacturing sector:

$$\mathrm{va}^j_{n,t} = \alpha^j_n + (\beta^j_{0,\mathrm{pre}} + \beta^j_{1,\mathrm{pre}} y_{n,t} + \beta^j_{2,\mathrm{pre}} y^2_{n,t})\mathbb{1}_{t\in\mathrm{pre}} + (\beta^j_{1,\mathrm{post}} y_{n,t} + \beta^j_{2,\mathrm{post}} y^2_{n,t})\mathbb{1}_{t\in\mathrm{post}} + \epsilon^j_{n,t}, \quad (1)$$

where $\mathrm{va}^j_{n,t}$ denotes the value added share of sector j in country n and year t, and y denotes log income per capita. The indicator function $\mathbb{1}_{t\in pre}$ takes the value of one when year $t \leq 1990$ and zero otherwise. Similarly, $\mathbb{1}_{t\in post}$ takes the value of one when year $t > 1990$. Country fixed effects α^j_n remove country-specific, time-invariant determinants of sectoral shares, such as geography, endowments, culture, and history. Our focus is to investigate whether the relationship between sectoral value added shares and income changes over time, so we allow for the coefficients of the quadratic specification to vary across the two periods. Post-1990 is the reference period, so β_0^j is the pre-1990 fixed effect relative to post-1990.

Our estimates in Table B.1 of the Appendix indicate that the pre-1990 coefficients are jointly different from the post-1990 coefficients. Given that the specification is quadratic in income per capita, it is difficult to discern from the coefficients alone whether deindustrialization is occurring.[3] Hence, Figure 2 visually contrasts the estimated relationships between sector value added shares and income per capita across the two periods for a "typical" country. We first construct a "typical" country undergoing growth in income per capita, spanning the range observed in the data. Moreover, we set this country's fixed effect to be the average of the estimated country fixed effects. We then trace out the predicted sectoral value added shares for this country over the entire income path for both the pre-1990 and post-1990 periods, separately, using the corresponding estimated coefficients in equation (1).

Figure 2: Deindustrialization: Predicted Sectoral Value Added Shares Pre-90 vs. Post-90



Notes: Each line plots the predicted value added share for a sector (y-axis), estimated from a balanced panel of 28 countries over 1971–2011 using equation (1) under the average country fixed effect and over the observed ranges of income per capita (x-axis). Dark lines - pre 1990; Light lines - post 1990. ROW is excluded from the calculations.

The figure shows the central facts of structural change in each period. It also shows that for countries at the same levels of income, the agriculture value added share is lower, but the services share is higher, in the post-1990 period than in the pre-1990 period. Most important, the Manufacturing panel shows deindustrialization: the hump-shaped relationship shifts down between the pre-1990 and post-1990 periods, with the peak share of the hump declining by 3.5 percentage points from 0.313 to 0.278. Formal tests reject the null hypothesis that the coefficients are the same across the two periods.

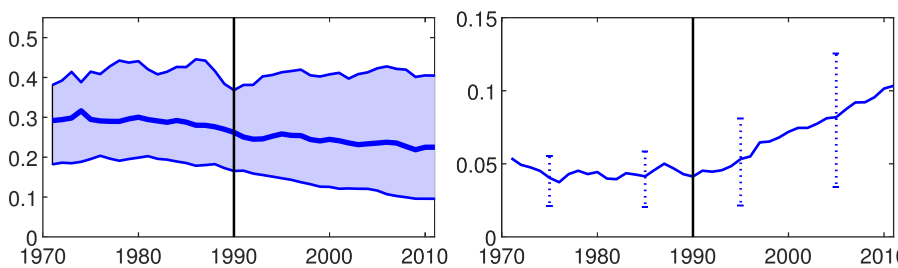
We conduct robustness checks on the pattern of deindustrialization in Appendix B and confirm (i) the statistical and economic significance of deindustrialization, and (ii) the presence of deindustrialization in a larger sample of 95 countries.

[3]If the coefficients on income per capita and income per capita squared were restricted to be the same across the two periods, then the pre-1990 fixed effect alone would be sufficient to infer the presence of deindustrialization. We report the results from this simple, illustrative specification in Table B.1.

Polarization In addition to the average sectoral value added shares—the first moment—across income levels and time periods, we also examine the cross-country dispersion of the sectoral value added share—the second moment—over time. The left panel of Figure 3 shows the cross-country distribution in manufacturing value added shares over our sample period. The shaded area displays the range of these shares. The median share — the dark solid line — declines over time, the share at the 100$^{\text{th}}$ percentile remains stable at about 40 percent, and the share at the 1$^{\text{st}}$ percentile falls after 1990. Thus, manufacturing value added shares have been increasingly polarized since 1990.

We quantify the degree of polarization over time using the variance of the log manufacturing value added share across countries, which describes the average squared percentage deviation from the mean share of each period.[4] The right panel of Figure 3 shows that the variance was relatively flat prior to 1991, then almost doubled from an average of 0.043 during that period to 0.074 in the post-1990 period. This increase reflects the contrasting experiences across countries. Latin American countries (e.g. Brazil and Mexico) have much lower manufacturing value added shares than Asian economies (e.g. South Korea and Taiwan), conditional on the same level of income (e.g., Sinha, 2021) in the post-1990 period.

Figure 3: Industry Polarization



Cross-Country Distribution   Log-variance

Notes: In the left panel, the middle line plots the median value of the manufacturing value added shares across 28 countries over time (x-axis), while the upper and lower bands correspond to the 100$^{\text{th}}$ and 1$^{\text{st}}$ percentiles, respectively. In the right panel, the solid line reports the variance of the log-manufacturing VA share across countries over time (x-axis), with 95% confidence intervals (based on 1000 bootstrap samples) reported every 10 years beginning with 1975. ROW is excluded from the calculations.

In Appendix B we show that the increased polarization post-1990 holds in a larger sample of 95 countries. Figure E.6 in the Appendix illustrates the corresponding patterns for agriculture and services. Neither of those sectors displays increased dispersion over time. Before turning to our model, we emphasize that these two interrelated patterns are distinct.

[4]Our concept is different from measures of sectoral specialization or concentration such as those used in Imbs and Wacziarg (2003) and related research. In Imbs and Wacziarg (2003), a Gini or Herfindahl or similar index of sectoral concentration is constructed for each country and plotted against per capita income. Our measure is constructed for manufacturing value-added across countries and plotted against time.

From an accounting perspective industry polarization can arise from three sources: countries on the upward part of the hump are nearing the peak; countries on the downward portion of the hump are hitting low levels; and overall deindustrialization. In other words, deindustrialization is neither necessary nor sufficient for industry polarization.

3 Model

In this section we introduce a general equilibrium model of global structural change. Along the lines of Uy, Yi, and Zhang (2013), Święcki (2017), and Sposi (2019), we employ a three-sector, multi-country, Ricardian model of trade. Two novel departures from the existing open economy structural change models are (i) the presence of scale effects in the production structure and (ii) the endogenous capital accumulation. There are N countries and three sectors: agriculture, industry, and services. Time is discrete and agents have perfect foresight. Each country admits a representative household with non-homothetic preferences, and firms are competitive. Countries can produce and trade a continuum of varieties in each sector, subject to "iceberg" trade costs. Time-varying and country-specific sectoral productivity and trade costs are the two key exogenous drivers of structural change in the model.

3.1 Households

A representative household in each country owns the raw factors of production (capital and labor) and chooses aggregate and sectoral levels of consumption and investment over time. Lifetime utility is the discounted sum of population-weighted period utility:

$$\sum_{t=1}^{\infty} \beta^{t-1} \psi_{n,t} L_{n,t} \ln\left(\frac{C_{n,t}}{L_{n,t}}\right), \tag{2}$$

where $C_{n,t}$ denotes aggregate consumption in country n and time t, $L_{n,t}$ denotes total labor, and $\beta < 1$ is the discount factor. The term $\psi_{n,t}$ is an exogenous shock to the discount factor, capturing external forces that impact on investment dynamics— demographics, capital taxes, and other distortions. In each period aggregate consumption is defined as a generalized, non-homothetic, CES aggregate over the three sector composite goods:

$$\sum_{j\in\{a,m,s\}} \omega_{c,n}^{j} \left(\frac{C_{n,t}}{L_{n,t}}\right)^{\frac{1-\sigma_c}{\sigma_c}\varepsilon_c^j} \left(\frac{c_{n,t}^{j}}{L_{n,t}}\right)^{\frac{\sigma_c-1}{\sigma_c}} = 1, \tag{3}$$

This draws from Comin, Lashkari, and Mestieri (2021). Aggregate consumption, $C_{n,t}$ is defined implicitly over each of the sector-j consumption levels, $c^j_{n,t}$.[5] The parameter $\sigma_c > 0$ governs the elasticity of substitution across sectors (price elasticity), and $\varepsilon^j_c > 0$ governs the *scale elasticity* of sector-j consumption (often called the income elasticity in the context of consumption demand). Specifically, it is the elasticity of sector-j consumption with respect to the scale (level) of the consumption index. Finally, $\omega^j_{c,n}$– the relative weight of the sector-j good within the bundle – is country-specific and captures time-invariant factors omitted from the model that affect sectoral consumption demand, such as taste, geography, or institutions.

When the scale elasticity ε^j_c is set at one for all sectors, equation (3) gives the standard homothetic CES consumption aggregation over sectoral goods. When the elasticity of substitution σ_c is also set to one, equation (3) becomes Cobb-Douglas. Without of loss of generality, one of the scale parameters can be normalized to one.

The household chooses consumption and investment over time to maximize utility specified by equations (2)–(3), subject to the following budget constraint in each period:

$$\underbrace{\sum_{j\in\{a,m,s\}} p^j_{n,t}c^j_{n,t}}_{P^c_{n,t}C_{n,t}} + \underbrace{\sum_{j\in\{a,m,s\}} p^j_{n,t}x^j_{n,t}}_{P^x_{n,t}X_{n,t}} = (1-\phi_{n,t})(R_{n,t}K_{n,t} + W_{n,t}L_{n,t}) + L_{n,t}T^P_t. \tag{4}$$

The left hand side of equation (4) accounts for the expenditure on consumption $c^j_{n,t}$ and investment $x^j_{n,t}$ in each sector j at price $p^j_{n,t}$. Just as $C_{n,t}$ bundles sectoral consumption in equation (3), the aggregate investment index, $X_{n,t}$, bundles sectoral investment $x^j_{n,t}$ in an analogous non-homothetic CES fashion. We denote the price elasticity by σ_x, the sector-j scale elasticity by ε^j_x, and sectoral weights by $\omega^j_{x,n}$. The price indices for aggregate consumption and investment are denoted by $P^c_{n,t}$ and $P^x_{n,t}$, respectively.

The right hand side of equation (4) accounts for income, and is adjusted for aggregate trade imbalances. Income accrues from capital $K_{n,t}$ and labor at the rates $R_{n,t}$ and $W_{n,t}$, respectively. We abstract from international borrowing and lending and model trade imbalances as transfers between countries, following Caliendo et al. (2018). A pre-determined share of GDP, $\phi_{n,t}$, is sent to a global portfolio, which in turn disperses a per-capita lump-sum transfer, T^P_t, to every country to ensure that global trade is balanced. Country n's net exports are $\phi_{n,t}(R_{n,t}K_{n,t} + W_{n,t}L_{n,t}) - L_{n,t}T^P_t$.[6]

The law of motion for capital stocks specifies that aggregate investment augments the

[5] Another approach developed recently to capture persistent non-homothetic preferences is the PIGL approach in Boppart (2014). While the two sets of preferences are similar on that dimension, they differ along other dimensions, such as whether the elasticity of substitution is constant or not.

[6] While the share of GDP allocated to the global portfolio $\phi_{n,t}$ is exogenous, the proceeds T^P_t are endogenous to clear the global market. This feature is particularly useful in the counterfactual analysis.

existing stock of capital subject to depreciation and adjustment costs:

$$K_{n,t+1} = (1-\delta)K_{n,t} + (X_{n,t})^{\lambda}\,(\delta K_{n,t})^{1-\lambda}\,, \tag{5}$$

This specification is based on Lucas and Prescott (1971). When $\lambda = 1$ there is no adjustment cost. When $\lambda < 1$, the efficiency of investment decreases with respect to its proportion to the existing capital stock. When $\lambda = 0$, then the adjustment cost is infinite.

3.2 Firms

There is a unit interval of tradable varieties in each sector indexed by $v \in [0,1]$. Production of each variety is carried out by competitive firms and sold internationally to firms that aggregate varieties into sectoral composite goods. The composite goods are then sold to satisfy local demand for final consumption and investment, and for intermediate-inputs.

Composite Goods Within each sector, all of the varieties are combined in a homothetic fashion with constant elasticity in order to construct a sectoral composite good:

$$Q^j_{n,t} = \left[\int q^j_{n,t}(v)^{1-1/\eta} dv\right]^{\eta/(\eta-1)}\,,$$

where η is the elasticity of substitution between varieties, which is constant across countries, sectors, and time. The term $q^j_{n,t}(v)$ is the quantity of variety v used by country n at time t to construct the sector-j composite good. Each country sources each variety from its cheapest origin location. The resulting composite good is the quantity of the sector-j composite good available in country n to use as an intermediate input or for final consumption or investment.

Individual Varieties Varieties can be produced using capital, labor and sectoral intermediate (composite) goods. The technology for country n to variety v in sector j is:

$$y^j_{n,t}(v) = a^j_n(v)\left(A^j_{n,t} k^j_{n,t}(v)^{\alpha} \ell^j_{n,t}(v)^{1-\alpha}\right)^{\nu^j_n} E^j_{n,t}(v)^{1-\nu^j_n}. \tag{6}$$

Production is a Cobb-Douglas aggregate of value added and intermediates, with value added share $\nu^j_n \in [0,1]$ that is constant over time. Value added is a Cobb-Douglas aggregate of capital $k^j_{n,t}(v)$ and labor $\ell^j_{n,t}(v)$ with capital share α. $E^j_{n,t}(v)$ denotes the intermediate input index used in sector j. Analogous to consumption and investment in equation (3), this index bundles composite intermediates from all sectors k, $e^{j,k}_{n,t}(v)$, in a non-homothetic CES fashion. The elasticity of substitution across sectoral inputs used by sector j is σ^j_e, the sector-k input scale elasticity is $\varepsilon_e^{j,k}$, and the sectoral input weights are $\omega_{e,n}^{j,k}$.

Country- and sector-specific value-added productivity, $A_{n,t}^j$, varies over time. The term $a_n^j(v)$ denotes country n's idiosyncratic productivity for producing variety v in sector j. Following Eaton and Kortum (2002), the idiosyncratic draws come from independent Fréchet distributions, with c.d.f.s given by $F_{n,t}^j(a) = \exp(-a^{-\theta^j})$. Without loss of generality, we assume the idiosyncratic productivity draws are constant over time.

Given factor prices and prices for output and intermediate inputs, firms maximize profit:

$$p_{n,t}^j(v)y_{n,t}^j(v) - R_{n,t}k_{n,t}^j(v) - W_{n,t}\ell_{n,t}^j(v) - P_{n,t}^{e,j}E_{n,t}^j(v),$$

where $P_{n,t}^{e,j}$ denotes sector-j's intermediate input cost index, and $P_{n,t}^{e,j}E_{n,t}^j = \sum\limits_{k\in\{a,m,s\}} p_{n,t}^k e_{n,t}^{j,k}$.

3.3 International Trade

Varieties that are traded internationally incur physical iceberg costs. Country n must purchase $d_{n,i,t}^j \geq 1$ units of any variety of sector j from country i in order for one unit to arrive at time t; $d_{n,i,t}^j - 1$ units melt away in transit. The trade costs vary across country pairs, across sectors, and over time. As a normalization we assume that $d_{n,n,t}^j = 1$ for all (n, j, t).

As in Eaton and Kortum (2002), the fraction of country n's expenditures allocated to goods produced by country i in sector j is given by:

$$\pi_{n,i,t}^j = \frac{\left((A_{i,t}^j)^{-\nu_i^j}u_{i,t}^j d_{n,i,t}^j\right)^{-\theta^j}}{\sum\limits_{i'=1}^{N}\left((A_{i',t}^j)^{-\nu_{i'}^j}u_{i',t}^j d_{n,i',t}^j\right)^{-\theta^j}}, \tag{7}$$

where the unit cost for a bundle of inputs for producers in sector j in country i is:

$$u_{i,t}^j = \left(\frac{R_{i,t}}{\alpha\nu_i^j}\right)^{\alpha\nu_i^j}\left(\frac{W_{i,t}}{(1-\alpha)\nu_i^j}\right)^{(1-\alpha)\nu_i^j}\left(\frac{P_{i,t}^{e,j}}{1-\nu_i^j}\right)^{1-\nu_i^j}. \tag{8}$$

The price of the sector-j composite good in country n is given by:

$$p_{n,t}^j = \gamma_j\left[\sum_{i=1}^{N}\left((A_{i,t}^j)^{-\nu_i^j}u_{i,t}^j d_{n,i,t}^j\right)^{-\theta^j}\right]^{-\frac{1}{\theta^j}}.[7] \tag{9}$$

[7] γ^j is a constant depending on η and θ^j.

3.4 Equilibrium

The model economy is summarized by time invariant parameters (β, ε_c^j, ε_x^j, $\varepsilon_e^{j,k}$, σ_c, σ_x, σ_e^j, θ, δ, λ, η, α, ν_n^j, $\omega_{c,n}^j$, $\omega_{x,n}^j$, $\omega_{e,n}^{j,k}$), time varying exogenous processes of sectoral productivities and trade costs $\{A_{n,t}^j,\ d_{n,i,t}^j\}$, the initial capital stock K_{n0}, processes of labor endowment $\{L_{n,t}\}$, and processes controlling trade imbalances $\{\phi_{n,t}\}$ and discount factor shifters $\{\psi_{n,t}\}$. We first define and then characterize the competitive equilibrium of the model.

Definition. A competitive equilibrium consists sequences of allocations $\{C_{n,t},\ X_{n,t},\ K_{n,t},\ c_{n,t}^j,\ x_{n,t}^j,\ k_{n,t}^j,\ l_{n,t}^j,\ E_{n,t}^j,\ e_{n,t}^{j,k},\ \pi_{nit}^j\}$ and prices $\{P_{n,t}^c,\ P_{n,t}^x,\ P_{n,t}^{e,j},\ p_{n,t}^j,\ R_{n,t},\ W_{n,t}\}$ that: (1) satisfy household optimization, (2) respect competitive pricing by firms, (3) reflect country's sourcing varieties from their least-cost supplier, and (4) market clearing. Table D.1 summarizes all of the equilibrium conditions.

Households' Optimization Given the sequences of prices, households optimize on the intertemporal decisions of aggregate consumption and investment, and on the intratemporal decisions of sectoral consumption and investment. Aggregate consumption and investment choices are determined by an intertemporal Euler equation:

$$\frac{C_{n,t+1}/L_{n,t+1}}{C_{n,t}/L_{n,t}} = \beta\left(\frac{\psi_{n,t+1}}{\psi_{n,t}}\right)\left(\frac{\frac{R_{n,t+1}}{P_{n,t+1}^x} - \Phi_2\left(K_{n,t+2}, K_{n,t+1}\right)}{\Phi_1\left(K_{n,t+1}, K_{n,t}\right)}\right)\left(\frac{P_{n,t+1}^x/P_{n,t+1}^c}{P_{n,t}^x/P_{n,t}^c}\right), \tag{10}$$

where Φ_i denotes the derivative of the investment function with respect to the i^{th} argument.[8]

The intratemporal decisions are characterized by the first order conditions as well. Given the non-homothetic CES structure, the expenditure shares across sectors depend on not only the relative prices, but also aggregate consumption per capita (instantaneous utility):

$$\frac{p_{n,t}^j c_{n,t}^j}{P_{n,t}^c C_{n,t}} = (\omega_{c,n}^j)^{\sigma_c}\left(\frac{p_{n,t}^j}{P_{n,t}^c}\right)^{1-\sigma_c}\left(\frac{C_{n,t}}{L_{n,t}}\right)^{(1-\sigma_c)(\varepsilon_c^j-1)}, \tag{11}$$

where the price index for consumption is given by:

$$P_{n,t}^c = \left(\sum_{j\in\{a,m,s\}}(\omega_{c,n}^j)^{\sigma_c}(p_{n,t}^j)^{1-\sigma_c}\left(\frac{C_{n,t}}{L_{n,t}}\right)^{(1-\sigma_c)(\varepsilon_c^j-1)}\right)^{\frac{1}{1-\sigma_c}}. \tag{12}$$

With non-unitary scale elasticities, changes in the scale of consumption (income) also impact

[8] $\Phi_1(K', K) = \frac{\delta^{1-1/\lambda}}{\lambda}\left(\frac{K'}{K} - (1-\delta)\right)^{(1-\lambda)/\lambda}$ and $\Phi_2(K', K) = \Phi_1(K', K)\left((\lambda-1)\left(\frac{K'}{K}\right) - \lambda(1-\delta)\right)$.

sectoral consumption allocations. As the price of the sector j good rises, relative to the other sectors, the price elasticity determines the response of sectors j's share in total spending. In an empirically relevant case with $\sigma_c < 1$, sector expenditure shares move positively with the corresponding sector's relative prices. Moreover, as aggregate consumption rises, households spend relatively more on goods from a sector with a higher scale elasticity. The magnitudes of the price and scale effects are given by $1-\sigma_c$ and $(1-\sigma_c)(\varepsilon_c^j - 1)$, respectively.

The allocation of investment expenditure across sectors and the definition of the aggregate investment price index follow a similar approach (see Table D.1 in the Appendix).

Firms' Optimization We suppress the variety index and lay out the optimal first order conditions at the sector level. Cost minimization implies that, within each sector, expenditure on factors and intermediate inputs exhaust the value of output:

$$R_{n,t}k_{n,t}^j = \alpha\nu_n^j p_{n,t}^j y_{n,t}^j, \qquad W_{n,t}\ell_{n,t}^j = (1-\alpha)\nu_n^j p_{n,t}^j y_{n,t}^j, \qquad P_{n,t}^{e,j}E_{n,t}^j = (1-\nu_n^j)p_{n,t}^j y_{n,t}^j.$$

For producers in sector j, the share of intermediate spending dedicated to goods from sector k, and the cost index of intermediate inputs, are calculated in an analogous way to sectoral consumption expenditure shares and the consumption price index. To avoid repetition, we delegate these equations to Table D.1 in the Appendix.

In contrast to models with homothetic production structures, scale effects in production imply that supply curves are not perfectly elastic. We illustrate the impact of scale through the lens of the cost function for sector j's intermediate inputs (suppressing time subscripts):

$$P_n^{e,j}E_n^j \equiv \Omega_n^j(\mathbf{p_n}, E_n^j) = \left(\sum_{k\in\{a,m,s\}} (\omega_{e,n}^{j,k})^{\sigma_e^j}(p_n^k)^{1-\sigma_e^j}\left(\frac{E_n^j}{L_n}\right)^{(1-\sigma_e^j)(\varepsilon_e^{j,k}-1)}\right)^{\frac{1}{1-\sigma_e^j}},$$

where the price vector includes all sectoral prices: $\mathbf{p_n} = (p_n^a, p_n^m, p_n^s)$. The elasticity of the cost function Ω_n^j with respect to scale E_n^j (hereafter, "cost elasticity") is given by:

$$\frac{\partial\Omega_n^j(\mathbf{p}_n, E_n^j)}{\partial E_n^j}\frac{E_n^j}{\Omega_n^j} = \sum_{k\in\{a,m,s\}} h_n^{j,k}(\varepsilon_e^{j,k} - 1) \equiv \bar{\varepsilon}_n^j, \tag{13}$$

where $h_n^{j,k}$ denotes the cost share of sector-k inputs in the total intermediate input cost of sector j. Intuitively, the elasticity of the cost function with respect to the scale is the cost-share-weighted average of scale parameters, denoted by $\bar{\varepsilon}_n^j$. If production is homothetic CES, i.e., $\bar{\varepsilon}_n^j = 0$, the cost of intermediates and the output price do not depend on the scale. In contrast, with non-homothetic CES production, where at least one of the sectoral scale elasticity parameters differs from one, the cost of intermediate inputs, and thus the output price, depends on the scale. Specifically, if $\bar{\varepsilon}_n^j > 1$, the cost of production and the output price both increase with the scale in sector j, and vice versa. As a technical note, this reflects Engel aggregation, as discussed in Hanoch (1975), and implies that $J-1$ of the scale elasticities are independent. In other words, one of the scale elasticities can be normalized.

Feasibility We begin by describing the domestic market clearing conditions:

$$K_{n,t} = \sum_{j\in\{a,m,s\}} k_{n,t}^j, \qquad L_{n,t} = \sum_{j\in\{a,m,s\}} \ell_{n,t}^j, \qquad q_{n,t}^j = c_{n,t}^j + x_{n,t}^j + \sum_{k\in\{a,m,s\}} e_{n,t}^{k,j}.$$

The first two conditions impose capital and labor market clearing in country n. The third condition requires, in each sector-country, that the use of the composite good (final demand for consumption and investment and intermediate input demand by all sectors) equals its supply (consisting of both domestically- and foreign-produced varieties).

The next condition requires that the value of output produced by country n-sector j to equal the value that all countries purchase from country n-sector j:

$$p_{n,t}^j y_{n,t}^j = \sum_{i=1}^{N} p_{i,t}^j Q_{i,t}^j \pi_{i,n,t}^j. \tag{14}$$

The aggregate resource constraint that requires the sum of net exports across sectors to equal the value of net transfers from each country:

$$\sum_{j\in\{a,m,s\}} \left(p_{n,t}^j y_{n,t}^j - p_{n,t}^j Q_{n,t}^j\right) = \phi_{n,t}(R_{n,t}K_{n,t} + W_{n,t}L_{n,t}) - L_{n,t}T_t^P. \tag{15}$$

The left-hand side is the value of gross production minus gross absorption. The right-hand side is the difference between income and spending, i.e., transfers or net exports.

Finally, the global portfolio's intake must equal its disbursements:

$$T_t^P \sum_{n=1}^{N} L_{n,t} = \sum_{n=1}^{N} \phi_{n,t}(R_{n,t}K_{n,t} + W_{n,t}L_{n,t}) - L_{n,t}T_t^P$$

3.5 Discussion

The primary driving forces of structural change are sector-biased productivity growth and trade integration, both operating through three channels: scale effects, price effects, and specialization. We now provide an intuitive overview of how these interact.

Let's first consider a scenario where productivity growth is uniform across sectors. In this case, the scale effects directly generate changes in sectoral expenditure shares in consumption, and notably, also in investment and intermediate inputs. The sector with the highest scale elasticity gains in sectoral expenditure shares. Unique to our non-homothetic production structure, these scale effects also induce changes in relative prices across sectors. When goods are gross complements, the sector with the steepest supply curve (or the highest cost elasticity) experiences growth in its relative price, consequently expanding its share in both final and intermediate expenditures. When productivity grows differentially across countries, the relative prices evolve at varying rates, causing changes in comparative advantage and specialization, and ultimately, influencing sectoral allocations.

Now consider the additional effects from sector-biased productivity growth. In this case, relative prices increase in sectors experiencing slower productivity growth, shifting sectoral expenditure shares toward those sectors. In addition, when these sector biases differ across countries, comparative advantage adjusts, impacting sectoral shares through specialization.

Finally, the effects of declining trade costs over time shape each countries sectoral specialization. In addition, as trade costs decline, resources are allocated more efficiently, boosting real income and activating scale effects. When trade costs decline at different rates across sectors, the sector with the fastest decline undergoes a decline in its relative price, all else equal, triggering price effects. Our model has only two primary driving forces, but, owing to the three channels, it can deliver a rich set of implications.

4 Calibration

In this section we calibrate our dynamic trade model, which will be used to investigate the forces that drive the two evolving patterns of structural change over time. To ensure comparability with the empirical patterns, our analysis covers the same 28 countries as in the empirical analysis, along with a rest-of-world aggregate, from 1971 to 2011.

4.1 Data Description

Our model calibration draws from several data sources, including the Penn World Table (Feenstra, Inklaar, and Timmer, 2015, PWT), WIOD, the Organization for Economic Cooperation and Development (OECD), GGDC, EU KLEMS, UNIDO, United Nations Comtrade Database, and World Bank's World Development Indicators (WDI). We introduce these data briefly here and discuss details in Appendix A.

Our sample countries and years are the same as in the empirical section. The primary source of sectoral value added, gross output, consumption and investment spending, intermediate inputs, and bilateral trade is the WIOD, spanning the 1995–2011 period for all countries. For these data prior to 1995, we explore several sources and at times resort to imputation due to data availability issues. We assemble complete sectoral value added data using first UNIDO, second GGDC, and at last EUKLEMS. We obtain sectoral gross output from EU KLEMS and OECD, and impute missing values using projection. For sectoral investment, consumption, intermediate inputs, we turn to OECD and national statistics for a subset of country-years, and then fill missing values using the RAS method.[9] We complete bilateral trade data for agriculture and manufacturing using Comtrade. We impute bilateral services trade shares using WDI's total export and imports for each country and observed proportionality in country-level imports and exports in 1995.

Regarding prices, we begin by computing sectoral value-added price indexes as the ratio of nominal value added to real value added at constant 2005 prices, using UNIDO, GGDC, and EU KLEMS. We then build sectoral gross-output price indexes using value-added prices and the model's input-output structure in equation (C.1) of the Appendix. Finally, we convert gross-output price indexes to gross-output price levels, using comparable cross-country gross-output price levels for 2005 from the GGDC productivity-level database.

We construct data for the rest-of-world aggregate (ROW) by taking the difference between the world aggregate series and the sum of the corresponding series across the 28 sample countries. The ROW, whose main role is to absorb trade flows outside of our sample countries, is excluded from the analysis of deindustrialization and polarization.

4.2 Time-Invariant Parameters

The key parameters governing structural change are the price and scale elasticities. We describe in detail how to estimate these parameters for consumption demand; the parameters for investment and intermediate input demand by each sector are estimated analogously.

The estimation of consumption demand parameters relies on the model-implied relationship between relative sectoral expenditures, relative prices and aggregate consumption—equation (11). The sector weights $\omega^j_{c,n}$ are constant over time, and the identification of elasticities comes from within-country variation over time. We estimate elasticities to capture the trend relationship between changes in observed sectoral expenditure, sectoral prices, and total expenditure. To filter out short-run fluctuations and noise in the data, we use Hodrick-Prescott (HP) trends of these series with smoothing coefficient 6.25 in the estimation. We then choose $\omega^j_{c,n}$ to match each country's observed expenditure shares in 1971.

[9] The RAS method is commonly used by national statistics agencies to compute input-output values in between benchmark measurement years. McDougall (1999) provides a thorough description of the method.

4.2.1 Estimation of Price and Scale Elasticities

We estimate the price and scale elasticities to minimize the squared difference between the observed changes in relative sectoral consumption expenditures and the corresponding model-implied changes given the observed changes in relative prices and estimated changes in the scale of consumption. We express the optimal sectoral expenditure and the total expenditure functions in terms of changes (see Appendix C for the derivation). For any variable b, let $\widehat{b}_t = b_t/b_{t-1}$ be the change over time. Our estimating equations, formally, are

$$\frac{\widehat{p^j_{n,t}c^j_{n,t}}}{\widehat{p^m_{n,t}c^m_{n,t}}} = \left(\frac{\widehat{p}^j_{n,t}}{\widehat{p}^m_{n,t}}\right)^{1-\sigma_c} \left(\frac{\widehat{C}_{n,t}}{\widehat{L}_{n,t}}\right)^{(1-\sigma_c)(\varepsilon^j_c-1)} + v^j_{n,t}, \tag{16}$$

$$\frac{\widehat{P^c_{n,t}C_{n,t}}}{\widehat{L}_{n,t}} = \left(\sum_{k\in\{a,m,s\}} \left(\frac{p^k_{n,t-1}c^k_{n,t-1}}{P^c_{n,t-1}C_{n,t-1}}\right) (\widehat{p}^k_{n,t})^{1-\sigma_c} \left(\frac{\widehat{C}_{n,t}}{\widehat{L}_{n,t}}\right)^{(1-\sigma_c)\varepsilon^k_c}\right)^{\frac{1}{1-\sigma_c}}. \tag{17}$$

The left-hand side of equation (16) is the observed change in the sector-j expenditure, relative to sector m, for country n at date t. The right-hand side, taken together with a set of elasticities, yields the model-predicted change in sectoral expenditure share, depending on the observed changes in the relative price and the unobserved change in the scale of per-capita consumption.[10] The error between the predicted and observed sectoral expenditure share is $v^j_{n,t}$. Had we observed $\widehat{C}_{n,t}$, we could estimate the elasticities directly by applying a non-linear least square regression. We do not observe the model-consistent $\widehat{C}_{n,t}$ in the data, so we use the model-implied expenditure function, shown in equation (17), to infer $\widehat{C}_{n,t}$ from the observed changes in per-capita expenditure, sectoral spending share in the prior year, and changes in sectoral prices, given a set of the elasticities. As we described in Section 3.4, the scale elasticities can only be identified up to a scalar. As in Comin, Lashkari, and Mestieri (2021), we normalize $\varepsilon^m_c = 1$, which has no effects on sectoral allocations.

We use an iterative estimation procedure similar to the one used by Deaton and Muellbauer (1980) in estimating AIDS demand models with non-homotheticities. We start with an initial guess of the elasticities $(\sigma_c, \varepsilon^a_c, \varepsilon^s_c)$. Given these elasticities, we solve for $\widehat{C}_{n,t}$ using equation (17). Then, given the inferred values for $\widehat{C}_{n,t}$, we use the non-linear least square regression specified in equation (16) to find a new set of elasticities.[11] We iterate the above procedure until we reach a fixed point, yielding a final estimate of the elasticities. This estimation also recovers $\widehat{C}_{n,t}$, which we utilize later on.

[10] One advantage of writing the estimating equation in terms of changes is that the sector weights disappear and are effectively replace with observed sectoral spending shares over time. This reduces the number of parameters involved in the optimization problem that underlies nonlinear least squares.

[11] The non-homothetic aggregator is defined only for positive elasticities, so we iterate on their log-values.

As we mentioned above, we apply an analogous procedure to estimate the elasticities for investment demand and the three sectors' intermediate demand. Table 1 reports the estimates. Each demand system involves estimating 3 parameters from 2240 observations (pooling 2 sectors and 28 countries over 40 year-changes, with ROW excluded). We bootstrap standard errors (in parentheses) using 1000 samples and cluster at the country level.

Table 1: Elasticity Estimates

	Final demand		**Intermediate demand**		
	Cons	Inv	Agr	Mfg	Srv
Price elasticities					
σ	0.232	0.292	0.211	0.009	0.265
	(0.046)	(0.150)	(0.109)	(0.003)	(0.054)
Scale elasticities					
ε^a	0.102	0.300	1.248	0.373	0.647
	(0.005)	(0.153)	(0.194)	(0.035)	(0.100)
ε^s	1.333	1.080	1.036	0.879	1.332
	(0.093)	(0.107)	(0.066)	(0.043)	(0.063)
R^2	0.05	0.31	0.11	0.21	0.06
$\mathrm{F}_{(H_0:\, \varepsilon^j=1)}$	14.6	919.6	93.0	448.4	121.8

Notes: Each column reports the elasticity estimates for one of the five demand systems. For each system, we estimate three parameters to from 2240 observations using constrained NLS regressions. The manufacturing scale effect within each demand system is normalized so that $\varepsilon^m = 1$. Standard errors (in parentheses) are bootstrapped using 1000 sample iterations, clustered at the country level. The F statistic tests the general specification against a restricted one with no scale effects (i.e., scale elasticities $\varepsilon^a = \varepsilon^s = 1$). The critical value for the F statistic at the 0.01 significance level is 4.6. This test statistic only approximately follows an F distribution when using NLS.

We test our specification against a restricted one with no scale effects ($\varepsilon^a = \varepsilon^s = 1$). The reported F statistics indicate that a homothetic CES demand structure is rejected in favor of a non-homothetic CES demand structure with scale effects, for each of the five demand systems. Indeed, non-homothetic consumption demand is a staple in the structural change literature. Non-homothetic demand structures for investment and intermediate inputs have remained essentially unexplored in the structural change literature. Below we discuss the elasticity estimates for each demand system separately.

Consumption Demand The first column of Table 1 reports the price elasticity, $\sigma_c = 0.23$, and the scale elasticities $(\varepsilon^a_c, \varepsilon^s_c) = (0.10, 1.33)$. Thus, sectoral composites are complements in consumption demand, implying that consumption spending reallocates over time to sectors with increasing relative prices. The fact that the services (agriculture) has the highest (lowest) scale elasticity among the three sectors, implies that consumption spending moves towards servies (away from agriculture) as the scale of consumption grows over time.

Our elasticity estimates for consumption demand are broadly consistent with those in Comin, Lashkari, and Mestieri (2021). Our price elasticity is on the lower end of their range of estimates (0.2–0.57), reflecting in part the fact that we use sector expenditure shares on the left-hand side, whereas they use sector employment shares. Our scale elasticities are also consistent with their estimates. They tackle endogeneity of sectoral prices to sectoral demand using household level data and find that these estimates are robust.

Investment Demand The results are reported in the second column of Table 1. Agriculture has the lowest scale elasticity in investment demand. The services sector has the highest scale elasticity, but ε_x^s is not statistically, significantly different from $\varepsilon_x^m = 1$. The price elasticity σ_x is 0.29, which indicates a strong degree of complementary. The available estimates of the price elasticity in the literature, limited to a homothetic CES investment aggregator with no scale effects, span a wide wage. For example, Herrendorf, Rogerson, and Valentinyi (2021) estimate this parameter to be 0 between goods and services using data for United States. In contrast, García-Santana, Pijoan-Mas, and Villacorta (2021) estimate this parameter to be 0.52 using data from for 49 countries. When we restrict our estimation to exclude scale effects, our estimated price elasticity is 0.38.

Intermediate Demand We next describe the elasticity parameters for intermediate demand. As shown in the last three columns of Table 1, intermediate inputs are complementary in all three sectors: $\sigma_e^a = 0.21$, $\sigma_e^m = 0.01$, and $\sigma_e^s = 0.27$. Thus, in response to a declining relative price of manufacturing to services over time, in each of the sectors, relative spending on intermediate inputs shifts away from manufacturing and toward services. This increase in indirect demand for services through the input-output structure adds to the effect of the increase in services final demand described above.

The scale elasticises display a unique pattern in that each sector has the highest scale elasticity with respect to it's own sector's input. For instance, among intermediates used by the agriculture sector, the scale elasticity is the highest for agriculture inputs: $\varepsilon_e^{a,a} = 1.25$. Similarly, among intermediates used by the manufacturing (services) sector, the scale elasticity is the highest for manufacturing (services) inputs. In addition to the own-sector scale effects, for each intermediate demand system, the scale elasticity of services exceeds that of manufacturing, and the scale elasticity of manufacturing exceeds that of agriculture.

The scale elasticities reinforce the structural change process through the input-output structure. As final demand for services increases, the scale of service production must increase relative to the other sectors. In turn, service producers draw more resources from their own sector via intermediate inputs through the scale effect, further driving up demand for service production. As a consequence of moving up the marginal cost curve in services more quickly than in other sectors, the relative price of services increases. This feature is absent in homothetic production structures that are commonly used in the literature.

4.2.2 Calibration of Sectoral Demand Weights

We now briefly explain how we calibrate the country-specific sectoral weight parameters for the consumption aggregator, with further details in Appendix C. Given the estimated elasticities, we set the sector weights ω_c^j and the level of consumption $C_{n,1}$ to match the observed sectoral expenditure shares, as in equation (11), and observed total expenditure, defined by multiplying both sides of equation (12) by aggregate consumption per capita, for each country in 1971. With this calibrated $C_{n,1}$, we can construct consumption scale $C_{n,t}$ over time—using the changes over time $\hat{C}_{n,t}$ from the elasticities estimation—and the consumption price index $P^c_{n,t}$, for each country.

The weights for the other four demand systems are calibrated analogously. Similarly, we obtain the scales of investment, $X_{n,t}$, and sector-j intermediate input demand, $E^j_{n,t}$, and the associated price indices, $P^x_{n,t}$, and $P^{e,j}_{n,t}$. These series have no direct counterparts in the data, but we use them in the calibration of the productivity processes in section 4.3.

4.2.3 Remaining Time-Invariant Parameters

We compute ν^j_n as the average ratio—from 1971 to 2011—of value added to gross output for each sector j and country n. Table 2 reports the average ratio across countries for each sector. On average, services has the highest ratio, and manufacturing the lowest.

Simonovska and Waugh (2014) estimate the trade elasticity for manufacturing to be 4. We apply this estimate to all sectors: $\theta^j = 4$. The elasticity of substitution between varieties within the composite good plays no quantitative role in the model other than satisfying $\eta < 1 + \theta^j$ (see Eaton and Kortum, 2002). Following the literature we set $\eta = 2$.

The discount factor is 0.96 to target an annual real interest rate of 4% in the long run. Capital's share in value added α is 0.33, as in Gollin (2002). The depreciation rate δ is set at 6%, a standard value in macro models using annual data.

The adjustment cost λ is 0.83 to match a steady-state investment rate of 0.18.[12] [13]

[12]In the steady state, when there are no changes in the discount factor $\psi_{n,t}$, then the investment rate in current prices is $\frac{P^x_n X_n}{r_n K_n + w_n L_n} = \frac{\alpha\delta}{\left(\frac{1}{\lambda}\right)\left(\frac{1-\beta}{\beta}\right)+\delta}$.

[13]This value is consistent with that used by Eaton, Kortum, Neiman, and Romalis (2016). Having $\lambda < 1$ proves useful in the model to avoid producing counterfactually volatile capital stocks. Relative to quadratic

Table 2: Time-Invariant Parameters

	ν^a	0.57	(0.40, 0.81)
Value added shares in output	ν^m	0.37	(0.29, 0.45)
	ν^s	0.61	(0.48, 0.71)
Trade elasticity	θ^j	4	
Discount factor	β	0.96	
Capital share in value added	α	0.33	
Capital depreciation rate	δ	0.06	
Adjustment cost elasticity	λ	0.83	

Note: For the shares of value added in output, we report mean of the of the cross-country distribution, along with the 2.5^{th} and 97.5^{th} percentiles in parenthesis.

4.3 Time-Varying Exogenous Processes

In this section, we describe how we calibrate the labor endowments, capital stocks, and, importantly, the sectoral fundamental productivities and sectoral bilateral trade costs. We also describe our calibration of the trade imbalances and preference shifters.

We first describe the calibration of labor endowments and capital stocks. For each sample country, the labor series $\{L_{n,t}\}$ is directly taken from the data: the numbers of persons engaged across the three broad sectors. We set the initial capital stock to be the 1971 value provided by the Penn World Table. The capital stocks in subsequent years are built using the scale of investment obtained in Section 4.2.2, and the law of motion for capital in equation (5). We use the capital stock series to impute the rental rate for capital, which is in turn used in calibrating fundamental productivities and trade costs as described below.

We next calibrate the series of sectoral fundamental productivities $\{A^j_{n,t}\}$ in two steps. The first step is to compute measured sectoral productivities using data on sectoral prices, wage and rental returns to capital. The measured productivity is defined as

$$Z^j_{n,t} \equiv B^j_n \frac{\left(R^{\alpha}_{n,t} W^{1-\alpha}_{n,t}\right)^{\nu^j_n} \left(P^{e,j}_{n,t}\right)^{1-\nu^j_n}}{p^j_{n,t}}, \tag{18}$$

where $B^j_n = \left(\alpha\nu^j_n\right)^{-\alpha\nu^j_n} \left((1-\alpha)\nu^j_n\right)^{-(1-\alpha)\nu^j_n} \left(1-\nu^j_n\right)^{-(1-\nu^j_n)}$. The wage (rental) rate is calculated as current-USD GDP times the labor (capital) share in GDP, divided by the number of workers (capital stock). The price index for intermediates used by sector j, $P^{e,j}_{n,t}$, is obtained

capital adjustment costs commonly used in the macro literature, this specification has the feature that investment is endogenously irreversible. Investment irreversibility is desirable for two reasons. First, gross fixed capital formation is non-negative in the data. Second, in our model, the composite investment (a non-homothetic CES aggregate of sectoral investment demand) is defined only for positive values.

as a by-product of the estimation of the elasticities described in Section 4.2.2.

The second step is to compute the fundamental productivity, A^j_{nt}, from the measured productivity, Z^j_{nt}, using data on sectoral home trade shares:

$$A^j_{n,t} = \left(\gamma^j Z^j_{n,t} \left(\pi^j_{n,n,t}\right)^{\frac{1}{\theta^j}}\right)^{\frac{1}{\nu^j_n}}. \tag{19}$$

This adjustment accounts for Ricardian selection, as in Finicelli, Pagano, and Sbracia (2013).

We then calibrate the sequences of bilateral trade costs, $\{d^j_{n,i,t}\}$, to reconcile the observed pattern of trade and relative price difference:

$$d^j_{n,i,t} = \left(\frac{\pi^j_{n,i,t}}{\pi^j_{i,i,t}}\right)^{-\frac{1}{\theta_j}} \left(\frac{p^i_{n,t}}{p^j_{i,t}}\right). \tag{20}$$

In cases where $\pi^j_{n,i,t} = 0$ in the data, we set $d^j_{n,i,t}$ at 10^8, large enough to ensure that $\pi^j_{n,i,t} \approx 0$ in the model. In cases where the implied cost is less than 1, we set $d^j_{n,i,t} = 1$.

Finally, we calibrate the series for the trade imbalances, $\phi_{n,t}$, and preference shifters, $\psi_{n,t}$. $\phi_{n,t}$ is set at the ratio of net exports to GDP so that there are no transfers from the global portfolio in the baseline.[14] $\psi_{n,1}$ is initialized at 1 for all countries in 1971, and the subsequent changes $\psi_{n,t+1}/\psi_{n,t}$ are computed to reconcile the consumption growth rate with the real rate of return to investment described by the Euler equation (10).

We now present the estimated series of the two key exogenous driving forces of structural change: sectoral productivities and trade costs. The top panel of Figure 4 plots the interquartile range of the cross-country productivity distribution for each sector. Agriculture (services) has the highest (lowest) growth rate of fundamental productivity; the annual growth rate of the cross-country median fundamental productivity is 3.2% in agriculture, 2.4% in manufacturing, and 1.4% in services. Among the three sectors, agriculture (services) shows the greatest (least) cross-country variation in productivity, measured by the mean interquartile ratio.[15] Though there is substantial churning within each sectors' distribution, the cross-country variation is stable over time.

Importantly, sector-biased productivity growth systematically differs in rich (top-tertile) and poor (bottom-tertile) countries and also varies over the two periods. In rich countries, the manufacturing productivity growth rate exceeds that of services by about 0.5 percentage

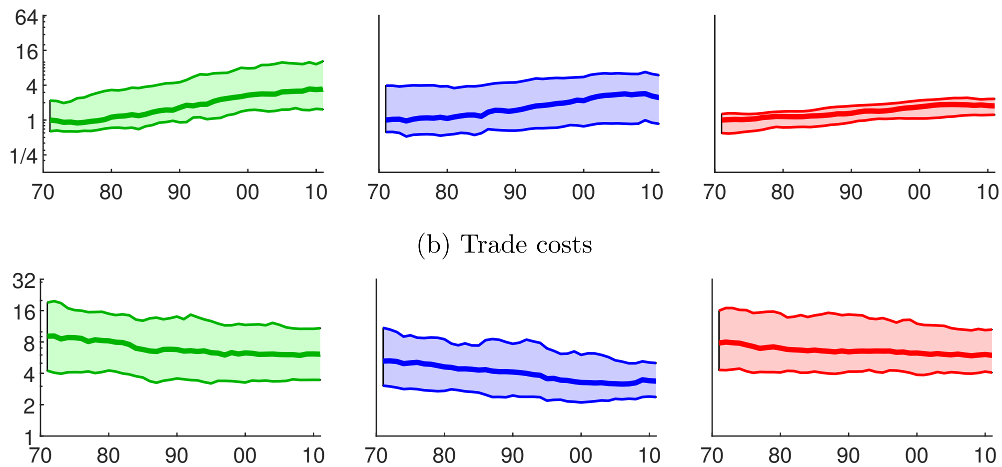
[14] In this setup, the current account is not determined by capital searching for the highest yield across countries, but instead by the exogenous $\phi_{n,t}$ process and the balancing of the global portfolio. That is, real interest rates – representing marginal products of capital – exhibit variation across countries and there is no mechanism to arbitrage those differences away.

[15] This finding is consistent with Caselli (2005), Restuccia, Yang, and Zhu (2008), and Gollin, Lagakos, and Waugh (2014), and is also in line with the Balassa-Samuelson hypothesis.

points in both periods. The sector bias also runs in the same direction in middle income countries. In poor countries, services productivity growth exceeds that of manufacturing by 1.3 percentage points in the pre-1990 period, and reduces to about 0.7 in the post-1990 period. These features influence deindustrialization, as we show later on.

Figure 4: Sectoral Fundamental Productivity and Trade Costs

(a) Fundamental productivity



Agriculture Manufacturing Services

Notes: Each figure reports the cross-country distribution, where the solid line denotes the median value, and the ranges correspond to the 25th and 75th percentiles of the distribution over time (x-axis). In the top panel, sectoral productivities across countries are normalized by the respective US values in 1971.

The lower panel plots the cross-country distribution of the estimated trade costs for each sector over time. Clearly, trade costs are generally lower in manufacturing than in the other two sectors at any point in time. Although trade costs decline in all sectors, they decline at a faster rate in the manufacturing sector than in the agriculture and service sectors. The manufacturing sector also displays more rapidly declining cross-country variation over time. The findings are the manifestation of global trade integration over the past half century. An important feature of this trade integration is that it was systematically more pronounced in rich versus poor countries: on average, rich countries have lower manufacturing trade costs. Finally, we find that outward trade costs exceed inward trade costs for countries in the lower tertile of the income distribution: The median inward trade cost is 2.6 and the median outward trade cost is 5.6. For countries in the top tertile, the median inward cost is 2.4 and the median outward cost is 2.7. This characteristic is consistent with Waugh (2010).

4.4 Solution Method and Model Fit

With forward-looking households, we need to specify the time-varying processes subsequent to the sample period. We assume that each country's investment rate, measured in current prices, converges geometrically to a common value of 0.18 across countries over the span of 25 years (from 2012 to 2036).[16] We further assume that all of the post-2011 target moments remain constant at their 2011 values in order to infer the parameters in all periods.

We next solve the baseline model numerically. The key is to solve for the sequences of capital stocks that satisfy the intertemporal Euler equations in all countries.[17] After obtaining the equilibrium, we check the model fit with respect to the data.

It is important to clarify targeted versus non-targeted moments. The calibration targets the observed factor prices (equivalently, aggregate income), sectoral output prices, and bilateral trade shares over time, to identify time-varying sectoral productivity and bilateral trade costs. Also, the estimation of the five demand systems targets the sectoral shares, but only in the initial year of 1971 for each country. Subsequent sectoral shares within consumption, investment, and intermediates are non-targeted moments that respond to changes in prices and associated scales through the estimated elasticities.

We also want to clarify an adjustment made to the model GDP deflator, defined as a geometric average of the sectoral prices, weighted by sectoral expenditure shares on consumption and investment. Though the model matches the sectoral prices by construction, the model GDP deflator does not perfectly align with its data counterpart, due to (i) differences in the aggregation specification and (ii) errors in the model-implied expenditure weights. We introduce a "wedge" to reconcile this discrepancy such that real income per capita in the baseline model coincides with its counterpart in the data.[18]

We first check on the model implications on patterns of structural change over time. As discussed earlier, we choose sectoral weights in the model to match the observed sectoral shares in 1971. Observations in subsequent 40 years are non-targeted moments, and the baseline model performs well in reproducing these changes. In the upper row of Figure 5, percent changes in sectoral value added shares in the model (y-axis) track well to those in the data (x-axis).[19] Specifically, in terms of changes in sectoral value added shares over time, the correlation between the model and the data is 0.8 on average across the three sectors. In terms of the actual shares in levels, the corresponding correlation is 0.99.

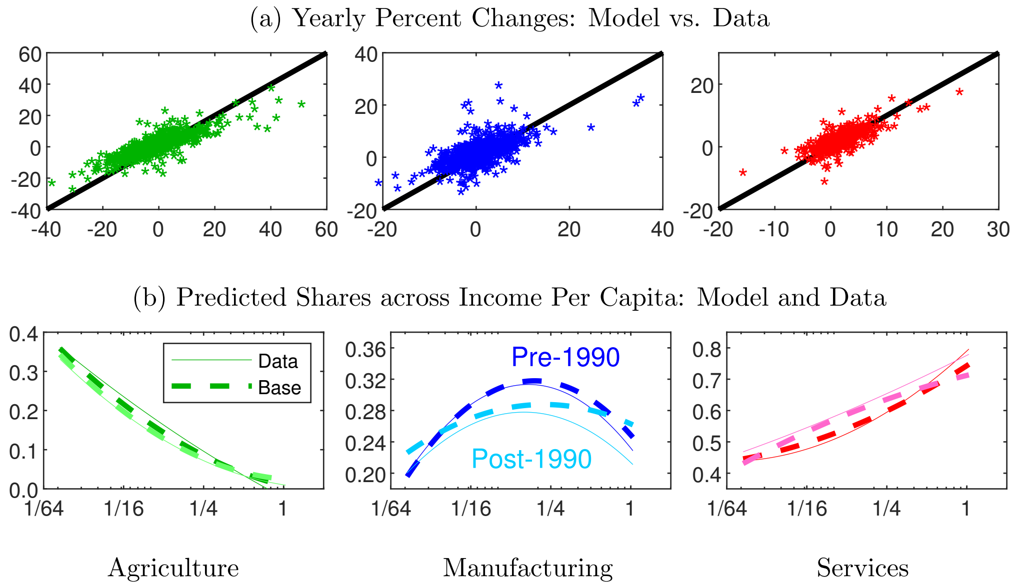
[16] Figure E.3 in the Appendix depicts the paths for the aggregate investment rates and cthe capital-labor ratios of our sample countries. These projections do not impact the baseline outcomes from 1971-2011.

[17] Our method is based on Ravikumar, Santacreu, and Sposi (2019). For details see Appendix D.

[18] This wedge has no impact on equilibrium allocations. In counterfactual experiments, we keep the wedge fixed but allow the GDP deflator to adjust to changes in sectoral prices and expenditure weights.

[19] Percent changes in agriculture are often large, since the underlying shares are very small in many cases.

Figure 5: Baseline Model Fit: Sectoral Value Added Shares

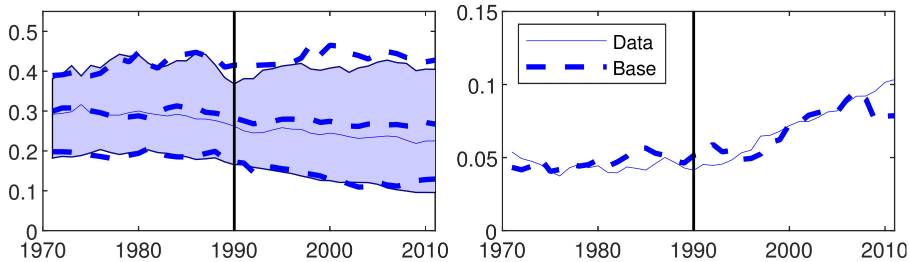


Note: The upper-row scatter plots percent changes in model value added shares (y-axis) against data shares (x-axis) with the 45^o line on the diagonal. The bottom-row line plots depict the predicted value added share for a sector (y-axis), estimated from a balanced panel of 28 countries over 1971–2011 using equation (1) under the average country fixed effect and over the observed ranges of income per capita (x-axis). Solid lines - data; Dashed lines - model. Dark lines - pre 1990; Light lines - post 1990. ROW is excluded from the calculations. The regression is applied separately to the actual data and to the model-generated data.

The bottom three panels of Figure 5 contrast the predicted paths for the sectoral value added shares over income per capita *within* a typical country in the data and in the model. These predicted paths—which are not targeted by the calibration—are a true test of the model fit. Clearly, the model reproduces the patterns of structural change well, with the pre-1990 curve aligning closer to the data than the post-1990 curve. Moreover, the model implies a decline in the peak share of the hump-shaped relationship between the manufacturing value added share and income by 3.0 percentage points from the pre-1990 to post-1990 periods—about 86% of the 3.5-percentage point decline in the data.

The baseline model also replicates the pattern of industry polarization over time. The left panel of Figure 6 compares the cross-country distribution of manufacturing value added shares in the model with actual data. The model tracks well the upper and lower bounds of the distribution, as well as the median up until 2008. Post 2008, the lowest manufacturing value added share in the model is slightly higher than that observed in the data. In the right panel, it is evident that the baseline model successfully reproduces the increasing log-variance in the data. The log-variance increased from 0.043 to 0.074 from the pre-1990 period to the post-1990 period. Our calibrated model yields an increase in the log-variance from 0.046 to 0.069 across the two periods, so it explains almost three-fourths of industry polarization. Similar results for agriculture and services are presented in Figure E.6 of the Appendix. The baseline model delivers a relatively constant log-variance in agriculture and a declining log-variance in services over time, consistent with the patterns in the data.

Figure 6: Industry Polarization: Baseline Model and Data



Notes: Dashed lines - data; Solid lines - model. In the left panel, the middle line plots the median value of the manufacturing value added shares across countries over time (x-axis), while the upper and lower bands correspond to the 100^{th} and 1^{st} percentiles, respectively. In the right panel, log-variance reports the variance of the log-manufacturing VA share across countries over time (x-axis). ROW is excluded from the calculations.

Finally, we demonstrate that the calibrated model effectively reproduces other key data moments well. Figure E.4 of the Appendix compares sectoral prices, trade shares, consumption expenditure shares, investment shares and intermediate input shares in the model with actual data. The calibration targets sectoral prices and bilateral trade shares, resulting in an almost perfect fit between the model and data in the upper two panels.

The calibration also replicates well the data on sectoral shares of consumption, investment, and intermediate inputs in each sector. The correlation between the data and the model is 0.99 (0.98) for sectoral consumption (investment) shares. The model also aligns well with the intermediate input shares, with correlations of 0.71, 0.97 and 0.98 for sectoral intermediate input shares in agriculture, manufacturing and services, respectively. It is worth noting that while we target the expenditure shares in 1971, the changes over time are free variables. The correlations between the model and data for changes in sectoral expenditure shares are as follows: 0.61 for consumption, 0.10 for investment, and 0.51, 0.61, 0.51 for intermediate spending by agriculture, manufacturing, and services, respectively. The corresponding plots underpinning these numbers are in Figure E.5.

5 Quantitative Analysis

In this section we quantify the role of the two driving forces in shaping global structural change across time through three counterfactuals. In the first counterfactual, we remove both driving forces from the baseline: countries stay in autarky and have the constant relative productivity (CRP) growth rate across the three sectors every period. We call this the *autarky-CRP scenario*. In the second one, we remove only sector-biased productivity growth. We call this the *CRP scenario*. In both scenarios, the country-specific, sector-neutral fundamental productivity growth rate in each sector is constructed as the average growth rate of the calibrated sectoral fundamental productivity growth rate, weighted by sectoral value-added shares. In the third scenario, we remove trade so that countries stay in autarky throughout. We call this the *autarky scenario*. We then compare the equilibrium outcomes from each of these scenarios to those in the baseline.

Our findings indicate that trade integration is the key behind industry polarization, but on its own, it does not contribute to the process of deindustrialization over time. Sector-biased productivity growth alone accounts for 60% of the extent of deindustrialization generated in the baseline model, occurring through the decline in the relative price of manufacturing to services across the two periods. The interaction of sector-biased productivity growth and trade integration explains about 40% of the deindustrialization phenomenon.

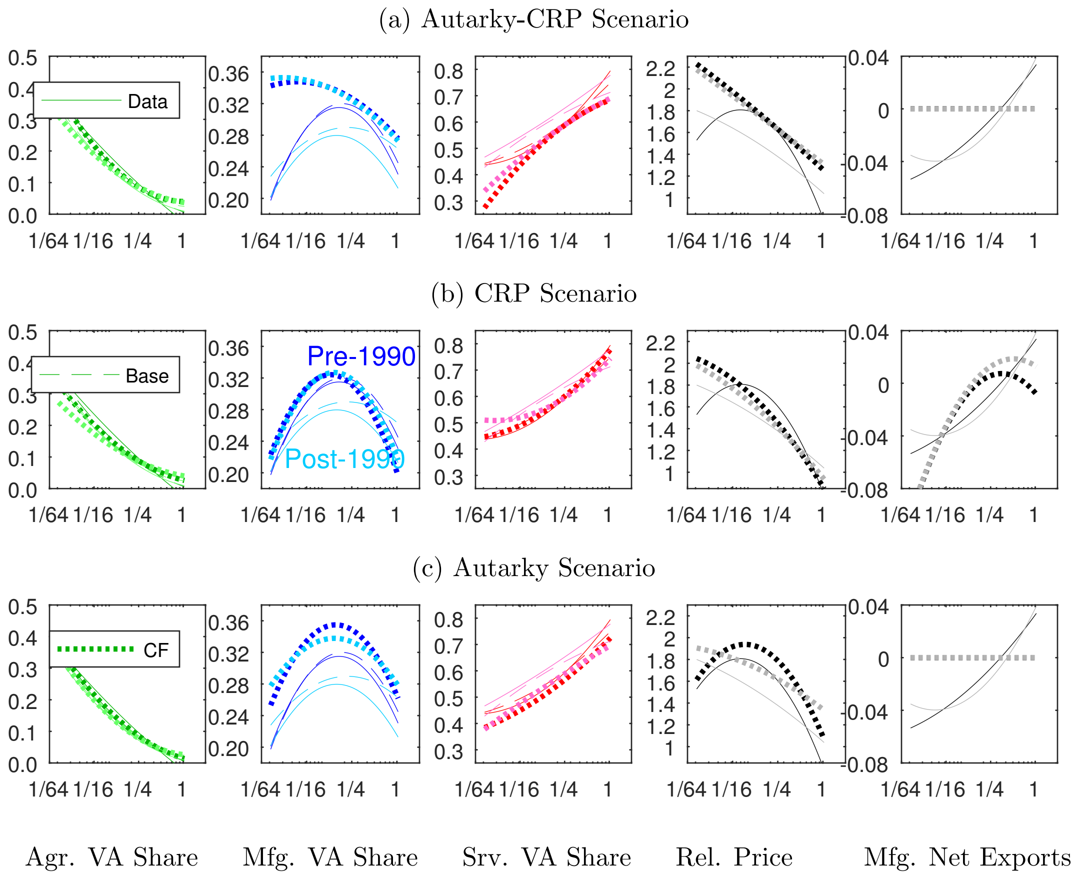
5.1 Deindustrialization

For each scenario, we apply regression (1) to the model-generated output to infer the counterfactual relationships between sectoral value added shares and income across the pre-1990 and post-1990 periods. Our focus is on unraveling the mechanisms that give rise to the hump-shaped relationship between the manufacturing value added share and income, termed hereafter as "the manufacturing hump". Of greater significance, our interest lies in uncovering the economic forces driving the decline of the manufacturing hump over time.

To achieve this, we examine the relationships between income per capita and (i) the price of manufacturing relative to services, and (ii) the ratio of manufacturing net exports to GDP across the two periods, using the same regression. As we will see below, in the baseline model, the relative price of manufacturing also follows a hump pattern, and the relationship with per-capita income shifts down over time. In addition, manufacturing net exports as a share of total GDP is positively related to per-capita income. These relationships shed light on the economics behind the manufacturing hump, while the changes of these relationships across the two periods inform us about the contributing factors to deindustrialization.

Each panel of Figure 7 plots the fitted relationships in each counterfactual using dotted lines. The pre-1990 period is represented by the darker lines, while the post-1990 period is represented by the lighter lines. The first three columns of each panel present the predicted paths for each sector's share in value added across income per capita, the fourth column illustrates the predicted paths for the price of manufacturing relative to services, and the last column depicts the predicted path for the ratio of manufacturing net exports to GDP. To facilitate comparison, we also plot the corresponding data relationships in solid lines and those implied by our baseline model in dashed lines. Because our calibration directly targets sectoral prices and trade flows, the implied paths for relative prices and net exports in the baseline coincide with those in the data.

Figure 7: Predicted Sectoral Value Added Shares Across Income per Capita



Notes: The fitted curves are based on regressions of the variable of interest on income (y-axis), interacted with the two period dummies, and country fixed effects, over income per capita (x-axis). Solid lines refer to the data; the dashed lines refer to the baseline model; the dotted lines refer to the counterfactuals. Dark (light) lines refer to pre-1990 (post-1990).

Autarky-CRP scenario In this scenario, sector-neutral productivity growth within each closed economy gradually boosts (per-capita) income over time. By assumption, there are no sector-biased productivity effects or trade effects. Rather, the driving forces for structural change are primarily scale effects in final demand (due to non-homothetic consumption and investment demand), and to a lesser extent, scale effects in intermediate demand. These scale effects impact relative prices, specifically, the relative price of manufacturing to services. The outcomes of this scenario are presented in the top row of Figure 7.

As shown in the first column, non-homothetic final demand alone accounts for the observed trend in agriculture: as countries get richer, the agriculture value-added share decreases. However, the same non-homotheticities generate significantly higher manufacturing shares and lower services shares at low income levels compared to the data, as illustrated by the second and third columns. This discrepancy can be understood through the fourth column: with increasing income and sectoral production, the scale effects in production drive up the relative production costs of services to manufacturing, implying a downward slope in the manufacturing relative price. This, in turn, results in a a negative relationship between manufacturing value added shares and income per capita, given the complementarity of goods across sectors in both final and intermediate demand. Consequently, the scale effects in consumption and intermediate demand alone do not give rise to either the manufacturing hump or deindustrialization over time, as the scale effects are independent of the time period.

CRP Scenario In comparison to the preceding counterfactual, trade integration introduces new mechanisms to sectoral reallocation, as illustrated in the second row of Figure 7. Notably, trade integration gives rise to a manufacturing hump. When contrasted with the previous scenario, two key differences emerge. First, for low-income countries, trade lowers their manufacturing value-added shares, given that their manufacturing net imports constitute around 10 percent of GDP, as shown by the dotted lines in the last column. This results from the feature that manufacturing import barriers are, on average, lower than manufacturing export barriers for the poorest tertile of countries. This is in contrast to countries in the top tertile where inward and outward barriers are similar. Also, the model implies that manufacturing net exports increase with income, except for the richest countries, qualitatively consistent with the data and driving the increasing part of the hump. Second, for rich countries, trade pushes down their manufacturing value added shares owing to lower manufacturing relative prices, as shown in the fourth column. This primarily stems from the substantially lower calibrated manufacturing trade costs in richer countries.

Despite the crucial role of trade in generating a manufacturing hump, it is important to note that trade integration by itself does not lead to deindustrialization. This is primarily because the reduction in trade costs over time is not substantial enough to significantly impact the relationship between the manufacturing relative price and income across the two periods. Thus, there is no discernible shift in the manufacturing hump.

Autarky Scenario In this scenario, sector-biased productivity growth operates in the absence of trade. Shown in the third row of Figure 7, sector-biased productivity growth induces a pronounced manufacturing hump and gives rise to deindustrialization. The key to achieving both outcomes is that sector-biased productivity growth generates relative prices similar to those in the data, as shown in the fourth column. This is the only counterfactual that generates a hump-shaped pattern in manufacturing relative prices and a significant downward shift of manufacturing relative prices over the two periods.

To understand these model implications, we first focus on the pre-1990 period, in which manufacturing productivity growth exceeded that of services by an average of 0.5 percentage points per year in the top income tertile, while in the bottom tertile it was less than that of services by 1.3 percentage points per year. Hence, over time, as the pattern of sector-biased productivity transforms along these tertiles, the relative price of manufacturing first rises, and then falls, with respect to income per capita, thereby generating the hump pattern in manufacturing relative prices in the data. In turn, this hump pattern in manufacturing relative prices generates a manufacturing hump—albeit significantly higher than the observed hump—owing to the complementarity among goods in both final and intermediate demand.

Now consider the dynamics in the post-1990 period. Manufacturing productivity continued to outpace services by 0.5 percentage points annually in the top income tertile, while in the bottom tertile it lagged behind services by only 0.7 percentage points annually. As a result, the hump in the relationship between the relative price and income flattened in the second period. Moreover, this hump of relative prices shifted downward after 1990 compared to before 1990, a result of the cumulative effect of faster manufacturing productivity growth than services productivity growth over time in middle- and high-income countries. All else equal, this delivered significantly lower manufacturing relative prices in the post-1990 period, which in conjunction with low elasticities of substitution, led to lower manufacturing value-added shares. These price dynamics in the two periods regulate the hump in manufacturing value added shares and drive deindustrialization across the two periods. The peak manufacturing share declines by 1.7 percentage points—approximately 60 percent of the decline in the baseline model, and almost half of the decline observed in the data.

Interaction of the Two Forces The three counterfactual exercises demonstrate that sector-biased productivity growth alone accounts for 60 percent of the magnitude of deindustrialization generated by the baseline model, while trade integration alone accounts for none. Therefore, the interaction of the two driving forces constitutes the remaining 40 percent of the decline in the peak manufacturing value added shares across the two periods.

The interaction of the two forces is reflected in the dynamics of the manufacturing relative price and in the pattern of sectoral trade imbalances. In terms of its impact on prices, first, compared to autarky, the presence of trade lowers manufacturing relative prices because trade costs are lower in manufacturing compared to services. Second, openness to trade permits technological change in a country's trading partners to influence its own relative prices. Third, trade integration, or the decline in trade costs, amplifies the said transmission of productivity growth in trading partners on a country's own relative prices over time. All three forces show that the price dynamics in any trading country are shaped not only by changes in its fundamental productivity, but also by those occurring in its trading partners. Moreover, trade's effect on relative prices is larger in the post-1990 period than in the pre-1990 period, reflecting the cumulated changes in technology over a longer period of time.

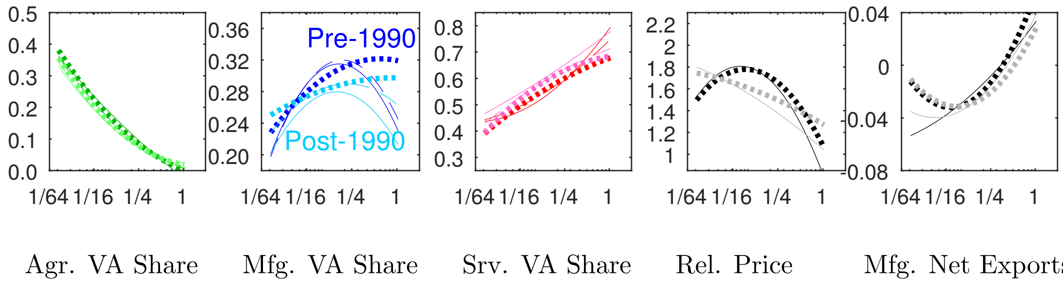
Complementing the effects on relative prices, the interaction effect also shows up in sectoral trade imbalances. After all, the third effect described above is larger the larger are (gross) imports. The fact that the degree of sector-biased productivity growth, as well as the degree of sectoral trade integration, differs across countries necessarily implies that comparative advantage shifts over time. In an increasingly open economy, countries increasingly specialize in their sector(s) of comparative advantage, directly influencing the allocation of factors across sectors. Over time, these forces lead to a lower manufacturing net exports curve post-1990 relative to pre-1990 for most countries. At the peak, (between 1/16 and 1/4 on the x-axis in the fifth column of Figure 7), the decline is about 0.8 percentage points of GDP, which is the majority of the interaction effect.

To quantify the interaction of the two driving forces in another way, we conduct an additional counterfactual—*Constant Trade Costs Scenario*—wherein trade costs are held constant at the initial 1971 values, and all other exogenous processes take the same values as in the Autarky counterfactual. The sole deviation from the Autarky scenario is that trade costs are finite rather than infinite, allowing for trade. The results are shown in Figure 8.

The introduction of trade with sector-biased productivity growth results in a more substantial decrease in the peak manufacturing value added share, amounting to 2.4 percentage points—significantly surpassing the 1.7-percentage-point decline in the Autarky scenario. Declining trade costs since 1971 in the baseline further accentuate the interaction effect, accounting for the remaining 0.6-percentage-point reduction in the peak share to reach the overall 3.0-percentage-point decline. Moreover, as discussed in the CRP scenario, trade integration alone contributes nothing to the peak decline. Therefore, the amplification is attributable solely to the interplay between trade and sector-biased productivity growth. In Appendix E, we discuss two specific cases, Mexico and Turkey, that also provide evidence of the interaction effect.

Figure 8: Predicted Sectoral Value Added Shares Across Income per Capita

(a) Constant Trade Cost Scenario



Notes: The fitted curves are based on regressions of the variable of interest on income (y-axis), interacted with the two period dummies, and country fixed effects, over income per capita (x-axis). Solid lines refer to the data; the dashed lines refer to the baseline model; the dotted lines refer to the counterfactuals. Dark (light) lines refer to pre-1990 (post-1990).

5.2 Industry Polarization

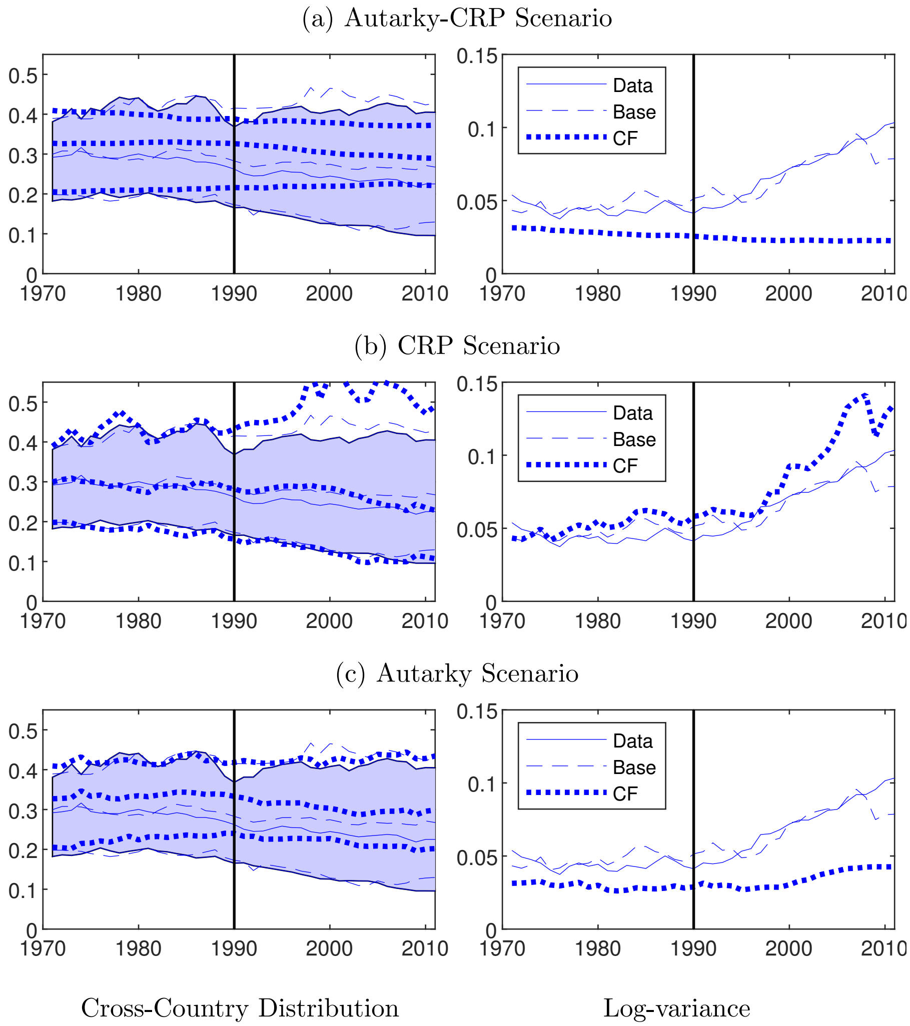
We now turn to the implications of the two driving forces for industry polarization. Figure 9 illustrates with dotted lines the evolution of industry polarization for the three counterfactuals. For the ease of comparison, we also plot the patterns of polarization in the baseline model with solid lines and those in the data with dashed lines. The left panel illustrates the cross-country distribution of manufacturing value added shares over time, and the right panel shows the cross-country variance of the log manufacturing share over time.

Start with the autarky-CRP scenario. The top-left panel clearly shows that the world distribution of manufacturing value added shares is relatively stable over time, while the top-right panel indicates a slight decline in the log-variance. Thus, the scale effects alone in this scenario work in the opposite direction of industry polarization observed in the data.

We next present the implications of trade integration for industry polarization in the CRP scenario in the middle panel of Figure 9. As indicated in the left panel, the top manufacturing value added share experiences a notable increase over time, while the bottom share undergoes a significant decline over time. Consequently, the CRP scenario generates a substantial rise in the cross-country variance of these shares over time from 0.051 in the pre-1990 period to 0.096 in the post-1990 period – almost double that implied by the baseline model – as illustrated in the right panel. These findings suggest that trade integration alone plays a significant role in driving the dynamics of industry polarization.

Lastly, we consider the autarky scenario, illustrated in the lower panel. Both the top and bottom manufacturing value added shares move very little over time, and so the cross-country variance of the log shares is relatively flat. Hence, sector-biased productivity growth alone implies a small increase in industry polarization post 1990.

Figure 9: Predicted Industry Polarization: Baseline and Counterfactuals



Notes: Dashed lines - data; Solid lines - baseline model; Dotted line - counterfactual. In the left panels, the middle line plots the median value of the manufacturing value added shares across countries over time (x-axis), while the upper and lower bands correspond to the 100^{th} and 1^{st} percentiles, respectively. In the right panels, log-variance reports the variance of the log-manufacturing VA share across countries over time (x-axis). ROW is excluded from the calculations.

5.3 Further Analysis

We now conduct additional analysis to provide deeper insights into the connection with the closed economy structural change literature, as well as the role of non-homothetic production structure. In Appendix E.2 we also explore the role of aggregate trade imbalances and the effects of changes in the discount factor. The figures for each exercise are in Appendix E.

Re-calibrated Closed Economy The Autarky counterfactual shows that sector-biased productivity growth in closed economies can lead to deindustrialization, aligning with prior research (e.g. Huneeus and Rogerson, 2020; Fujiwara and Matsuyama, 2020). However, these closed economies exhibit only 50% of the deindustrialization observed in the data (60% of that in our baseline model) and show minimal industry polarization over time. A potential concern is that this counterfactual may not fully capture the ability of the closed-economy model to account for global structural change, because the sector-biased productivity growth rates are calibrated based on an open economy framework. To address this concern, we re-calibrate sectoral productivity in the closed economies to replicate prices observed in the data; in addition, sectoral expenditure shares are the same as in the baseline model.

We find that the re-calibrated closed economy yields a similar magnitude of deindustrialization as the Autarky counterfactual does: a 1.7-percentage-point decline in the peak manufacturing value added share (top row in Figure E.7). As a reminder, our baseline model generates a decline in the peak share of 3.0 percentage points, and the decline in the data is 3.5 percentage points. Hence, the re-calibrated closed economy model still leaves a significant portion of deindustrialization unexplained. While the re-calibrated productivity processes incorporate the impact of trade on relative prices, the closed economy cannot, by definition, capture sectoral trade imbalances brought about by shifting comparative advantage and specialization. Finally, the re-calibrated closed economy fails to generate a significant level of industry polarization (top row in Figure E.8), further reflecting the lack of increasing sectoral specialization over time. In fact, the cross-country distribution of manufacturing value added shares is very similar to that in the Autarky counterfactual, leading to a similar pattern in the log-variance in those shares.

Homothetic Production Structure To understand the role of scale effects, i.e., non-homotheticities, in production, we consider two alternative models. In the first, we counterfactually remove the scale effects in production by setting $\varepsilon_e^{j,k} = 1$, but keep almost all of the other parameters at their baseline calibrated values.[20] The demand structure for consumption and investment remain non-homothetic. We call this the *No Scale Effect Scenario*. This scenario does not generate relative prices consistent with the data, nor does it produce meaningful trade imbalances in manufacturing (second row in Figure E.7). As a result, the sectoral value added shares differ considerably from those in both the data and in the baseline model. In addition, the peak manufacturing value added share declines by only 2.1 percentage points. The degree of industry polarization is almost as large as in the baseline model (second row in Figure E.8).

We also consider a specification where we remove scale effects in production, but re-

[20] We re-calibrate the sector weights $\omega_{e,n}^{j,k}$ so that the sectoral intermediate demand shares line up with the data in 1971, as in the baseline model.

calibrate the remaining parameters. That is, we impose $\varepsilon_e^{j,k} = 1$ and re-estimate the price elasticities for intermediate demand.[21] We also re-calibrate the exogenous processes to match the same moments as in the baseline model. We call this the *Re-calibrated Homothetic-Production Model*. In this case, the equilibrium prices line up with those in the data, as do the trade flows. However, the hump shape for manufacturing value added shares across income is less pronounced and the peak share declines by 2.2 percentage points (third row in Figure E.7). Industry polarization remains significant.

These two exercises demonstrate the quantitative significance of non-homothetic intermediate demand in generating structural change and deindustrialization. In particular, both of these exercises produced a flatter hump in manufacturing value added shares than in the model with a non-homothetic production structure, and about 70 percent of the decline in the peak manufacturing value added share. In other words, the non-homothetic production structure accounts for about 30 percent of the deindustrialization in our baseline model.

6 Conclusion

In this paper, we first present evidence that the nature of structural change has evolved over time. We re-confirm recent evidence by Rodrik (2016) on deindustrialization, and also demonstrate a new pattern in the data – industry polarization. Over time, the peak of the manufacturing value-added share "hump" has declined by 3.5 percentage points, and the cross-country dispersion in the share of manufacturing in total value added has almost doubled. To explain these patterns, we employ a structural change framework with non-homothetic demand for consumption, investment, and intermediate inputs (scale effects), as well as international trade, input-output linkages, and capital accumulation. We focus on the role of two driving forces, sectoral TFP growth and declining trade costs.

Our calibrated model explains 86 percent of deindustrialization and 74 percent of industry polarization. To further understand the underlying sources and mechanisms, we conduct several counterfactual exercises. These exercises reveal the importance of sector-biased TFP growth in driving deindustrialization, and of declining trade costs in driving industry polarization. High productivity growth in manufacturing decreases the relative price of manufactured goods, which, coupled with sectoral consumption and sectoral investment elasticities of substitution that are less than one, leads to declining expenditure and value-added shares in manufacturing. Declining trade costs in manufacturing leads some countries to increasingly specialize in that sector, and other countries to reallocate their resources to other sectors, thus inducing increased dispersion of cross-country manufacturing value-added shares. Our

[21] The estimated price elasticities of intermediate demand are $(\sigma_e^a, \sigma_e^m, \sigma_e^s) = (0.17, 0.17, 0.12)$.

counterfactual exercises also point to the importance of non-linear interaction effects between sector-biased TFP growth and declining trade costs. Sector-biased TFP growth has a larger effect when it occurs in conjunction with trade integration, and vice versa. Each driving force leads to sectoral reallocation, and, together, the reallocation effects are multiplied.

The primary mechanism underlying the reallocation behind deindustrialization is relative prices. Both driving forces, especially the sector-biased TFP growth, lead to lower relative prices of manufactured goods. Over time, then, recently industrialized countries, facing lower prices of manufactured goods, have more limited opportunities to specialize in that sector, which then limits the peak of their manufacturing hump.

Yet, relative prices are not the entire story for deindustrialization. Were that the case, then a time path of TFP could be calibrated to match those prices in a closed economy setting, and would be able to explain as much as our baseline model. Instead, the re-calibrated closed economy model explains only a little more than half of the baseline model. In addition to relative prices, sectoral net export imbalances also matter. As we have shown, these imbalances are critical to understanding how trade integration can generate the manufacturing hump, and, how trade integration, in conjunction with sector-biased productivity growth, can generate almost half of deindustrialization.

Our story for industry polarization is simpler: trade integration is the main driver. Through increasingly revealed comparative advantage and specialization, trade integration facilitates sectoral specialization whereby some countries increase their manufacturing value-added shares and other countries decrease their shares.

Extending our production framework to include non-unitary elasticities of substitution between value-added and intermediates, and between capital and labor, would be worthwhile. We have not considered the possibility of spillovers from trade integration to technology diffusion across countries. Adding this to our model would enhance the interaction effect and magnify the importance of trade integration. In addition, current account imbalances are effectively exogenous in our model; treating them as endogenous could give more insight into whether the increase in global imbalances over time is connected to deindustrialization and industry polarization. Finally, our sample of countries is primarily middle-income and advanced economies. Studying the interaction of deindustrialization and low-income economies would be useful. We leave these and other exercises for future research.

References

Bauer, Arthur, Jocelyn Boussard, and Danial Lashkari. 2023. "Information Technology and Returns to Scale." *Working Paper* .

Betts, Caroline M., Rahul Giri, and Rubina Verma. 2017. "Trade, Reform, and Structural Transformation in South Korea." *IMF Economic Review* (65):745–791.

Boppart, Timo. 2014. "Structural Change and the Kaldor Facts in a Growth Model with Relative Price Effects and Non-Gorman Preferences." *Econometrica* 82 (6):2167–2196.

Caliendo, Lorenzo, Fernando Parro, Esteban Rossi-Hansberg, and Pierre-Daniel Sarte. 2018. "The Impact of Regional and Sectoral Productivity Changes on the U.S. Economy." *Review of Economic Studies* 85:2042–2096.

Caselli, Francesco. 2005. "Accounting for Cross-Country Income Differences." In *Handbook of Economic Growth*, edited by Philippe Aghion and Steven Durlauf, Handbook of Economic Growth, chap. 9. Elsevier, 679–741.

Comin, Diego, Danial Lashkari, and Martí Mestieri. 2021. "Structural Change with Long-Run Income and Price Effects." *Econometrica* 89 (1):311–374.

Cravino, Javier and Sebastian Sotelo. 2019. "Trade-Induced Structural Change and the Skill Premium." *American Economic Journal: Macroeconomics* 11 (3):289–326.

Deaton, Angus and John Muellbauer. 1980. "An Almost Ideal Demand System." *American Economic Review* 70 (3):395–419.

Eaton, Jonathan and Samuel Kortum. 2002. "Technology, Geography, and Trade." *Econometrica* 70 (5):1741–1779.

Eaton, Jonathan, Samuel Kortum, Brent Neiman, and John Romalis. 2016. "Trade and the Global Recession." *American Economic Review* 106 (11):3401–3438.

Feenstra, Robert C., Robert Inklaar, and Marcel Timmer. 2015. "The Next Generation of the Penn World Table." Forthcoming at the *American Economic Review*.

Felipe, Jesus, Aashish Mehta, and Changyong Rhee. 2019. "Manufacturing Matters ... but it's the Jobs that Count." *Cambridge Journal of Economics* 43:139–168.

Finicelli, Andrea, Patrizio Pagano, and Massimo Sbracia. 2013. "Ricardian Selection." *Journal of International Economics* 89 (1):96–109.

Fujiwara, Ippei and Kiminori Matsuyama. 2020. "A Technology-Gap Model of Premature Deindustrialization." Working Paper DP15530, CEPR.

García-Santana, Manuel, Josep Pijoan-Mas, and Lucciano Villacorta. 2021. "Investment Demand and Structural Change." *Econometrica* 89 (6):2751–2785.

Gollin, Douglas. 2002. "Getting Income Shares Right." *Journal of Political Economy* 110 (2):458–474.

Gollin, Douglas, David Lagakos, and Michael E. Waugh. 2014. "The Agricultural Productivity Gap." *Quarterly Journal of Economics* 129 (2).

Hanoch, Giora. 1975. "Production and Demand Models with Direct or Indirect Implicit Additivity." *Econometrica* 43 (3):395–419.

Haraguchi, Nobuya, Charles Fang Chin Cheng, and Eveline Smeets. 2017. "The Importance of Manufacturing in Economic Development: Has This Changed?" *World Development* 93:293–315.

Herrendorf, Berthold, Richard Rogerson, and Ákos Valentinyi. 2013. "Two Perspectives on Preferences and Structural Transformation." *American Economic Review* 103 (7):2752–2789.

———. 2021. "Structural Change in Investment and Consumption A Unified Analysis." *Review of Economic Studies* 88 (3):1311–1346.

Huneeus, Federico and Richard Rogerson. 2020. "Heterogeneous Paths of Industrialization." Working Paper 27580, National Bureau of Economic Research.

Imbs, Jean and Romain Wacziarg. 2003. "Stages of Diversification." *American Economic Review* 93 (1):63–86.

Kehoe, Timothy J., Kim J. Ruhl, and Joseph B. Steinberg. 2018. "Global Imbalances and Structural Change in the United States." *Journal of Political Economy* 126 (2):761–796.

Kongsamut, Piyabha, Sergio Rebelo, and Danyang Xie. 2001. "Beyond Balanced Growth." *Review of Economic Studies* 68 (4):869–882.

Lewis, Logan, Ryan Monarch, Michael Sposi, and Jing Zhang. 2021. "Structural Change and Global Trade." *Journal of the European Economic Association* 20 (1):476512.

Lucas, Robert E. and Edward C. Prescott. 1971. "Investment Under Uncertainty." *Econometrica* 39 (5):659–681.

Matsuyama, Kiminori. 2009. "Structural Change in an Interdependent World: A Global View of Manufacturing Decline." *Journal of the European Economic Association* 7 (2-3):478–486.

———. 2019. "Engle's Law in the Global Economy: Demand-Induced Patterns of Structural Change, Innovation, and Trade." *Econometrica* 87 (2):497–528.

McDougall, Robert. 1999. "Entropy Theory and RAS are Friends." GTAP Working Papers 300, Center for Global Trade Analysis, Department of Agricultural Economics, Purdue University.

Ngai, Rachel L. and Christopher A. Pissarides. 2007. "Structural Change in a Multisector Model of Growth." *American Economic Review* 97 (1):429–443.

Ravikumar, B., Ana Maria Santacreu, and Michael Sposi. 2019. "Capital Accumulation and Dynamic Gains from Trade." *Journal of International Economics* 119:93–110.

Restuccia, Diego, Dennis Tao Yang, and Xiaodong Zhu. 2008. “Agriculture and Aggregate Productivity: A Quantitative Cross-Country Analysis.” *Journal of Monetary Economics* 55 (2):234–250.

Rodrik, Dani. 2016. “Premature Deindustrialization.” *Journal of Economic Growth* 21 (1):1–33.

Sato, Ryuzo. 1977. “Homothetic and Non-Homothetic CES Production Functions.” *American Economic Review* 67 (4):559–569.

Simonovska, Ina and Michael E. Waugh. 2014. “The Elasticity of Trade: Estimates and Evidence.” *Journal of International Economics* 92 (1):34–50.

Sinha, Rishabh. 2019. “Input Substitutability and Cross-Country Variation in Sectoral Linkages.” *Economics Letters* 178:121–124.

———. 2021. “What Explains Latin America’s Low Share of Industrial Employment?” Working paper, World Bank.

Sposi, Michael. 2012. “Evolving Comparative Advantage, Structural Change, and the Composition of Trade.” Working paper, University of Iowa.

———. 2019. “Evolving Comparative Advantage, Sectoral Linkages, and Structural Change.” *Journal of Monetary Economics* 103:75–87.

Świecki, Tomasz. 2017. “Determinants of Structural Change.” *Review of Economic Dynamics* 24:95–131.

Teignier, Marc. 2018. “The role of trade in structural transformation.” *Journal of Development Economics* 130:45–65.

Timmer, Marcel P. 2012. “The World Input-Output Database (WIOD): Contents, Sources and Methods.” Working Paper 10, WIOD.

Timmer, Marcel P., Gaaitzen J. de Vries, and Klaas de Vries. 2014. “Patterns of Structural Change in Developing Countries.” GGDC Research Memorandum 149, Groningen Growth and Development Center.

Timmer, Marcel P., Erik Dietzenbacher, Bart Los, and Gaaitzen J. de Vries. 2015. “An Illustrated Guide to the World Input-Output Database: The Case of Global Automotive Production.” *Review of International Economics* 23 (3):575–605.

Trottner, Fabian. 2022. “Who Gains from Scale? Trade and Wage Inequality Within and Between Firms.” *Working Paper* .

Uy, Timothy, Kei-Mu Yi, and Jing Zhang. 2013. “Structural Change in an Open Economy.” *Journal of Monetary Economics* 60 (6):667–682.

Waugh, Michael E. 2010. “International Trade and Income Differences.” *American Economic Review* 100 (5):2093–2124.

Appendix A Data

We construct a balanced panel of 28 countries over period 1970–2011: Australia, Austria, Belgium-Luxembourg, Brazil, Canada, China, Cyprus, Germany, Denmark, Spain, Finland, France, United Kingdom, Greece, Hungary, Indonesia, India, Ireland, Italy, Japan, South Korea, Mexico, Netherlands, Portugal, Sweden, Turkey, Taiwan, and United States.

Using the International Standard Industrial Classification of All Economic Activities, Revision 4, we construct three broad sectors. Agriculture includes Agriculture, forestry and fishing (A). Manufacturing includes: Mining and quarrying (B); Manufacturing (C); Electricity, gas, steam and air conditioning supply (D); Water supply, sewerage, waste management and remediation activities (E). Services includes the remaining sectors from F to S.

Data are drawn from several sources. All shares are constructed with nominal values. The World Input-Output Database (WIOD, see Timmer et al. (2015)) forms the basis, providing data on sectoral value added, gross production, bilateral trade, consumption expenditures, investment expenditure, and input-output values in nominal values. We use the WIOD 2013 release which covers the years from 1995 to 2011. We supplement data prior to 1995 from other sources whenever available. For sectoral value added and gross output, we use data from EU-KLEMS, the GGDC 10-sector Database, and International Historical Statistics. For bilateral trade in agriculture and manufacturing, we use the UN Comtrade Database and the IMF's Direction of Trade Statistics. For services imports, we use World Development Indicators from the World Bank. For aggregate investment, we use the Penn World Table 9.0. Due to the limited availability of bilateral services import shares prior to 1995, we impute them using their averages over 1995–1997.

For the input-output (IO) tables prior to 1995, we use various data sources. The OECD provides data for Australia, Canada, Denmark, France, Italy, the Netherlands, and the United Kingdom. We also obtain the IO tables for Japan from the JIP Database, for South Korea from the Bank of Korea, and for the United States from the BEA. The tables provide sectoral investment in addition to sectoral input-output shares and sectoral value added shares in gross output. These IO tables are available in staggered years. We impute missing values for these countries with linear interpolation. For the remaining countries with no available IO tables prior to 1995, we impute the ratio of gross output to value added by estimating a relationship between those shares and income per capita using available data and then predicting the missing shares. Given sectoral gross production, we input-output shares and sectoral investment shares using the RAS method described below. Finally, we compute sectoral consumption shares by applying the national accounting identity.

We construct real data using the corresponding price indexes to deflate nominal data. The price indexes for aggregate income and investment are from the Penn World Table 9.1. We obtain sectoral value-added price indexes by dividing value added at current prices by value added at constant prices using EU-KLEMS, GGDC 10-sector Database, and United Nations National Accounts. For international comparability we use 2015 PPP prices in the GGDC Productivity Level Database to align these price indexes. For sectoral output prices, we gross up sectoral value-added prices using the model structure. The GDP deflator in the data is not a simple aggregation of sectoral prices weighted by sectoral final demand as in the model. To overcome this issue, we introduce an exogenous residual term to line up the GDP deflator in the model with that in the data.

Data for Rest-of-World We construct all variables for the Rest-of-World (ROW) as follows. For the sectoral data in WIOD, data for ROW are provided directly.

For the main aggregates, like GDP and population, we sum the variables across all countries in PWT, then subtract the sum of those same variables across the 28 countries in our sample.

For bilateral trade data prior to WIOD years, we compute bilateral trade between each country and ROW as follows. Consider the US. We first calculate US exports to world, then subtract US exports to the sum of the 28 sample countries. The remaining value is US exports to ROW.

For sectoral value added prior to WIOD years, we take from UNIDO. Similar to the way we build aggregates for ROW, we first sum across all countries, then subtract the corresponding sum for our 28 sample countries.

For price index construction, we take from UNIDO the ratio of value added in current prices to value added in constant prices. For each of these two moments, we first sum across all countries, then subtract the corresponding sum for our 28 sample countries. Finally, we take the ratio of the remaining values.

We have no data on PPP price levels to make them comparable to other countries in a given year. For this we impute the sector price levels by estimating a relationship between each sector's price level and GDP per capita, then use that relationship together with ROW's GDP per capita to impute the sector prices for ROW.

Missing Data in Input-Output Tables We now describe our procedure for imputing missing missing input-oputput data. We appeal to a RAS method, which was developed specifically to deal with missing data in input-output tables, (see McDougall, 1999).

In our setting we are missing data for some country-years prior to 1995. The missing data are intermediate spending by sector j on inputs from sector k (IO_{jk}), sectoral consumption and investment spending (Con_j, Inv_j). Let $\mathbf{X}$=(IO_{aa}, IO_{am}, IO_{as}, IO_{ma}, IO_{mm}, IO_{ms}, IO_{sa}, IO_{sm}, IO_{ss} Con_a, Con_m, Con_s, Inv_a, Inv_m Inv_s) be the set of variables missing for a given country-year. Let X^0 be the corresponding values observed in some base year (i.e., 1995).

We do have coimplete country-year data for all years on sectoral gross output, sectoral net exports, sectoral value added, and aggregate consumption and investment spending: GO_a, GO_m, GO_s, NX_a, NX_m, NX_s, VA_a, VA_m, VA_s, Con, and Inv.

Through the lens of an input-output table, we know the row sums and the column sums of the input-output matrix, but not necessarily the entries in the matrix. The RAS method makes bi-proportionate adjustment to the bilateral trade matrix so that both the columns sums and the row sums equal the known values, while the adjustments impose *minimum* deviations from the known data in a "close by" year. To implement this we construct a entropy-like loss function defined to be the weighted sum of log-deviations from the observed bilateral trade data, with weights given by the corresponding observed bilateral trade flows. We then minimize the loss function subject to row sums and column sums both equal to country production.

Formally, let I denote the number of variables, and J denotes the number of constraints

(J_r and J_c where $J_r + J_c = J$). We solve the constrained optimization problem:

$$\min_{\mathbf{X}} f(\mathbf{X}) = \sum_{i=1}^{I} X_i \ln\left(\frac{X_i}{eX_i^0}\right)$$

Subject to Row and Column Constraints (where e is the base of the natural logarithm).

Row Constraints:

$$\begin{aligned} IO_{aa} + IO_{ma} + IO_{sa} + Con_a + Inv_a &= GO_a - NX_a \\ IO_{am} + IO_{mm} + IO_{sm} + Con_m + Inv_m &= GO_m - NX_m \\ IO_{as} + IO_{ms} + IO_{ss} + Con_s + Inv_s &= GO_s - NX_s \end{aligned}$$

Column Constraints

$$\begin{aligned} IO_{aa} + IO_{am} + IO_{as} &= GO_a - VA_a \\ IO_{ma} + IO_{mm} + IO_{ms} &= GO_m - VA_m \\ IO_{sa} + IO_{sm} + IO_{ss} &= GO_s - VA_s \\ Con_a + Con_m + Con_s &= Con \\ Inv_a + Inv_m + Inv_s &= Inv \end{aligned}$$

Let $(\lambda_a, \lambda_m, \lambda_s)$ denote the Lagrange multiplier on the row constraints, respectively. Let $(\gamma_a, \gamma_m, \gamma_s, \gamma_c, \gamma_x)$ denote the Lagrange multiplier on the column constraints. The first order conditions are

$$\ln\left(\frac{IO_{ij}}{eIO_{ij}^0}\right) + 1 = \lambda_j + \gamma_i \tag{A.1}$$

$$\ln\left(\frac{Con_i}{eCon_i^0}\right) + 1 = \lambda_i + \gamma_c \tag{A.2}$$

$$\ln\left(\frac{Inv_i}{eInv_i^0}\right) + 1 = \lambda_i + \gamma_x \tag{A.3}$$

$$IO_{ij} = IO_{ij}^0 e^{\lambda_j + \gamma_i} \tag{A.4}$$

$$Con_i = Con_i^0 e^{\lambda_i + \gamma_c} \tag{A.5}$$

$$Inv_i = Inv_i^0 e^{\lambda_i + \gamma_x} \tag{A.6}$$

Using the constraints:

$$e^{\lambda_a}\left(IO^0_{aa}e^{\gamma_a}+IO^0_{ma}e^{\gamma_m}+IO^0_{sa}e^{\gamma_s}+Con^0_a e^{\gamma_c}+Inv^0_a e^{\gamma_x}\right)=GO_a-NX_a \tag{A.7}$$
$$e^{\lambda_m}\left(IO^0_{am}e^{\gamma_a}+IO^0_{mm}e^{\gamma_m}+IO^0_{sm}e^{\gamma_s}+Con^0_m e^{\gamma_c}+Inv^0_m e^{\gamma_x}\right)=GO_m-NX_m \tag{A.8}$$
$$e^{\lambda_s}\left(IO^0_{as}e^{\gamma_a}+IO^0_{ms}e^{\gamma_m}+IO^0_{ss}e^{\gamma_s}+Con^0_s e^{\gamma_c}+Inv^0_s e^{\gamma_x}\right)=GO_s-NX_s \tag{A.9}$$
$$e^{\gamma_a}\left(IO^0_{aa}e^{\lambda_a}+IO^0_{am}e^{\lambda_m}+IO^0_{as}e^{\lambda_s}\right)=GO_a-VA_a \tag{A.10}$$
$$e^{\gamma_m}\left(IO^0_{ma}e^{\lambda_a}+IO^0_{mm}e^{\lambda_m}+IO^0_{ms}e^{\lambda_s}\right)=GO_m-VA_m \tag{A.11}$$
$$e^{\gamma_s}\left(IO^0_{sa}e^{\lambda_a}+IO^0_{sm}e^{\lambda_m}+IO^0_{ss}e^{\lambda_s}\right)=GO_s-VA_s \tag{A.12}$$
$$e^{\gamma_c}\left(Con^0_a e^{\lambda_a}+Con^0_m e^{\lambda_m}+Con^0_s e^{\lambda_s}\right)=C \tag{A.13}$$
$$e^{\gamma_x}\left(Inv^0_a e^{\lambda_a}+Inv^0_m e^{\lambda_m}+Inv^0_s e^{\lambda_s}\right)=X \tag{A.14}$$

We now describe the algorithm for imputing the missing values.

- Given the initial guess of $(\lambda^{(0)},\gamma^{(0)})=0$, we can solve for the optimal $\mathbf{X}$ using equations (A.1), (A.2), and (A.3).
- We then update $(\lambda^{(k)},\gamma^{(k)})$ for $k=1,2,3,...$ as follows.
  - Using equations (A.7)-(A.8), we update $\lambda^{(k)}$ with $\gamma^{(k-1)}$.
  - Using equations (A.10)-(A.14), we update $\gamma^{(k)}$ with $\lambda^{(k-1)}$.
- Continue until $(\lambda^{(k-1)},\gamma^{(k-1)})$ are close enough to $(\lambda^{(k)},\gamma^{(k)})$.

Appendix B Robustness Check on Two Facts

This appendix illustrates that our baseline result of deindustrializaton over time is robust to outliers, alternative specifications, and a larger sample. Our polarization result is also robust to the larger sample and after controlling for the variation in manufacturing value added shares due to income per capita.

We first remove outliers, i.e., observations with standard errors larger than the three standard deviation. The result, reported in column (2) of Table B.1, is almost identical to the baseline result, reported in column (1). Thus, our results are not driven by outliers. We next examine the possibility of mis-specification bias by including two cubic terms of income per capita—one for each period—in the regression analysis. As shown by the results in column (3), the cubic terms are not statistically significant, and the adjusted R-square is 0.836, similar to 0.83 in the quadratic specification. The predicted relations between the manufacturing value added share and income per capita by the cubic specification are similar to those predicted in the baseline case for both periods. Thus, the deindustrialization finding is robust with a cubic specification.

We next present the results from a simple quadratic specification, where only the constant term of the quadratic is allowed to differ across the two periods. This specification is less flexible than the baseline specification, because it implies a parallel shift in the post-1990 curve relative to the pre-1990 curve. However, the benefit is that the pre-1990 fixed effect

Table B.1: Robustness of the Empirical Finding on Deindustrialization

	(1)	(2) Remove outliers	(3) Big Sample	(4) Cubic terms	(5) Simple form
Constant	0.203	0.201	0.032	0.192	0.199
	(0.010)	(0.010)	(0.037)	(0.012)	(0.010)
pre90	0.020	0.019	0.014	-0.041	0.029
	(0.024)	(0.024)	(0.007)	(0.035)	(0.008)
pre90×incpc	-0.090	-0.094	-0.071	-0.240	
	(0.038)	(0.037)	(0.022)	(0.087)	
pre90×incpc^2	-0.025	-0.026	-0.013	-0.112	
	(0.010)	(0.010)	(0.004)	(0.051)	
post90×incpc	-0.071	-0.078	-0.065	-0.121	
	(0.026)	(0.025)	(0.021)	(0.037)	
post90×incpc^2	-0.019	-0.020	-0.011	-0.065	
	(0.007)	(0.007)	(0.004)	(0.030)	
incpc					-0.084
					(0.024)
incpc^2					-0.023
					(0.006)
pre90×incpc^3				-0.014	
				(0.009)	
post90×incpc^3				-0.010	
				(0.006)	
Adj. R2	0.830	0.839	0.800	0.836	0.829
Chow Test:					
Wald ξ^2	0.001	0.003	0.004	0.000	0.000
Obs	1,148	1,142	3,895	1,148	1,148

Note: The null hypothesis for the Chow test is that the pre-1990 parameter values jointly equal the corresponding post-1990 parameter values.

describes the difference between the peak predicted manufacturing shares in the two periods. As shown in the last column of Table B.1, the coefficient of the pre-1990 period dummy is statistically significant and positive, and implies a shift down in the entire hump pattern by 2.9 percentage points of GDP, which is similar to the decline in the peak of our hump in our baseline case (3.5 percentage points).

We finally examine the results with the bigger sample of 95 countries from 1970–2010. We obtain data on manufacturing value added shares and income per capita for 135 countries spanning 1970–2010 from Felipe, Mehta, and Rhee (2019). We focus on a sub-sample of 95 countries whose maximum per-capita income over the sample period is above $1,000, in terms of 2010 U.S. PPP prices.[22] This larger sample includes many low and middle income countries; the average ratio of per-capita income of the richest to the poorest across periods is 317. In comparison, our baseline sample has this average ratio of 23. We cannot include the extended sample in the quantitative analysis, however, because complete data for other variables is not available.

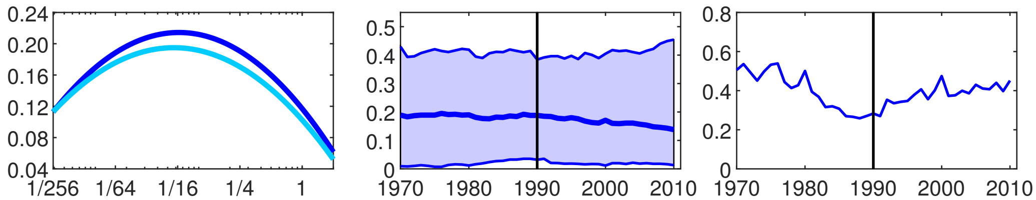
The countries are: Albania, Algeria, Andorra, Angola, Argentina, Australia, Austria, Belgium, Belize, Bhutan, Bolivia, Botswana, Brazil, Bulgaria, Cameroon, Canada, Chile, China, Colombia, Congo (Rep.), Costa Rica, Cote d'Ivoire, Cuba, Denmark, Djibouti, Dominican Republic, Ecuador, Egypt, El Salvador, Finland, France, Gabon, Greece, Guatemala, Guyana, Honduras, Hongkong, Hungary, India, Indonesia, Iran, Iraq, Ireland, Italy, Jamaica, Japan, Jordan, Lebanon, Libya, Liechtenstein, Luxembourg, Macao, Malaysia, Mauritius, Mexico, Monaco, Mongolia, Morocco, Namibia, Netherlands, New Zealand, Nicaragua, Norway, Oman, Panama, Paraguay, Peru, Philippines, Poland, Portugal, Puerto Rico, Qatar, Romania, San Marino, Saudi Arabia, Singapore, South Africa, South Korea, Spain, Sri Lanka, Suriname, Swaziland, Sweden, Switzerland, Syrian Arab Republic, Thailand, Trinidad and Tobago, Tunisia, Turkey, United Arab Emirates, United Kingdom, United States, Uruguay, Venezuela, and Zambia.

The result for the bigger sample, reported in the last column of the table, is similar to our baseline result, confirming the robustness of the deindustrialization finding. We conducted the Chow Test on the hypothesis that the parameters are the same across the two periods. The test consistently rejects the hypothesis, as illustrated in the last row of the table.

Figure B.1 illustrates the patterns of deindustrialization and polarization for this large sample. The left panel shows that the predicted relationship between income per capita and the manufacturing value added share shifts down over time. The peak manufacturing value added share declines by 2 percentage points from 21.4% in the pre-1990 period to 19.5% in the post-1990 period. Although including a large number of low and middle income countries implies lower predicted manufacturing value added curves over per capita income, the main pattern of deindustrialization over time remains robust. Similarly, the finding of increasing polarization since 1990 is also robust in this large sample. The unconditional and conditional variances display a U-shape, which declines from 1970 to 1990 and increases from 1990 to 2010. Not surprisingly, including these low and middle income countries generates much larger variances across countries, compared with our baseline sample.

[22] We also drop Equatorial Guinea due to poor quality data.

Figure B.1: Robustness with 95 countries over 1970–2010



Notes: In the left panel, the fitted curves are based on regressions of sectoral manufacturing VA shares on income (y-axis), interacted with the two period dummies, and country fixed effects, over income per capita (x-axis). Dark (light) lines refer to pre-1990 (post-1990). In the center panel, the middle line plots the median value of the manufacturing value added shares across countries over time (x-axis), while the upper and lower bands correspond to the 100$^{\text{th}}$ and 1$^{\text{st}}$ percentiles, respectively. In the right panel, log-variance reports the variance of the log-manufacturing VA share across countries over time (x-axis).

Appendix C ONLINE APPENDIX: Derivations

Grossing up prices Our production function specifies the mapping between value-added and gross output, so we can construct a corresponding mapping between value-added prices and gross output prices.

Let $p^{v,j}_{n,t}$ denote the sector j value added price in country n, time t, let $\mu^{j,k}_{n,t}$ denote sector k's share in intermediates spending by sector j, and ν^j_n the ratio of value added to gross output in sector j. We gross up the value added prices to obtain sectoral gross output prices ($p^j_{n,t}$) by solving the following system of equations:

$$\begin{bmatrix} \ln\left(p^a_{n,t}\right) \\ \ln\left(p^m_{n,t}\right) \\ \ln\left(p^s_{n,t}\right) \end{bmatrix} = \begin{bmatrix} 1-(1-\nu^a_n)\mu^{a,a}_{n,t} & (1-\nu^a_n)\mu^{a,m}_{n,t} & (1-\nu^a_n)\mu^{a,s}_{n,t} \\ (1-\nu^m_n)\mu^{m,a}_{n,t} & 1-(1-\nu^m_n)\mu^{m,m}_{n,t} & (1-\nu^m_n)\mu^{m,s}_{n,t} \\ (1-\nu^s_n)\mu^{s,a}_{n,t} & (1-\nu^s_n)\mu^{s,m}_{n,t} & 1-(1-\nu^s_n)\mu^{s,s}_{n,t} \end{bmatrix}^{-1} \begin{bmatrix} \nu^a_n \ln\left(p^{v,a}_{n,t}\right) \\ \nu^m_n \ln\left(p^{v,m}_{n,t}\right) \\ \nu^s_n \ln\left(p^{v,s}_{n,t}\right) \end{bmatrix}$$
$$- \begin{bmatrix} \nu^a_n \ln(\nu^a_n) + (1-\nu^a_n)\left(\ln(1-\nu^a_n) + \sum_{k\in\{a,m,s\}} \mu^{a,k}_{n,t} \ln\left(\mu^{a,k}_{n,t}\right)\right) \\ \nu^m_n \ln(\nu^m_n) + (1-\nu^m_n)\left(\ln(1-\nu^m_n) + \sum_{k\in\{a,m,s\}} \mu^{m,k}_{n,t} \ln\left(\mu^{m,k}_{n,t}\right)\right) \\ \nu^s_n \ln(\nu^s_n) + (1-\nu^s_n)\left(\ln(1-\nu^s_n) + \sum_{k\in\{a,m,s\}} \mu^{s,k}_{n,t} \ln\left(\mu^{s,k}_{n,t}\right)\right) \end{bmatrix} \tag{C.1}$$

Derivation of Estimation Equations We describe how er express first-order conditions and the expenditure function in terms of changes over time for the consumption aggregator. The aggregators for investment and the intermediate bundles in the three sectors are analogous.

Begin with the implicitly defined aggregator:

$$\sum_{j\in\{a,m,s\}} \omega^j_{c,n} \left(\frac{C_{n,t}}{L_{n,t}}\right)^{\frac{1-\sigma_c}{\sigma_c}\varepsilon^j_c} \left(\frac{c^j_{n,t}}{L_{n,t}}\right)^{\frac{\sigma_c-1}{\sigma_c}} = 1, \tag{C.2}$$

We've shown in the paper that the optimal sectoral spending shares are given by

$$\frac{p^k_{n,t-1}c^k_{n,t-1}}{P^c_{n,t-1}C_{n,t-1}} = (\omega^j_{c,n})^{\sigma_c}\left(\frac{p^j_{n,t}}{P^c_{n,t}}\right)^{1-\sigma_c}\left(\frac{C_{n,t}}{L_{n,t}}\right)^{(1-\sigma_c)(\varepsilon^j_c-1)}. \tag{C.3}$$

The change over time is clearly

$$\frac{\widehat{e}^j_{n,t}}{\widehat{e}^m_{n,t}} = \left(\frac{\widehat{p}^j_{n,t}}{\widehat{p}^m_{n,t}}\right)^{1-\sigma_c}\left(\frac{\widehat{C}_{n,t}}{\widehat{L}_{n,t}}\right)^{(1-\sigma_c)(\varepsilon^j_c-1)}$$

The total expenditure is $E_{n,t} = P^c_{n,t}C_{n,t}$. It is easy to show (and shown in prior work) that the price index is given by

$$P^c_{n,t} = \left(\sum_{j\in\{a,m,s\}}(\omega^j_{c,n})^{\sigma_c}(p^j_{n,t})^{1-\sigma_c}\left(\frac{C_{n,t}}{L_{n,t}}\right)^{(1-\sigma_c)(\varepsilon^j_c-1)}\right)^{\frac{1}{1-\sigma_c}}$$

Move the exponent over

$$(P^c_{n,t})^{1-\sigma_c} = \left(\sum_{j\in\{a,m,s\}}(\omega^j_{c,n})^{\sigma_c}(p^j_{n,t})^{1-\sigma_c}\left(\frac{C_{n,t}}{L_{n,t}}\right)^{(1-\sigma_c)(\varepsilon^j_c-1)}\right)$$

Divide by $(P^c_{n,t-1})^{1-\sigma_c}$

$$\left(\frac{P^c_{n,t}}{P^c_{n,t-1}}\right)^{1-\sigma_c} = \left(\sum_{j\in\{a,m,s\}}(\omega^j_{c,n})^{\sigma_c}(p^j_{n,t})^{1-\sigma_c}(P^c_{n,t-1})^{\sigma_c-1}\left(\frac{C_{n,t}}{L_{n,t}}\right)^{(1-\sigma_c)(\varepsilon^j_c-1)}\right)$$

Multiply and divide by $C_{n,t-1}/L_{n,t-1}$ to the appropriate power, with $\widehat{b}_t = b_t/b_{t-1}$ for any variable b:

$$\left(\widehat{P}^c_{n,t}\right)^{1-\sigma_c} = \sum_{j\in\{a,m,s\}}(\omega^j_{c,n})^{\sigma_c}(p^j_{n,t})^{1-\sigma_c}(P^c_{n,t-1})^{\sigma_c-1}\left(\frac{C_{n,t-1}}{L_{n,t-1}}\right)^{(\sigma_c-1)(\varepsilon^j_c-1)}\left(\frac{\widehat{C}_{n,t}}{\widehat{L}_{n,t}}\right)^{(1-\sigma_c)(\varepsilon^j_c-1)}$$

Multiply and divide by $p^j_{n,t-1}$ raised to the appropriate power

$$\left(\widehat{P}^c_{n,t}\right)^{1-\sigma_c} = \sum_{j\in\{a,m,s\}}\underbrace{(\omega^j_{c,n})^{\sigma_c}\left(\frac{p^j_{n,t-1}}{P^c_{n,t-1}}\right)^{1-\sigma_c}\left(\frac{C_{n,t-1}}{L_{n,t-1}}\right)^{(\sigma_c-1)(\varepsilon^j_c-1)}}_{\frac{p^k_{n,t-1}c^k_{n,t-1}}{P^c_{n,t-1}C_{n,t-1}}}(\widehat{p}^j_{n,t})^{1-\sigma_c}\left(\frac{\widehat{C}_{n,t}}{\widehat{L}_{n,t}}\right)^{(1-\sigma_c)(\varepsilon^j_c-1)}$$

Apply the definition of $\frac{p^k_{n,t-1}c^k_{n,t-1}}{P^c_{n,t-1}C_{n,t-1}}$ using the optimal expenditure share and move the exponent

$$\widehat{P}^c_{n,t} = \left(\sum_{j\in\{a,m,s\}} \left(\frac{p^k_{n,t-1} c^k_{n,t-1}}{P^c_{n,t-1} C_{n,t-1}} \right) (\widehat{p}^j_{n,t})^{1-\sigma_c} \left(\frac{\widehat{C}_{n,t}}{\widehat{L}_{n,t}} \right)^{(1-\sigma_c)(\varepsilon^j_c - 1)} \right)^{\frac{1}{1-\sigma_c}}$$

Multiply both sides by $\widehat{C}_{n,t}/\widehat{L}_{n,t}$ to arrive at change in total spending per capita:

$$\frac{\widehat{E}_{n,t}}{\widehat{L}_{n,t}} = \left(\sum_{j\in\{a,m,s\}} \left(\frac{p^k_{n,t-1} c^k_{n,t-1}}{P^c_{n,t-1} C_{n,t-1}} \right) (\widehat{p}^j_{n,t})^{1-\sigma_c} \left(\frac{\widehat{C}_{n,t}}{\widehat{L}_{n,t}} \right)^{(1-\sigma_c)\varepsilon^j_c} \right)^{\frac{1}{1-\sigma_c}} \tag{C.4}$$

Lining Up Expenditure Shares in 1971 To do this we rearrange the first-order condition in equation (C.3) and recognize that the three expenditure shares sum to 1. Then we apply Newton's method to solve for the unobserved consumption price index in 1971 $t = 1$. Given the price index, we compute the consumption index as the ratio of total expenditure to the price index. Finally, given the price and consumption indices, we recover the sector weights using the first-order conditions. These equations are summarizes as follows:

$$1 = \sum_{j\in\{a,m,s\}} \left(\left(\frac{p^j_{n,1} c^j_{n,1}}{P^c_{n,1} C_{n,1}} \right) \left(\left(\frac{p^j_{n,1}}{P^c_{n,1}} \right) \left(\frac{C_{n,1971}}{L_{n,1}} \right)^{\varepsilon^j_c - 1} \right)^{\sigma_c - 1} \right)^{\frac{1}{\sigma_c}}$$

$$C_{n,1} = \frac{\text{Observed total expenditure in 1971}}{P^c_{n,1}}$$

$$\omega^j_c = \left(\left(\frac{p^j_{n,1} c^j_{n,1}}{P^c_{n,1} C_{n,1}} \right) \left(\left(\frac{p^j_{n,1}}{P^c_{n,1}} \right) \left(\frac{C_{n,1}}{L_{n,1}} \right)^{\varepsilon^j_c - 1} \right)^{\sigma_c - 1} \right)^{\frac{1}{\sigma_c}}$$

Appendix D ONLINE APPENDIX: Algorithm and Equilibrium Conditions

Numerical Algorithm Algrorithm D.1 describes the methodology to compute the equilibrium, while Table D.1 lists the entire set of equilibrium conditions in our model. To solve for the equilibrium, we use nested iterations. In the outer loop, we iterate over investment rates. In the inner loop, we compute the sub-equilibrium to solve for prices and quantities.

Algorithm D.1 Numerical Solution

1. Guess a $N \times T$ matrix of nominal investment rates $\boldsymbol{\rho}_t \in \mathbb{R}^{NT}$.
2. Solve for the sub-equilibrium.
   (a) In period t, capital stocks across countries, $\{K_{n,t}\}$, are pre-determined.
      i. Make a guess at a vector of wages, $\mathbf{W}_t$, normalized such that $\sum_{n=1}^{N} w_{n,t} L_{n,t} = 1$.
         A. Compute $R_{n,t} = \frac{\alpha}{1-\alpha} \frac{W_{n,t} L_{n,t}}{K_{n,t}}$ using conditions F1, F2, M1 and M2.
         B. Compute global portfolio transfers T_t^P using condition M6.
         C. Compute $p_{n,t}^j$ and $\pi_{n,i,t}$, using conditions F6–F8.
         D. Compute $P_{n,t}^x$ and $P_{n,t}^{e,j}$, using conditions H4 and F5, respectively.
         E. Compute $X_{n,t} = \frac{\rho_{n,t}(R_{n,t} K_{n,t} + W_{n,t} L_{n,t})}{P_{n,t}^x}$.
         F. Compute $P_{n,t}^c$ and $C_{n,t}$, jointly using conditions H3 and H6.
         G. Compute $c_{n,t}^j$ and $x_{n,t}^j$, using conditions H1 and H2, respectively.
         H. Compute $y_{n,t}^j$, $E_{n,t}^j$, $e_{n,t}^{j,k}$, and $Q_{n,t}^j$ using conditions F3, F4, M3 and M4.
         I. Compute factor demand $k_{n,t}^j$ and labor $\ell_{n,t}^j$ using conditions F1 and F2.
      ii. Check for the labor market clearing condition M2. If the market clears, stop. Otherwise, update $\mathbf{W}_t$ and return to step i.
   (b) Compute $K_{n,t+1}, \Phi_1$ and Φ_2 for every country using conditions H7, H8 and H9.
   (c) Return to step (a) and continue through period T.
3. Given sequences of prices and quantities, check the Euler condition H5. If it holds, stop. Otherwise, update $\boldsymbol{\rho}_t$ and return to step 2.

Table D.1: Equilibrium conditions

(F1)	$R_{n,t}k^j_{n,t} = \alpha\nu^j_n p^j_{n,t}y^j_{n,t}$	$\forall(n,j,t)$
(F2)	$W_{n,t}\ell^j_{n,t} = (1-\alpha)\nu^j_n p^j_{n,t}y^j_{n,t}$	$\forall(n,j,t)$
(F3)	$P^{e,j}_{n,t}E^j_{n,t} = (1-\nu^j_n)p^j_{n,t}y^j_{n,t}$	$\forall(n,j,t)$
(F4)	$e^{j,k}_{n,t} = L_{n,t}(\omega^{j,k}_{e,n})^{\sigma^j_e}\left(\frac{p^k_{n,t}}{P^{e,j}_{n,t}}\right)^{-\sigma^j_e}\left(\frac{E^j_{n,t}}{L_{n,t}}\right)^{(1-\sigma^j_e)\varepsilon^{j,k}_e+\sigma^j_e}$	$\forall(n,j,k,t)$
(F5)	$(P^{e,j}_{n,t})^{1-\sigma^j_e} = \sum\limits_{k\in\{a,m,s\}}(\omega^{j,k}_{e,n})^{\sigma^j_e}(p^k_{n,t})^{1-\sigma^j_e}\left(\frac{E^j_{n,t}}{L_{n,t}}\right)^{(1-\sigma^j_e)(\varepsilon^{j,k}_e-1)}$	$\forall(n,j,t)$
(F6)	$(p^j_{n,t})^{-\theta^j} = \gamma^j\sum\limits_{i=1}^{N}\left((A^j_{i,t})^{-\nu^j_i}u^j_{i,t}d^j_{n,i,t}\right)^{-\theta^j}$	$\forall(n,j,t)$
(F7)	$u^j_{n,t} = \left(\frac{R_{n,t}}{\alpha\nu^j_i}\right)^{\alpha\nu^j_i}\left(\frac{W_{n,t}}{(1-\alpha)\nu^j_i}\right)^{(1-\alpha)\nu^j_i}\left(\frac{P^{e,j}_{n,t}}{1-\nu^j_i}\right)^{1-\nu^j_i}$	$\forall(n,j,t)$
(F8)	$\pi^j_{n,i,t} = \frac{\left((A^j_{i,t})^{-\nu^j_i}u^j_{i,t}d^j_{n,i,t}\right)^{-\theta^j}}{\sum\limits_{i'=1}^{N}\left((A^j_{i',t})^{-\nu^j_{i'}}u^j_{i',t}d^j_{n,i',t}\right)^{-\theta^j}}$	$\forall(n,i,j,t)$
(H1)	$c^j_{n,t} = L_{nt}(\omega^j_{c,n})^{\sigma_c}\left(\frac{p^j_{n,t}}{P^c_{n,t}}\right)^{-\sigma_c}\left(\frac{C_{n,t}}{L_{n,t}}\right)^{(1-\sigma_c)\varepsilon^j_c+\sigma_c}$	$\forall(n,j,t)$
(H2)	$x^j_{n,t} = L_{nt}(\omega^j_{x,n})^{\sigma_x}\left(\frac{p^j_{n,t}}{P^x_{n,t}}\right)^{-\sigma_x}\left(\frac{X_{n,t}}{L_{n,t}}\right)^{(1-\sigma_x)\varepsilon^j_x+\sigma_x}$	$\forall(n,j,t)$
(H3)	$(P^c_{n,t})^{1-\sigma_c} = \sum\limits_{j\in\{a,m,s\}}(\omega^j_{c,n})^{\sigma_c}(p^j_{n,t})^{1-\sigma_c}\left(\frac{C_{n,t}}{L_{n,t}}\right)^{(1-\sigma_c)(\varepsilon^j_c-1)}$	$\forall(n,t)$
(H4)	$(P^x_{n,t})^{1-\sigma_x} = \sum\limits_{j\in\{a,m,s\}}(\omega^j_{x,n})^{\sigma_x}(p^j_{n,t})^{1-\sigma_x}\left(\frac{X_{n,t}}{L_{n,t}}\right)^{(1-\sigma_x)(\varepsilon^j_x-1)}$	$\forall(n,t)$
(H5)	$\frac{C_{n,t+1}/L_{n,t+1}}{C_{n,t}/L_{n,t}} = \beta\left(\frac{\psi_{n,t+1}}{\psi_{n,t}}\right)\left(\frac{R_{n,t+1}/P^x_{n,t+1}-\Phi_2(K_{n,t+2},K_{n,t+1})}{\Phi_1(K_{n,t+1},K_{n,t})}\right)\left(\frac{P^x_{n,t+1}/P^c_{n,t+1}}{P^x_{n,t}/P^c_{n,t}}\right)$	$\forall(n,t)$
(H6)	$P^c_{n,t}C_{n,t} + P^x_{n,t}X_{n,t} = (1-\phi_{n,t})(R_{n,t}K_{n,t}+W_{n,t}L_{n,t}) + T^P_t L_{n,t}$	$\forall(n,t)$
(H7)	$X_{n,t} = \Phi\left(K_{n,t+1},K_{n,t}\right) \equiv \delta^{1-\frac{1}{\lambda}}\left(\frac{K_{n,t+1}}{K_{n,t}}-(1-\delta)\right)^{\frac{1}{\lambda}}K_{n,t}$	$\forall(n,t)$
(H8)	$\Phi_1(K_{n,t+1},K_{n,t}) = \frac{\delta^{1-1/\lambda}}{\lambda}\left(\frac{K_{n,t+1}}{K_{n,t}}-(1-\delta)\right)^{(1-\lambda)/\lambda}$	$\forall(n,t)$
(H9)	$\Phi_2(K_{n,t+1},K_{n,t}) = \Phi_1(K_{n,t+1},K_{n,t})\left((\lambda-1)\left(\frac{K_{n,t+1}}{K_{n,t}}\right)-\lambda(1-\delta)\right)$	$\forall(n,t)$
(M1)	$K_{n,t} = \sum\limits_{j\in\{a,m,s\}}k^j_{n,t}$	$\forall(n,t)$
(M2)	$L_{n,t} = \sum\limits_{j\in\{a,m,s\}}\ell^j_{n,t}$	$\forall(n,t)$
(M3)	$Q^j_{n,t} = c^j_{n,t} + x^j_{n,t} + \sum\limits_{k\in\{a,m,s\}}e^{k,j}_{n,t}$	$\forall(n,j,t)$
(M4)	$p^j_{n,t}y^j_{n,t} = \sum\limits_{i=1}^{N}p^j_{i,t}Q^j_{i,t}\pi^j_{i,n,t}$	$\forall(n,t)$
(M5)	$\sum\limits_{j\in\{a,m,s\}}\left(p^j_{n,t}y^j_{n,t} - p^j_{n,t}Q^j_{n,t}\right) = \phi_{n,t}(R_{n,t}K_{n,t}+W_{n,t}L_{n,t}) - L_{n,t}T^P_t$	$\forall(n,t)$
(M6)	$\sum\limits_{n=1}^{N}L_{n,t}T^P_t = \sum\limits_{n=1}^{N}\phi_{n,t}(R_{n,t}K_{n,t}+W_{n,t}L_{n,t})$	$\forall(t)$

Appendix E ONLINE APPENDIX: Additional Figures and Analysis

This appendix presents additional figures mentioned in the main text, as well as additional analysis surrounding them.

E.1 Additional Figures

Data Figures Figures E.1 below showcases the dynamics of the cross-country distribution of each sector's value-added shares, agriculture in the top row, manufacturing in the middle row, and services in the bottom row. In each year, we have labeled the top three and bottom three countries in the distribution, with all other countries names positioned to the right of the plots. Figure E.2 below displays the dynamics of the cross-country distribution of each sector's net export to GDP ratios.

Calibration Figures Figure E.3 illustrates the equilibrium path for the investment rate in the left panel and the capital-labor ratio in the right panel for the baseline model. Each line represents a sample country over both the in-sample years (1971-2011) as well as the projected years (2011-2060). The investment rates in all countries converge to 0.18 by 2036. The capital stocks converge after that but prior to 2060.

Model Fit Figures Figures E.4 and E.5 illustrate the fit of the calibrated baseline model (y-axis) with the data (x-axis). Figure E.4 shows the overall performance of the calibration in terms of targeting sectoral prices and bilateral trade shares for all three sectors. Figure E.5 presents the performance of the baseline model in terms of sectoral shares of consumption, investment, and intermediates used by sector.

Figure E.6 illustrates the cross-country distributions and corresponding log-variances of the agriculture and services value added shares over time. The solid lines are for the data and the dashed lines are for the baseline model.

Counterfactual Figures Figure E.7 plots the predicted paths for the sectoral value added shares over income per capita within a typical country in the first three columns. The solid line is the data, the dashed line is the baseline, and the dotted line is the corresponding counterfactual scenario. The last two columns are the predicted paths for (i) the price of manufacturing relative to services and (ii) the ratio of manufacturing net exports to GDP. For the last two columns, values in the baseline equal those in the data, by construction.

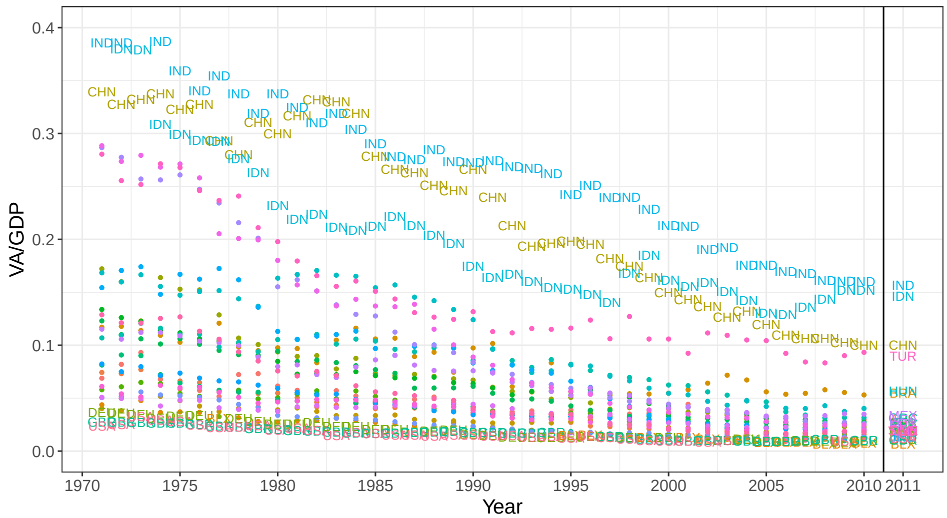
Figure E.8 plots (i) the world distribution of manufacturing value added shares over time and (ii) the log-variance of the said distribution. The solid line is the data, the dashed line is the baseline, and the dotted line is the corresponding counterfactual scenario.

E.2 Additional Analysis

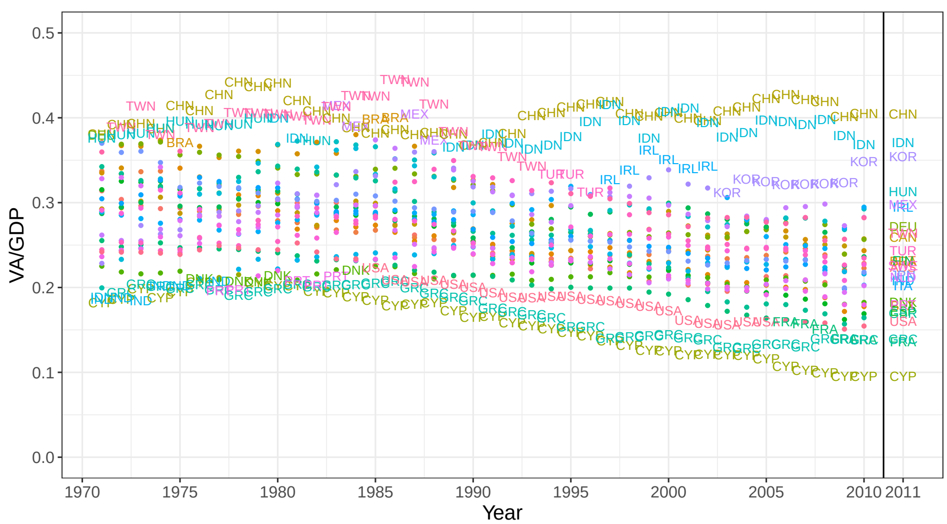
We now explore the role of aggregate trade imbalances and of a time-varying discount factor in accounting for both deindustrialization and industry polarization.

Figure E.1: World Distribution of Sectoral Value Added to GDP Ratios

(a) Agriculture



(b) Manufacturing



(c) Services

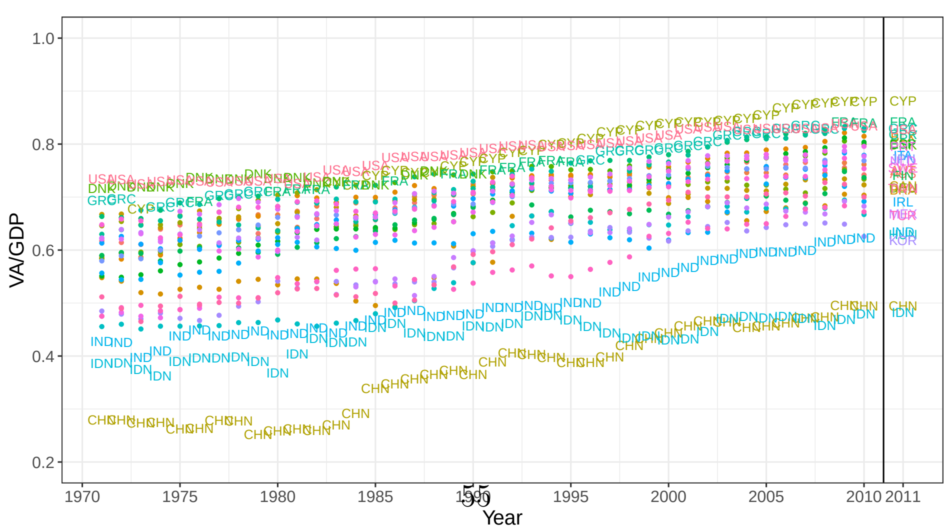
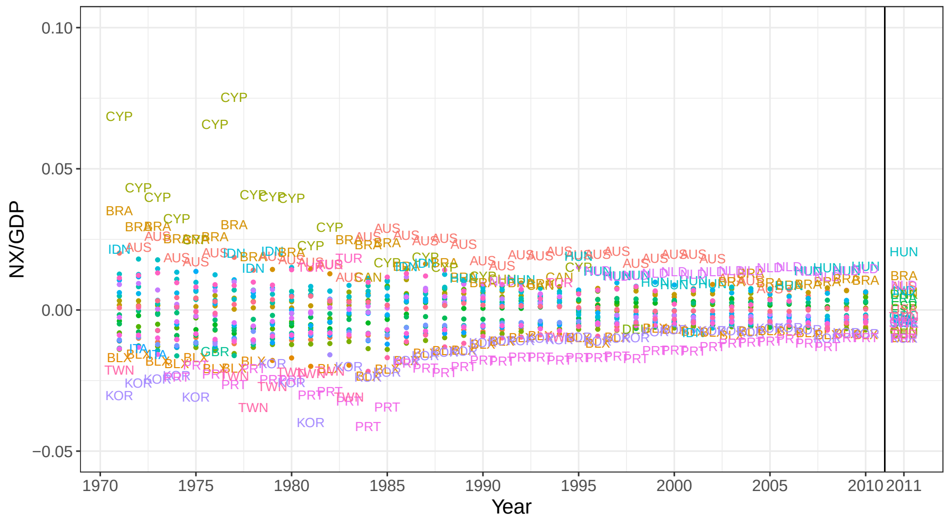
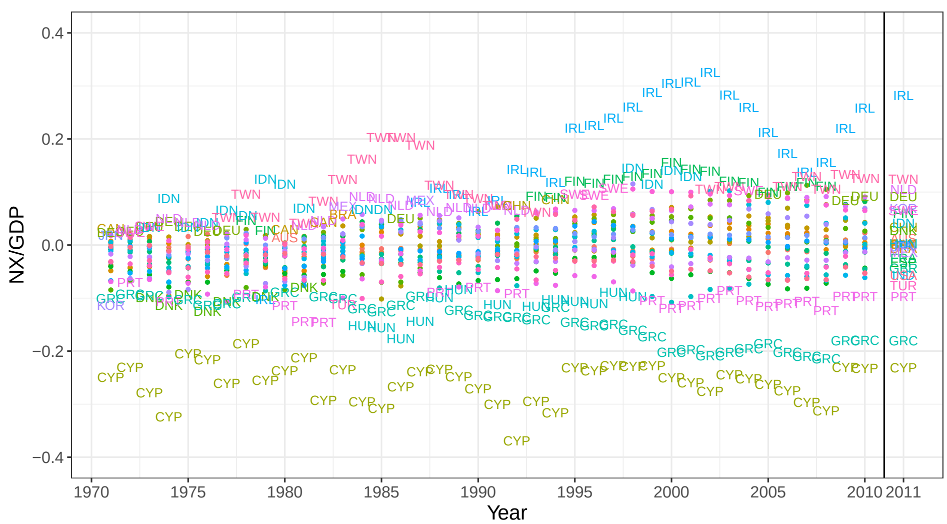


Figure E.2: World Distribution of Sectoral Net Export to GDP Ratios

(a) Agriculture



(b) Manufacturing



(c) Services

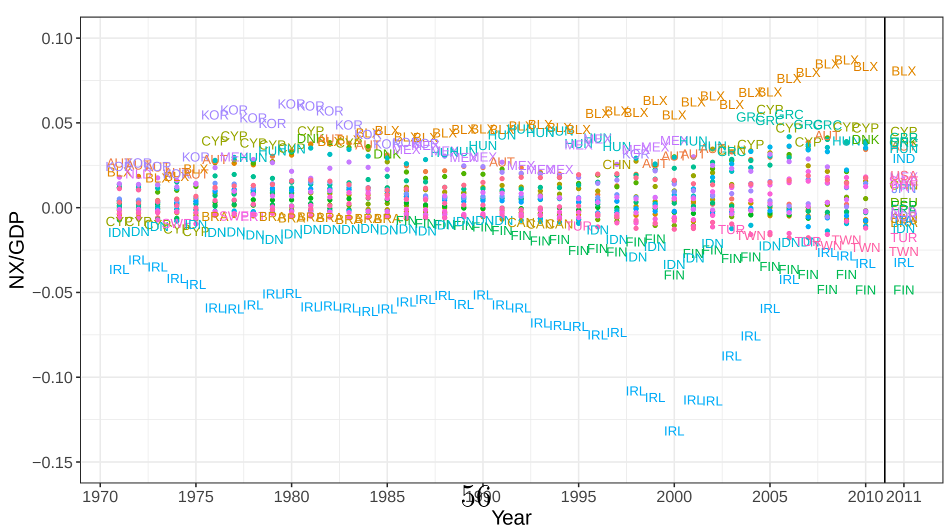
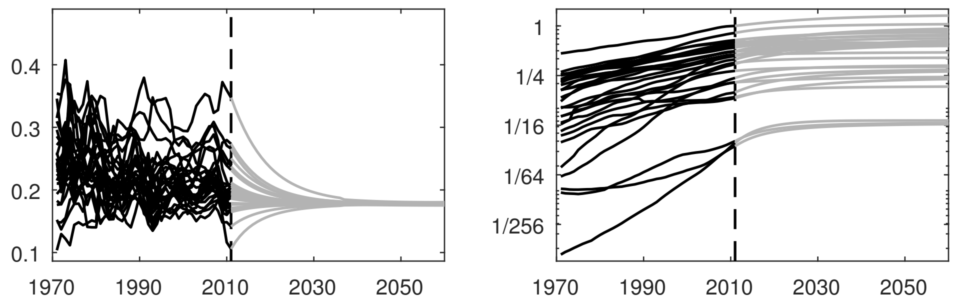


Figure E.3: Investment Rate and Capital per Worker Dynamics



Investment Rate

Capital-Labor Ratio

Notes: The dark lines are for the in-sample period, 1971-2011. The lighter lines are for the projection period, 2011-2060.

Aggregate Trade Imbalances Our baseline model differs from the Autarky scenario by incorporating both gross trade flows and aggregate trade imbalances. To assess the contribution of gross trade versus net trade, we construct a scenario in which aggregate trade is balanced in each country and each year. Specifically, we set $\phi_{n,t} = 0$ for all (n, t). Other parameters, including trade costs, are at their baseline values. Sectoral imbalances still emerge owing to comparative advantage, as in Uy, Yi, and Zhang (2013).

The peak manufacturing value added share declines by 2.6 percentage points across the two periods (fourth row in Figure E.7), similar to the 3.0 percentage point decline in the baseline model, suggesting that aggregate imbalances do not play a significant role in deindustrialization. Trade integration and sectoral trade imbalances matter for deindustrialization, as we have discussed above, but aggregate imbalances matter less.

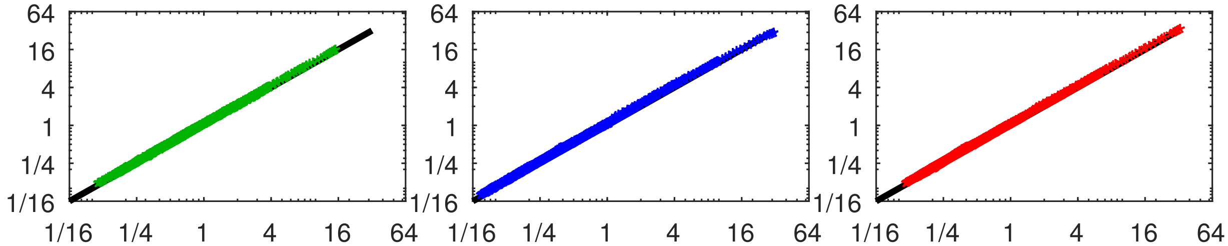
However, the absence of trade imbalances does play a significant role in industry polarization. Without such imbalances, the log-variance in manufacturing value-added shares increases from an average of 0.033 prior to 1991, to 0.043 in the post-1990 period (fourth row in Figure E.8). This represents a smaller variance in each year, as well as a smaller increase over time, than in the baseline model where it increases from 0.046 to 0.069. These results reflect the fact that manufacturing net exports are positively correlated with aggregate net exports, because imbalances in agriculture and services typically do not fully offset manufacturing imbalances. Hence, imposing aggregate balanced trade attenuates manufacturing imbalances and reduces cross-country dispersion in manufacturing value added shares.

Constant Discount Factor We finally consider the importance of matching the aggregate saving rate. In the baseline model, the saving rate was matched to the data by choosing a sequence of country-specific discount factor "shocks", $\psi_{n,t+1}$. In the long-run steady state, this sequence settles down to a constant value. We now consider the implications of removing time and country variation is this parameter so that $\psi_{n,t} = 1$ for all countries and years. All other exogenous forces remain at their baseline values.

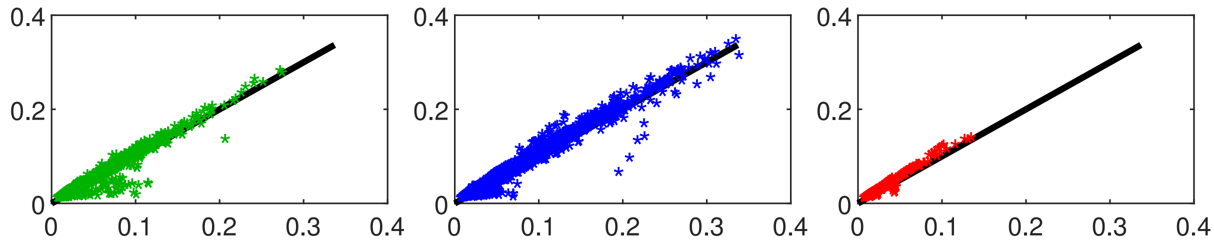
This scenario gives rise to the same relative prices, sectoral shares in final demand and intermediate demand, and trade flows, as in the baseline model. The key difference relative

Figure E.4: Model Fit for Sectoral Prices and Bilateral Trade Shares

(a) Prices, U.S.=1 in 2011



(b) Bilateral trade shares



Agriculture Manufacturing Services

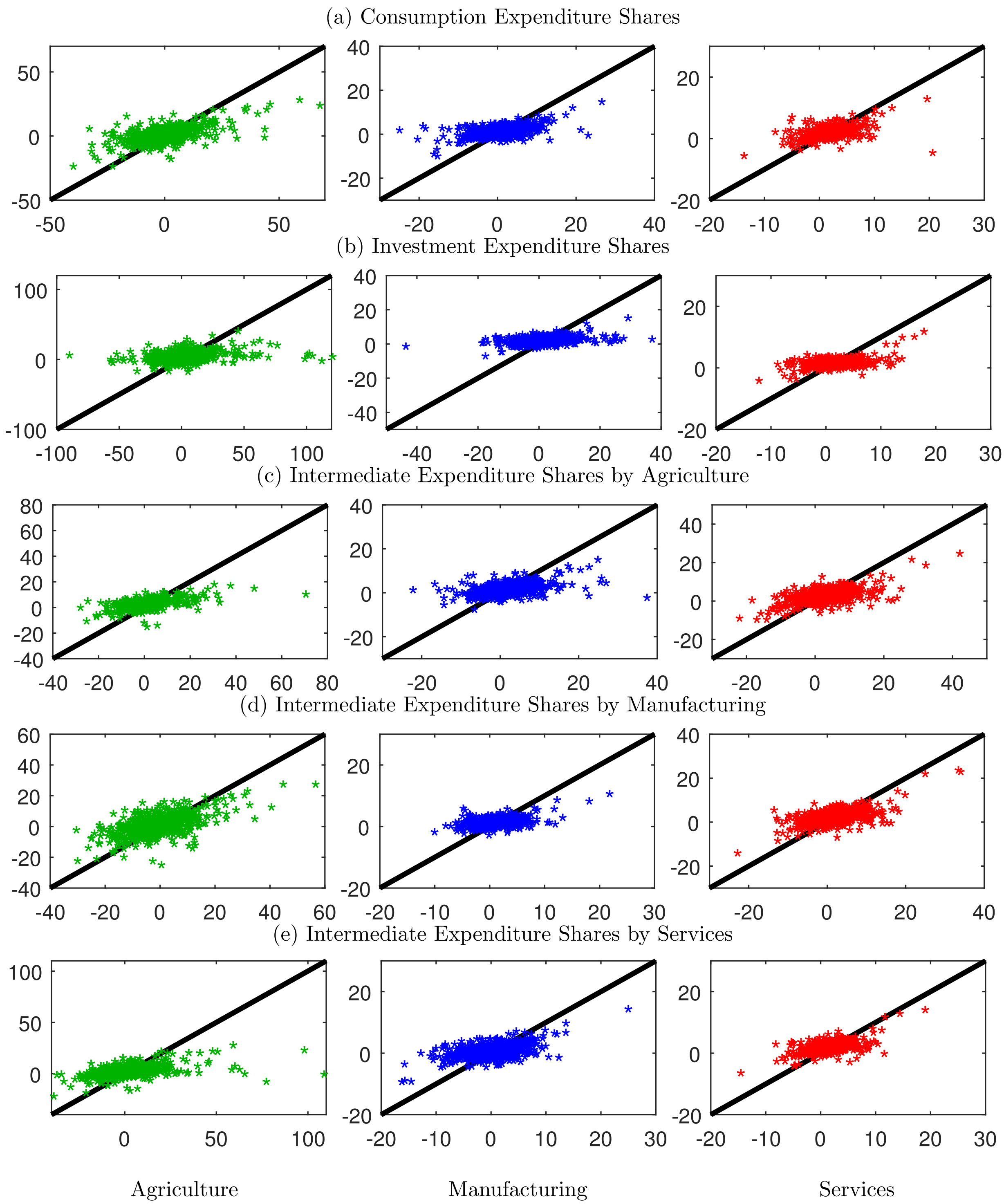
Notes: Model (y-axis) vs Data (x-axis). The top row plots the sectoral price relative to the wage, $p^j_{n,t}/w_{n,t}$, so that units are comparable to the data. The bottom row plots the sectoral bilateral trade share, $\pi^j_{n,i,t}$.

to the baseline model is that the aggregate saving rate and investment rate are not in line with the data, implying different outcomes for the sectoral value-added shares.

As a result, the hump shape for the manufacturing value added share becomes flatter (bottom row in Figure E.7). This is because the investment rate itself gives rise to a hump shape pattern with respect to income in the data and in the baseline (see Figure E.9 in the Appendix). As shown in García-Santana, Pijoan-Mas, and Villacorta (2021), the hump shape in the investment rate is important for generating the hump shape in the manufacturing value added share. In their paper they achieve the hump in the investment rate by also introducing an intertemporal wedge in the Euler equation. Following their interpretation, one can perceive our discount factor shock as a time-varying investment-specific technology shock. By contrast, in this scenario, the predicted path for the investment rate is relatively flat in both periods. Also, the magnitude of deindustrialization is dampened: the peak manufacturing value added share declines by 2.5 percentage points in this scenario, compared to 3.0 percentage points in the baseline model.

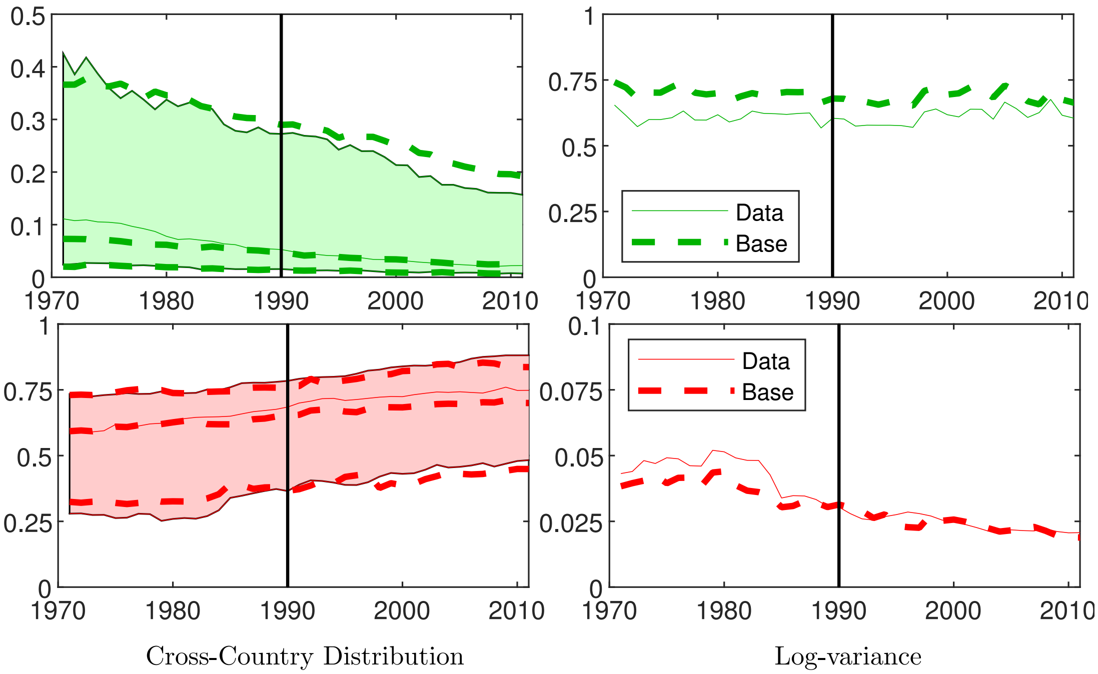
Figure E.9 plots the predicted relationship between the aggregate investment rate and income per capita, using regression 1, for bnoth the pre-1990 and post-1990 periods. It shows the predicted paths emerging from both the baseline modela dn from the Cosntant-Discount-Factor scenario.

Figure E.5: Model Fit for Annual Percent Changes in Sectoral Expenditure Shares



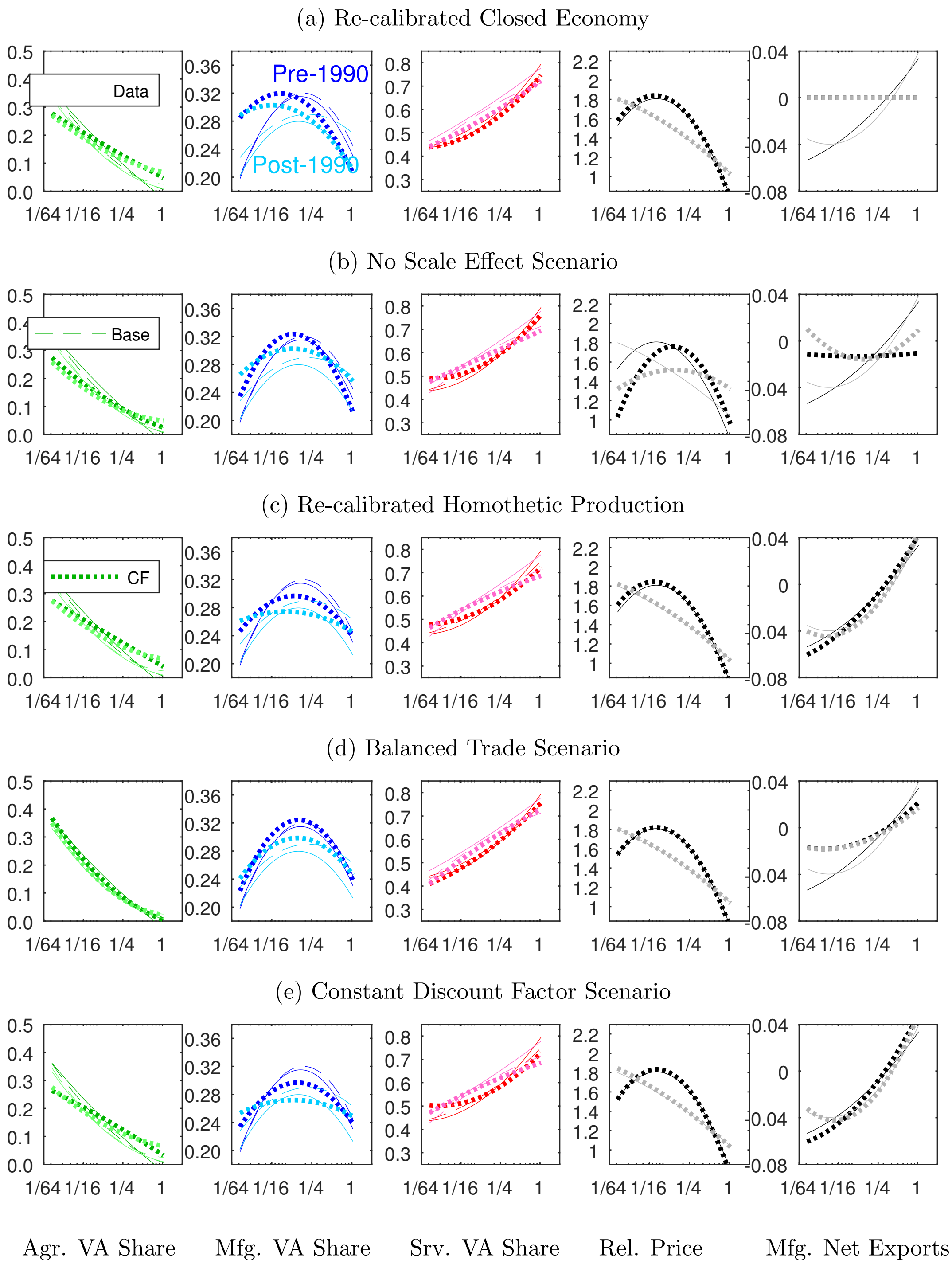
Notes: Model (y-axis) vs Data (x-axis).

Figure E.6: Variance in VA shares of Agriculture and Services:
Baseline Model and Data



Notes: Dashed lines - data; Solid lines - baseline model. In the left panels, the middle line plots the median value of the manufacturing value added shares across countries over time (x-axis), while the upper and lower bands correspond to the 100$^{\text{th}}$ and 1$^{\text{st}}$ percentiles, respectively. In the right panels, log-variance reports the variance of the log-manufacturing VA share across countries over time (x-axis). ROW is excluded from the calculations.

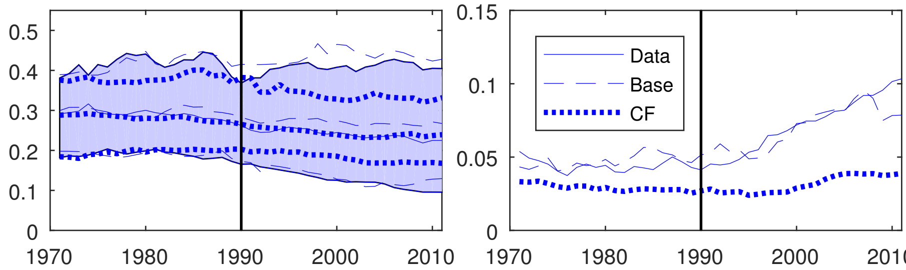
Figure E.7: Predicted Sectoral Value Added Shares Across Income per Capita



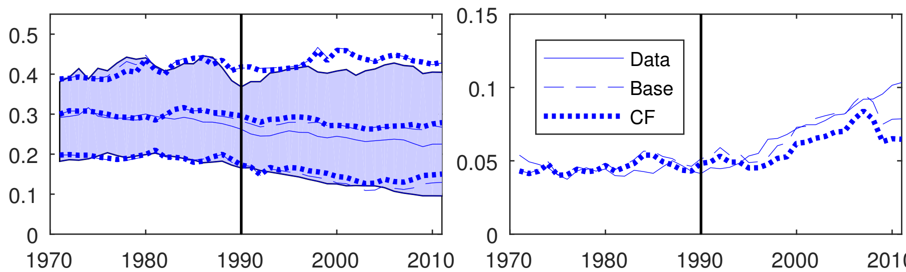
Notes: The fitted curves are based on regressions of the variable of interest on income (y-axis), interacted with the two period dummies, and country fixed effects, over income per capita (x-axis). Solid lines refer to the data; the dashed lines refer to the baseline model; the dotted lines refer to the counterfactuals. Dark (light) lines refer to pre-1990 (post-1990).

Figure E.8: Predicted Industry Polarization – Baseline and Additional Scenarios

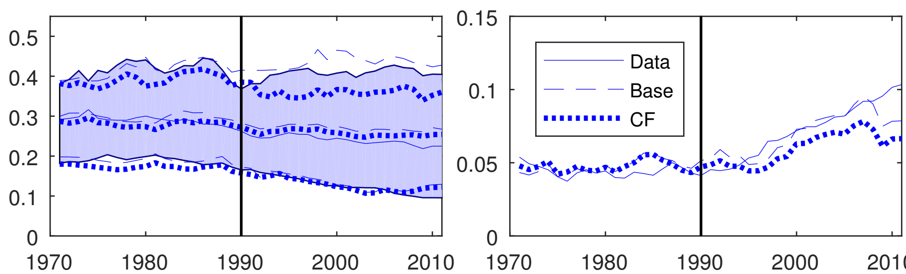
(a) Re-calibrated Closed Economy



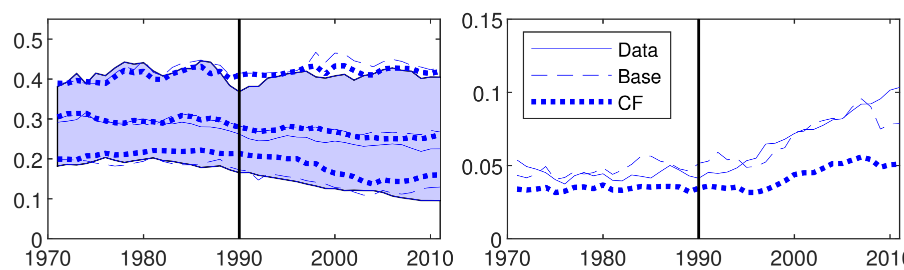
(b) No Scale Effect Scenario



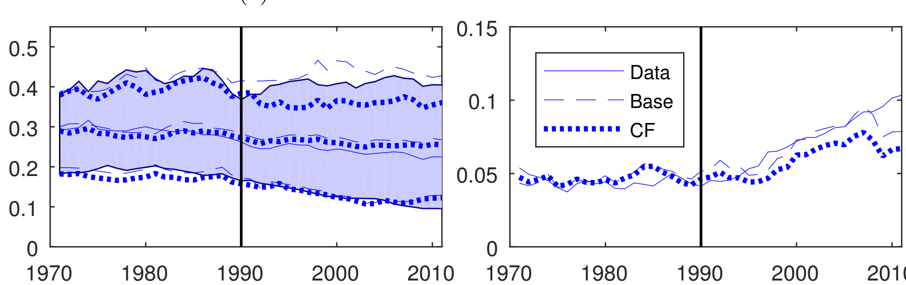
(c) Re-calibrated Homothetic Production



(d) Balanced Trade Scenario



(e) Constant Discount Factor Scenario

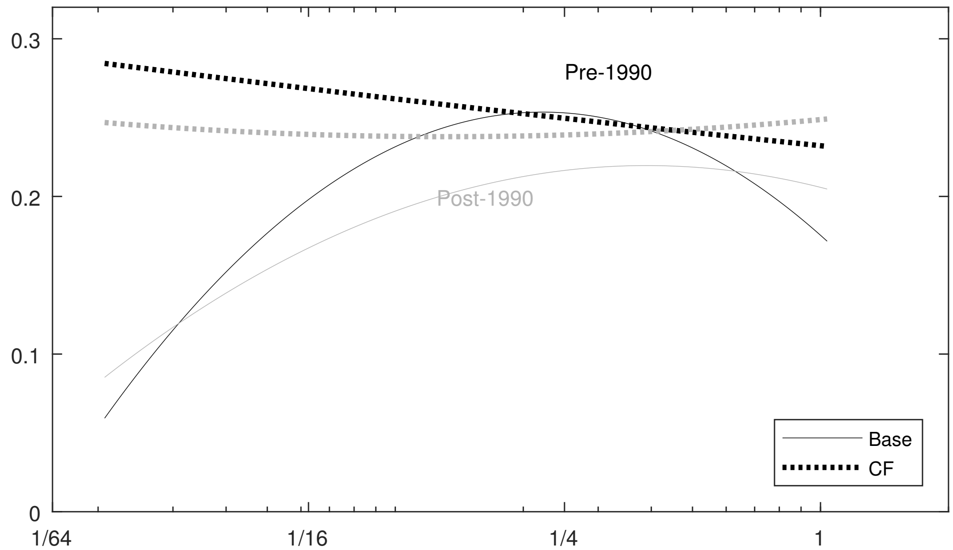


Cross-Country Distribution   Log-variance

Notes: Dashed lines - data; Solid lines - baseline model; Dotted line - counterfactual. In the left panels, the middle line plots the median value of the manufacturing value added shares across countries over time (x-axis), while the upper and lower bands correspond to the 100$^{\text{th}}$ and 1$^{\text{st}}$ percentiles, respectively. In the right panels, log-variance reports the variance of the log-manufacturing VA share across countries over time (x-axis). ROW is excluded from the calculations.

Figure E.9: Predicted Investment Rate Across Income per Capita

(a) Constant Discount Factor Scenario



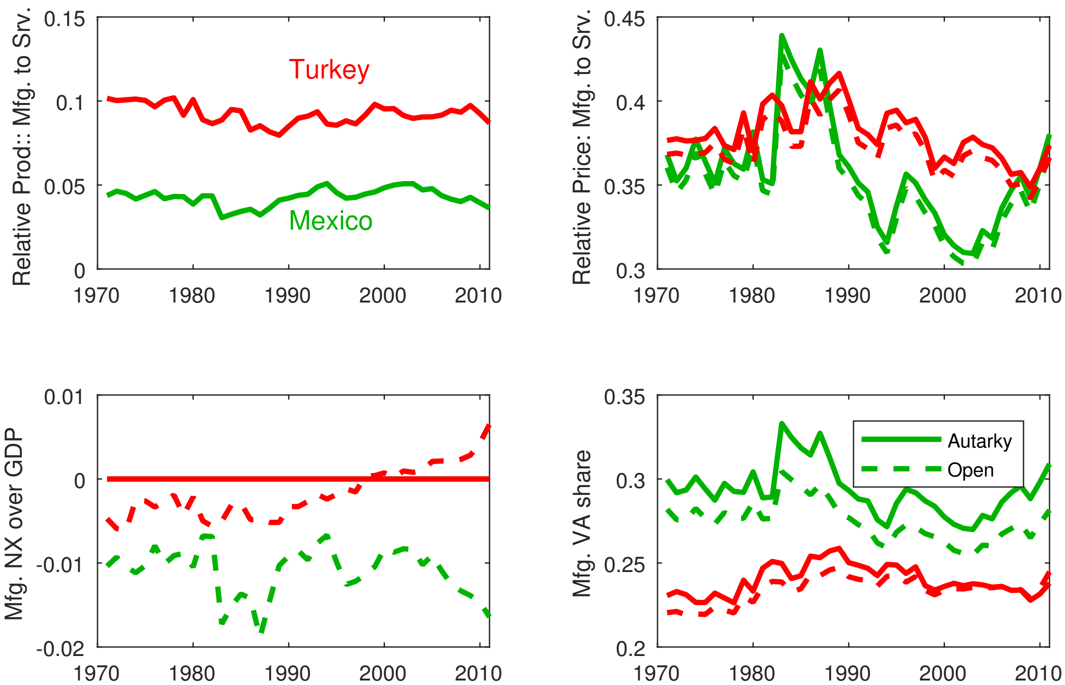
Notes: The fitted curves are based on regressions of the investment rate on income (y-axis), interacted with the two period dummies, and country fixed effects, over income per capita (x-axis). Solid lines refer to the data; the dashed lines refer to the baseline model; the dotted lines refer to the counterfactuals. Dark (light) lines refer to pre-1990 (post-1990).

E.3 Interaction Between Sector-Biased Productivity Growth and Trade Integration

Consider Mexico and Turkey as examples that illustrate how the interaction effect works through both prices and through net exports. Both countries have relatively small sector bias in their productivity growth compared to other countries, i.e., the gap between the productivity growth rates in manufacturing and services is close to zero, while for most countries in the sample the gap is positive. The top left panel of Figure E.10 plots the productivity paths for the two countries. As such, under the autarky scenario, the price of manufacturing relative to services changes little from 1971 to 2011, as in other countries; see the solid lines in top right panel of Figure E.10. In the constant trade cost scenario (trade costs are finite but held constant at their 1971 levels) – see the dashed lines in the top right panel of Figure E.10 – the relative price of manufacturing is lower for both countries over the sample period. To be sure, since trade costs are constant, there is no impact of changes in trade costs on changes in relative prices. This illustrates the interaction effect through prices.

For these two countries, the interaction effect through quantities can be traced back to comparative advantage patterns. Recall the top left panel of Figure E.10: Turkey has a higher relative productivity in manufacturing than Mexico, a.k.a., a comparative advantage in manufacturing vis-à-vis to Mexico. The bottom left panel of Figure E.10 plots the ratio of manufacturing net export to GDP for both countries. In autarky these series are zero. In the open economy with constant trade costs, Mexico initially has a larger trade deficit than Turkey in manufacturing. Turkey then graduates to a surplus by 2011. In sum, relative to autarky, trade lowers the manufacturing value added share for Mexico both because of the decline in the relative price and the trade deficit in manufacturing. For Turkey, trade lowers its manufacturing value added share through the relative price, but boosts it through the eventual trade surplus, with the latter effect dominating for the last few periods of our sample. This is illustrated in the bottom right panel with Mexico having a larger reduction in its manufacturing value added share relative to autarky, compared to Turkey.

Figure E.10: Outcomes Under Autarky and Under Constant Trade Costs: Mexico and Turkey



Notes: "Autarky" refers to the counterfactual scenario where trade costs are st to be prohibitively high. "Open" refers to the counterfactual where trade costs are held constant at 1971 levels.