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# PREMATURE DEINDUSTRIALIZATION AND INDUSTRY POLARIZATION

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**ABSTRACT**

We document two key patterns of structural change: premature deindustrialization and rising industry polarization. Using a dynamic open-economy model with sector-biased technological change (SBTC), we evaluate the role of trade in these shifts. Trade alone does not cause premature deindustrialization, but its interaction with SBTC—transmitting global technological change, amplifying the decline in manufacturing's relative price over time, and generating manufacturing trade imbalances across countries—deepens premature deindustrialization over time. Industry polarization, by contrast, emerges only through trade-driven specialization, as countries diverge along lines of comparative advantage.

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# 1 Introduction

Beyond per-capita income growth, probably the most important feature of countries' long-run development is structural change, a phenomenon well-documented since Kuznets (1973). 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 show that countries now undergo *premature deindustrialization*: at the same level of GDP per capita, they allocate a smaller share of total value-added to manufacturing than their counterparts did decades ago, suggesting diminished opportunities for industrialization. We add a new dimension to this evidence by documenting *industry polarization*: a widening cross-country dispersion in manufacturing shares over time. While, on average, countries exhibit a declining manufacturing share, the cross-country variance in these shares has increased over time, reflecting growing divergence. These new facts show that the process of structural change itself is evolving over decades.

What drives these evolving patterns of structural change? The period we examine overlaps with the "second golden age of trade" marked by falling trade costs and unprecedented trade integration. These forces make international trade a natural suspect: unlike domestic drivers, trade transmits technological change across borders, reshaping relative prices and leading to sectoral trade imbalances; in addition, increasing trade integration over time reveals more comparative advantage, further amplifying the above channels, potentially driving both premature deindustrialization and industry polarization. While prior research emphasizes aggregate technical change interacting with non-homothetic preferences (the Engel effect) and/or differential technological change across sectors interacting with low substitution elasticities (the Baumol effect), trade's contribution—and its own interaction with these forces—to premature deindustrialization and polarization remains unknown. We address this gap using a dynamic multi-country open-economy model, calibrated to over two dozen countries, to quantify the role of trade in shaping these global patterns.

We show that sector-biased technological change (SBTC)—defined as aggregate technological progress occurring unevenly across sectors—is necessary for premature deindustrialization. SBTC reduces the relative price of manufacturing compared to services, though by itself, it accounts for less than half of the observed effect. Trade alone does not cause premature deindustrialization, but its interaction with SBTC—transmitting global technological change across countries—amplifies the decline in manufacturing's relative price and generates manufacturing trade imbalances through specialization, deepening premature deindustrialization. Industry polarization, by contrast, emerges only through trade-driven specialization as countries evolve along lines of comparative advantage.

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 dynamic, multi-country, three-sector model features both intrasectoral and intersectoral Ricardian trade, with trade flows driven by SBTC and trade costs. Our model also embeds non-homothetic CES preferences, input-output linkages and endogenous capital accumulation.[1] Trade follows an Eaton-Kortum structure, with sectoral trade costs evolving over time reflecting trade integration and driving sectoral reallocation according to comparative advantage. The non-homothetic CES preferences allow relative prices and income to shape sectoral consumption demand, capturing both the Engel and Baumol effects central to structural change. SBTC embodies sector-specific productivity growth alongside scale effects in intermediate input and investment bundles. These scale effects parallel income effects in consumption demand, whereby sectoral demand shares within investment and intermediate spending depend not only on relative prices, but also on scale.

To align with our empirical analysis, we calibrate the model to the same set of countries and time frame. As part of this process, we estimate three sets of key elasticities using data on sectoral relative prices and expenditure. Substitution elasticities across sectors in consumption, investment, and intermediate inputs are all below one, indicating complementarity across sectors. Income elasticities are highest for services and lowest for agriculture, consistent with Engel effects. Scale elasticities are more nuanced: sectoral expansion most strongly boosts intermediate input demand within the same sector.

We then calibrate sectoral fundamental productivity and trade costs to match observed sectoral prices and bilateral trade flows across countries and over time. In the data, the relative price of manufactured goods to services declines with income per capita, while

[1] Recent research has shown that evolving investment patterns is also a key feature of structural change. See García-Santana, Pijoan-Mas, and Villacorta (2021) and Herrendorf, Rogerson, and Valentinyi (2021).

manufacturing net exports as a share of GDP rise with income. Our calibrated sectoral productivity correlates positively with income per capita, with median growth rates highest in agriculture, followed by manufacturing, and lowest in services. Trade costs decline with income per capita, with manufacturing showing both the lowest level and fastest rate of decline, followed by agriculture, and again lowest in services.

Our baseline model closely replicates the patterns of premature deindustrialization and industry polarization. Using the same regression as for the data, our model implies a 2.6-percentage-point decline in the peak manufacturing value-added share from the pre- to post-1990 periods, three-quarters of the decline in the data, which demonstrates its ability to explain premature deindustrialization. The model also explain over two-thirds of the observed increase in the cross-country dispersion of manufacturing shares across the two periods, capturing industry polarization. Finally, the model reproduces broader structural change patterns across countries including heterogeneity in peak manufacturing shares.

Trade, and especially its interaction with SBTC, plays an essential role in explaining premature deindustrialization and industry polarization. To make this clear, we conduct two sets of counterfactuals. First, we compare the baseline (*SBTC-Trade*) scenario with an *SBTC-Autarky* scenario, where trade is removed by setting prohibitive trade costs. Second, to isolate the interaction between trade and SBTC, we contrast *SNTC-trade* and *SNTC-autarky* scenarios, where SNTC (sector-neutral technological change) features uniform productivity growth across sectors and no scale effects in intermediate input and investment bundles. By construction, the SNTC-autarky scenario delivers constant manufacturing relative prices over time within each closed economy. These counterfactual results show that neither trade integration nor SBTC alone can account for both patterns. SBTC is essential for premature deindustrialization, while trade drives industry polarization. Only their interaction can jointly explain both patterns.

SBTC accounts for 60 percent of the baseline decline. Its primary channel is the sustained fall in the relative price of manufacturing to services over time, driven by faster productivity growth in manufacturing relative to services and scale effects in production across many countries. These forces together pushed manufacturing relative prices substantially lower post-1990 than pre-1990. Under "Baumol" elasticities (less than one), this decline reduced global manufacturing expenditure as a share of global GDP and indeed, in the data, it has fallen by about five percentage points in recent decades. As a result, at similar income levels, later industrializers face fewer opportunities to reach the industrial peaks of early ones, often bypassing manufacturing to move directly into services.

The remaining 40 percent of the baseline premature deindustrialization arises from the interaction between SBTC and trade integration, which jointly shape relative prices and sectoral trade imbalances. Three mechanisms underlie this interaction. First, trade openness, in and of itself, lowers the relative price of manufactured goods because trade costs are lower for manufacturing than for services. Second, trade affects quantities differentially across countries and sectors by revealing comparative advantage and leading to specialization. These forces produce manufacturing trade imbalances, which intensify after 1990 as trade and SBTC effects accumulate over time. Third, openness transmits sector-biased technological change from trading partners to the home country; that is, trade integration enables countries to "import" SBTC from other countries through both prices and quantities. Finally, further trade integration over time amplifies each of these transmissions.

Industry polarization arises solely through trade-driven specialization: countries with a comparative disadvantage in manufacturing increasingly import manufactured goods and see their manufacturing value-added shares decline, while those countries with a comparative advantage experience the opposite. Trade integration alone (SNTC-Trade) generates industry polarization stronger than observed since 1990, while both SBTC-autarky and SNTC-autarky scenarios generate virtually no increase in industry polarization. Our result that the SNTC-trade scenario overstates industry polarization relative to the baseline (SBTC-trade) scenario indicates that SBTC dampens the effects of increased specialization. To summarize the outcomes of our counterfactuals, the interaction between trade and SBTC amplifies premature deindustrialization, but mitigates industry polarization.

We use the experiences of India, South Korea, and China to illustrate how trade, interacting with technological change, drives both premature deindustrialization and industry polarization. India, a late industrializer, never reached the industrial peaks of early industrializers: its manufacturing value-added share peaked at just 0.26, below South Korea's 0.36 peak. Meanwhile, post-1990, China—another later industrializer—saw its manufacturing value-added share rise by nearly four percentage points as India's fell by four, widening global dispersion. Our baseline model replicates these divergent paths. In the SBTC-Autarky scenario, India's share is about four percentage points higher than in the SBTC-Trade scenario at low income levels—closer to Korea's—because the closed economy "forces" India to produce more domestically, underscoring the role of trade in premature deindustrialization. Autarky also dampens industry polarization: by not revealing China's comparative advantage in manufacturing and India's in services, from 1990 onward, India's manufacturing value-added share rises by two percentage points while China's falls by five. Consequently, by 2011, the manufacturing share gap between China and India is 10.6 percentage points, instead of 18.7 percentage points in the baseline model, with a zero net export gap, instead of 8.8 percentage points in the baseline model.

To fully gauge the closed-economy's contribution, we re-calibrate three versions of closed-economy models and compare their performance to the baseline. While all core elements—sector-biased productivity growth, non-homothetic preferences, and non-homothetic production structures—are essential for capturing part of baseline premature deindustrialization, none individually, or even together, can generate industry polarization. This weaker performance stems from the closed economy's inability to capture the dual impact of trade integration: price effects from falling manufacturing relative prices and quantity effects from specialization. While their re-calibrated productivity processes account for trade's influences on relative prices, these models cannot, by definition, capture sectoral trade imbalances driven by shifting comparative advantage and specialization.

The starting point for our paper is Rodrik (2016), which was the first to document premature deindustrialization in a wide swath of countries. Recently, Felipe, Mehta, and Rhee (2019) and Haraguchi, Cheng, and Smeets (2017) provide further evidence for premature deindustrialization in a larger sample of countries.[2] The two papers most closely related to ours are Huneeus and Rogerson (2024) and Fujiwara and Matsuyama (2020). Huneeus and Rogerson (2024) show that heterogeneous paths of agricultural productivity across countries are a key driver of both structural change and premature deindustrialization. Fujiwara and Matsuyama (2020) explain premature 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 income per capita at that hump. Like these two papers, we study sectoral technological change, but in an open-economy setting focused on trade, and 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 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

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

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 premature 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 Premature Deindustrialization and Polarization

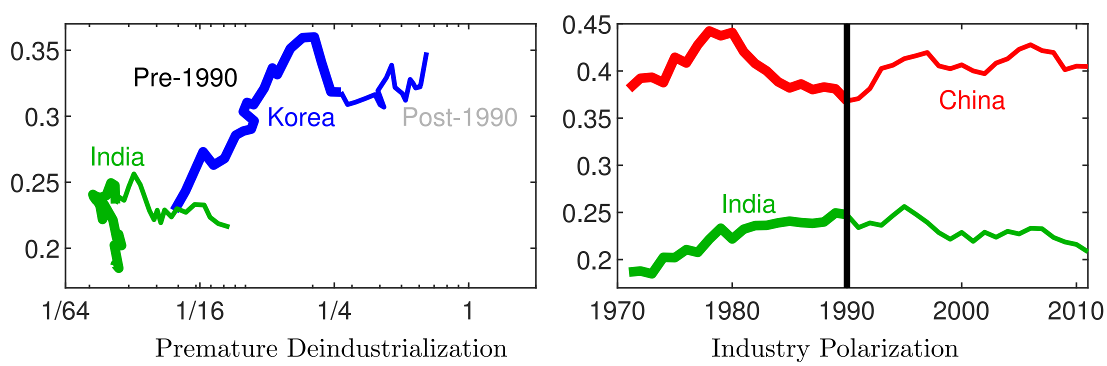
We document two interrelated facts of global structural change. First, we contribute to the evidence on *premature deindustrialization*: countries that have developed more recently tend to experience a greater share of resources effectively "bypassing" manufacturing, transitioning directly from agriculture to services. Second, we highlight a rising cross-country dispersion in manufacturing value-added shares over time, a phenomenon we refer to as *industry polarization*. Before presenting the cross-country evidence, we illustrate these dynamics with brief case studies of India, South Korea, and China.

## 2.1 Illustrative Examples: India, South Korea, and China

Owing to the rapid development of its IT and health services industries, India is often cited as a country that has bypassed manufacturing, transitioning directly from agriculture to services. Of course, this is not literally true, but the data strongly suggest premature deindustrialization for India. A comparison with South Korea provides a clear contrast. The left panel of Figure 1 plots manufacturing value-added shares against income per capita for both countries for each year between 1971 and 2011. South Korea's manufacturing value-added share displays the familiar hump-shaped pattern with respect to income per capita (and time), peaking at 0.36. By contrast, India's manufacturing value-added share displays only a modest hump pattern, peaking at just 0.26. In 2011, India's income per capita was 9 percent of the US, and its manufacturing value-added share was 0.21. When South Korea reached the same relative income level in 1976, its manufacturing value-added share was 0.29—eight percentage points higher than India's. These contrasting trajectories underscore the phenomenon of premature deindustrialization.[3]

While South Korea's experience was fairly typical among early industrializers, late industrializers have followed more diverse paths. For example, China has emerged as the quintessential growth miracle and the world's manufacturing powerhouse, sharply contrasting with India. The right panel of Figure 1 illustrates manufacturing value-added shares for India and China over time. Both countries began integrating into the global economy in the early 1990s. Over the 1990–2011 period, China's manufacturing value-added share averages about 40 percent and rises by 3.7 percentage points. By contrast, India's share falls by 4 percentage points over the same period. These divergent paths depict the growing dispersion in manufacturing value-added shares across countries in the post-1990 period—industry polarization. This example illustrates that not all late industrializers are destined for low manufacturing shares. Rather, it illustrates that late industrializers are more likely to experience low shares compared to their early-industrializing counterparts.

Figure 1: Case Studies: India, South Korea, and China




Notes: In both panels, the y-axis represents the manufacturing value-added share. In the left panel, the x-axis shows real income per capita at PPP prices relative to United States in 2011, while in the right panel, the x-axis shows the year. Thick lines correspond to the pre-1990 period, and thin lines to the post-1990 period.

In all three countries, trade appears to play a significant role for both patterns.[4] For example, South Korea's rapid industrialization coincided with extensive trade-promoting

[3]South Korea's experience resembles that of early industrializers, such as Japan, Taiwan, France, Italy, Spain, and Denmark, but contrasted with that of later industrializers, such as Mexico, Brazil, and Indonesia, as also documented in Huneeus and Rogerson (2024). See Rodrik (2016) and Amirapu and Subramanian (2015) for further discussions of India's premature deindustrialization.

[4]Rodrik (2016) presents suggestive evidence that trade plays a role in premature deindustrialization.

reforms starting in the early 1960s.[5] The country moved rapidly from manufacturing net export deficits to surpluses, so that at its manufacturing value-added share peak, South Korea's manufacturing net export surplus was 4.5 percent of GDP. At that time, global competition remained relatively limited, allowing many early industrializers to follow broadly similar paths of development and structural change. Trade integration in India and China, however, occurred decades later under significantly different global conditions.[6] By this time, the global technological frontier had advanced significantly and international competition had intensified, revealing India's comparative advantage in services and China's in manufacturing. Indeed, from 1990 to 2011, India's manufacturing net exports as a share of GDP declined by 5 percentage points, while China's increased by more than 8 percentage points. These changes mirror the changes in these countries' manufacturing value-added shares.[7]

## 2.2 Cross-Country Evidence

We now explore whether the evidence from the earlier examples applies more broadly across countries. 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

[5]These reforms included a "duty drawback" system, eliminating tariffs on the imported inputs used for exported goods. See Uy, Yi, and Zhang (2013) and Connolly and Yi (2015) for details.

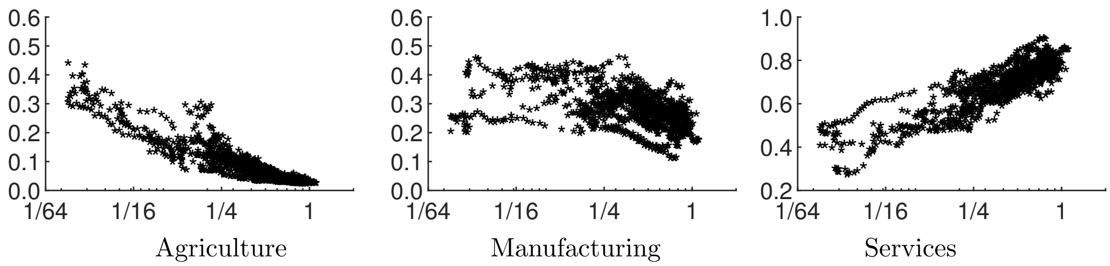
[6]India's trade integration in the 1990s included tariff reductions, easing import licensing, and eliminating industrial licensing requirements for most sectors. China liberalized manufacturing trade in the 1980s through special economic zones, followed by broader tariff cuts in the 1990s, and then WTO accession in 2001.

[7]Brazil offers another useful comparison. Its trade integration after 1990 was far more modest than China's and lost to China in manufacturing comparative advantage. In the 1980s, Brazil's manufacturing net export share exceeded China's by 3.3 percentage points, but by 1991–2011, Brazil trailed China by 3.2 percentage points. This reversal amounts to more than half of the 12.6 percentage-point gap in manufacturing value-added shares between the two countries.

Industrial Development Organization (UNIDO), the Groningen Growth and Development Centre (Timmer, de Vries, and de Vries, 2014, GGDC), and EU KLEMS.

**Premature Deindustrialization** Figure 2 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 2: 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.

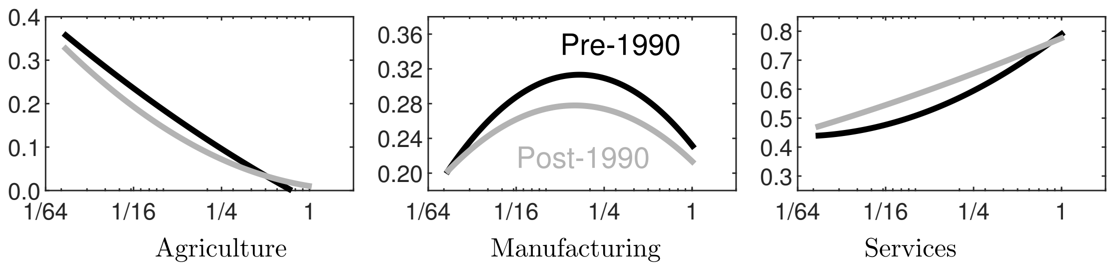
What is less known is that the hump pattern of the manufacturing value-added share tends to be higher for early industrializers than later ones. We now establish the pattern of premature deindustrialization systematically. Following the analysis in Rodrik (2016), we estimate the relationships for the 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:

$$\mathrm{va}_{n,t}^{j} = \alpha_n^j + (\beta_{0,\mathrm{pre}}^j + \beta_{1,\mathrm{pre}}^j y_{n,t} + \beta_{2,\mathrm{pre}}^j y_{n,t}^2)\mathbb{1}_{t\in\mathrm{pre}} + (\beta_{1,\mathrm{post}}^j y_{n,t} + \beta_{2,\mathrm{post}}^j y_{n,t}^2)\mathbb{1}_{t\in\mathrm{post}} + \epsilon_{n,t}^j, \quad (1)$$

where $\mathrm{va}_{n,t}^j$ 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 $\alpha_n^j$ 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 $\beta_0^j$ 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 premature deindustrialization is occurring.[8] Hence, Figure 3 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 typical country's fixed effect to be the average of the estimated country fixed effects. We then trace out the predicted sectoral value-added shares the entire income path for both the pre-1990 and post-1990 periods, separately, using the estimated coefficients in equation (1).

Figure 3: Premature Deindustrialization




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 all 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 premature 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.[9]

We conduct robustness checks on the pattern of premature deindustrialization in Appendix B and confirm (i) the statistical and economic significance of deindustrialization

[8]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 premature deindustrialization. We report the results from this simple, illustrative specification in Table B.1.

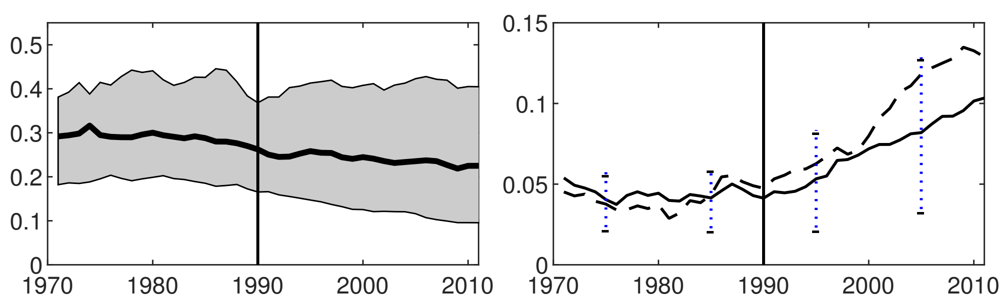
[9]Rodrik (2016) documents another aspect of premature deindustrialization: a decline over time in the income level at which the manufacturing peak occurs. This pattern does not appear in our sample, which includes a relatively larger share of advanced economies compared to Rodrik's.

(Table B.1), and (ii) the presence of premature deindustrialization in a larger sample of 95 countries (left panel of Figure B.1).

**Industry 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 4 shows the cross-country distribution in manufacturing 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. The fall in the median share, coupled with rising dispersion, suggests that deindustrialization is not uniform. Instead, manufacturing value-added shares have been increasingly polarized since 1990.

Early industrializers followed a broadly similar, hump-shaped trajectory in manufacturing, while later industrializers have displayed diverse pathways. Some countries experienced premature deindustrialization, never reaching the higher peak manufacturing value-added shares seen among early industrializers, while others managed to sustain or even expand their manufacturing shares for extended periods. India and China showcase these contrasting experiences, as illustrated in Figure 1. Sinha (2021) and Huneeus and Rogerson (2024) provide additional evidence highlighting such divergent experiences, particularly when comparing late industrializers in Latin America with their counterparts in Asia.

Figure 4: Industry Polarization




Cross-Country Distribution    Log-variance

Notes: In the left panel, the middle line plots the median manufacturing value-added share 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 cross-country variance of the log-manufacturing value-added share over time (x-axis), with 95% confidence intervals (based on 1000 bootstrap samples) reported at 10-year intervals starting from 1975. The dashed line depicts the GDP-weighted variance of the log-manufacturing share. ROW is excluded from all calculations.

We quantify the degree of polarization over time using the variance of the log manufacturing value-added share across countries.[10] The right panel of Figure 4 shows that the variance

[10]Our concept is different from measures of sectoral specialization or concentration, such as those used

was relatively flat prior to 1990, then doubled from 0.045 in 1990 to 0.103 in 2011. Additionally, we plot the GDP-weighted cross-country variance of the log-manufacturing share as a dashed line. The GDP-weighted variance exhibits an even sharper post-1990 rise than its unweighted counterpart, indicating a more pronounced global divergence in manufacturing shares once economic size is taken into account.

Appendix B reports the variance of the manufacturing share for a larger sample of 95 countries, confirming the post-1990 rise in dispersion, even though the log-variance declined between 1970 to 1990. Figure C.2 in the appendix illustrates the corresponding patterns for agriculture and services; neither sector displays increased dispersion over time.

# 3 Model

In this section, we introduce a general equilibrium model of global structural change. Following Uy, Yi, and Zhang (2013), Święcki (2017), and Sposi (2019), we employ a multi-country Ricardian trade model with three-sectors: agriculture, industry, and services. Time is discrete, agents have perfect foresight, and trade is subject to "iceberg" trade costs. Each country features a representative household with non-homothetic preferences, as well as variety firms, composite firms, and bundle firms. Exogenous sectoral productivity and trade costs, both time-varying and country-specific, drive structural change in the model. Two novel departures distinguish our model from the existing open economy structural change models: scale effects in production and endogenous capital accumulation.

## 3.1 Households

A representative household in each country owns the raw factors of production (capital and labor) and chooses 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 a discount factor shock, capturing external forces that affect saving dynamics, such as demographics, capital taxes, and other distortions.

in Imbs and Wacziarg (2003) and related research. In Imbs and Wacziarg (2003), indices like the Gini or Herfindahl measure concentration across sectors within each country are plotted against per capita income. By contrast, our measure captures dispersion in manufacturing value-added across countries over time.

Drawn from Comin, Lashkari, and Mestieri (2021), aggregate consumption is defined implicitly as a non-homothetic CES bundle over the sector composite goods $c^j_{n,t}$:

$$\sum_{j\in\{a,m,s\}} \omega^j_{c,n} \left(\frac{C_{n,t}}{L_{n,t}}\right)^{\frac{1-\sigma_c}{\sigma_c}\varepsilon^j_c} \left(\frac{c^j_{n,t}}{L_{n,t}}\right)^{\frac{\sigma_c-1}{\sigma_c}} = 1. \tag{3}$$

Here, $\sigma_c > 0$ governs the elasticity of substitution across sectors (*price elasticity*), and $\varepsilon^j_c > 0$ governs the *scale elasticity* of sector-$j$ consumption (commonly referred to as the income elasticity in consumption demand).[11] When the scale elasticities $\varepsilon^j_c$ are equal at $\bar{\varepsilon}$, the function becomes homothetic and homogeneous of degree $\bar{\varepsilon}$. Further, when $\bar{\varepsilon} = 1$, equation (3) exhibits constant returns to scale and reduces to a standard homothetic CES aggregator. Finally, when the elasticity of substitution $\sigma_c$ is also set to one, the formulation simplifies to Cobb-Douglas. The weights $\omega^j_{c,n}$ represent the relative importance of each sector within the consumption bundle. They are country-specific and capture time-invariant factors omitted from the model, such as taste, geography, or institutional characteristics.

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

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

where the left hand side captures the expenditure on consumption and investment $X_{n,t}$. Specifically, $p^j_{n,t}$ is the price of sector-$j$ good, while $P^x_{n,t}$ and $P^c_{n,t}$ are the average prices per unit of investment and consumption bundles, respectively. The right hand side represents income, adjusted for trade imbalances. Households earn returns on capital $K_{n,t}$ and labor $L_{n,t}$ at rates $R_{n,t}$ and $W_{n,t}$, respectively. Following Caliendo et al. (2018), the model abstracts from international borrowing and lending, treating trade imbalances as transfers. Specifically, a pre-determined share of GDP, $\phi_{n,t}$, is allocated to a global portfolio, which redistributes a per-capita lump-sum transfer $T^P_t$ to all countries to ensure balanced global trade. Country $n$'s net exports are thus given by $\phi_{n,t}(R_{n,t}K_{n,t} + W_{n,t}L_{n,t}) - L_{n,t}T^P_t$.[12]

The law of motion for the capital stock specifies that the investment bundle augments

[11] An alternative approach to modeling non-homothetic preferences is the PIGL formulation in Boppart (2014). While the two specifications share some features, they differ in whether the elasticity of substitution remains constant.

[12] While the allocation share $\phi_{n,t}$ is exogenous, the transfers $T^P_t$ adjust endogenously to clear the global market, which is particularly useful in the counterfactual analysis.

the existing stock subject to depreciation and adjustment costs:

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

where $\delta$ is the depreciation rate, and $\lambda \in [0,1]$ governs adjustment costs, following Lucas and Prescott (1971). When $\lambda = 1$ there are no adjustment costs. When $\lambda < 1$, the efficiency of investment decreases with respect to its proportion of the existing capital stock, while $\lambda = 0$ implies infinite adjustment costs.

**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. Aggregate consumption and investment choices are determined by an intertemporal Euler equation:

$$\frac{C_{n,t+1}/L_{n,t+1}}{C_{n,t}/L_{n,t}} = \beta \left(\frac{\psi_{n,t+1}}{\psi_{n,t}}\right) \left(\frac{\frac{R_{n,t+1}}{P^x_{n,t+1}} - \Phi_2\left(K_{n,t+2}, K_{n,t+1}\right)}{\Phi_1\left(K_{n,t+1}, K_{n,t}\right)}\right) \left(\frac{P^x_{n,t+1}/P^c_{n,t+1}}{P^x_{n,t}/P^c_{n,t}}\right), \tag{6}$$

where $\Phi_i$ denotes the derivative of the investment function with respect to the $i^{\text{th}}$ argument.[13]

The intratemporal decisions are characterized by the following first order conditions:

$$\frac{p^j_{n,t} c^j_{n,t}}{P^c_{n,t} C_{n,t}} = (\omega^j_{c,n})^{\sigma_c} \left(\frac{p^j_{n,t}}{P^c_{n,t}}\right)^{1-\sigma_c} \left(\frac{C_{n,t}}{L_{n,t}}\right)^{(1-\sigma_c)(\varepsilon^j_c - 1)}, \tag{7}$$

where the price index for consumption is given by:

$$P^c_{n,t} = \left(\sum_{j \in \{a,m,s\}} (\omega^j_{c,n})^{\sigma_c} (p^j_{n,t})^{1-\sigma_c} \left(\frac{C_{n,t}}{L_{n,t}}\right)^{(1-\sigma_c)(\varepsilon^j_c - 1)}\right)^{\frac{1}{1-\sigma_c}}. \tag{8}$$

With non-identical scale elasticities, changes in the scale of consumption also impact sectoral consumption allocations. The sector with the greatest scale elasticity $\varepsilon^j_c$ will realize the greatest increase in spending in response to an increase in per-capita consumption. 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

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

from a sector with a higher scale elasticity. The magnitudes of the price and scale effects are governed by $1-\sigma_c$ and $(1-\sigma_c)(\varepsilon_c^j - 1)$, respectively.

## 3.2 Firms

The model economy features three types of firms: variety firms, composite firms, and bundle firms. Each variety firm specializes in a tradable variety, indexed by $v \in [0,1]$, within its sector and produces with capital, labor and sector-specific intermediate input bundles. Composite firms source these varieties globally and produce a sector-level CES composite of the varieties to meet domestic demand by households for consumption and by assembly firms. Bundle firms combine the sectoral composites into investment bundles and sector-specific intermediate-input bundles in a non-homothetic-CES fashion.

**Variety Firms** Varieties are produced using capital, labor and sectoral intermediate bundles. Country $n$'s technology for variety $v$ in sector $j$ is:

$$y_{n,t}^j(v) = a_n^j(v)\left(A_{n,t}^j k_{n,t}^j(v)^\alpha \ell_{n,t}^j(v)^{1-\alpha}\right)^{\nu_n^j} E_{n,t}^j(v)^{1-\nu_n^j}. \tag{9}$$

Production is a Cobb-Douglas aggregate of value added factors and an intermediate bundle, with a country-specific, time-invariant value-added share $\nu_n^j \in [0,1]$. Value added is a Cobb-Douglas aggregate of capital $k_{n,t}^j(v)$ and labor $\ell_{n,t}^j(v)$ with capital share $\alpha$. $E_{n,t}^j(v)$ denotes the intermediate input bundle.

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 $F^j(a) = \exp(-a^{-\theta^j})$. Without loss of generality, we assume the idiosyncratic productivity draws are constant over time.

Markets for each tradable variety are perfectly competitive. Given factor prices and prices for output and the intermediate input bundle, 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 the price of sector-$j$'s intermediate input bundle.

Optimality implies that total expenditure on factors and the intermediate input bundles exactly equals the value of output with the variety index suppressed:

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

**Composite Firms** Within each sector, composite firms combine all of the varieties to construct a sectoral composite good in a homothetic CES fashion:

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

where the elasticity of substitution between varieties, $\eta$, is constant across countries, sectors, and time, and $q^j_{n,t}(v)$ is the quantity of variety $v$ in the sector-$j$ composite good $Q^j_{n,t}$.

Composite firms source each variety globally from the cheapest origin location subject to physical iceberg trade costs: they purchase $d^j_{n,i,t} \geq 1$ units of any variety of sector $j$ from country $i$ in order for one unit to arrive at country $n$ in time $t$; $d^j_{n,i,t} - 1$ units melt away in transit. The trade costs vary across country pairs, across sectors, and over time. As a normalization we assume that $d^j_{n,n,t} = 1$ 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:

$$\pi^j_{n,i,t} = \frac{\left((A^j_{i,t})^{-\nu^j_i} u^j_{i,t} d^j_{n,i,t}\right)^{-\theta^j}}{\sum_{i'=1}^{N} \left((A^j_{i',t})^{-\nu^j_{i'}} u^j_{i',t} d^j_{n,i',t}\right)^{-\theta^j}}, \tag{10}$$

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

$$u^j_{i,t} = \left(\frac{R_{i,t}}{\alpha \nu^j_i}\right)^{\alpha \nu^j_i} \left(\frac{W_{i,t}}{(1-\alpha)\nu^j_i}\right)^{(1-\alpha)\nu^j_i} \left(\frac{P^{e,j}_{i,t}}{1-\nu^j_i}\right)^{1-\nu^j_i}. \tag{11}$$

Markets for sectoral composite goods are also perfect competitive, giving rise to the price of the sector-$j$ composite good in country $n$:

$$p^j_{n,t} = \gamma_j \left[\sum_{i=1}^{N} \left((A^j_{i,t})^{-\nu^j_i} u^j_{i,t} d^j_{n,i,t}\right)^{-\theta^j}\right]^{-\frac{1}{\theta^j}}, \tag{12}$$

where $\gamma^j$ is a constant depending on $\eta$ and $\theta^j$.

**Bundle Firms** Bundle firms combine sectoral composites to make either investment bundles or sector-specific intermediate input bundles in a non-homothetic CES fashion, similar to the consumption bundle in equation (3). Specifically, for sector-$j$ intermediate input bundles, the elasticity of substitution across composite inputs is $\sigma^j_e$, the corresponding scale elasticities are $\varepsilon^{j,k}_e$, and the weights assigned to sectoral inputs are $\omega^{j,k}_{e,n}$. Analogously, the parameters for investment bundles are $\sigma_x, \varepsilon_x^j$, and $\omega_{x,n}^k$.

Given that the bundling technology is non-constant-returns-to-scale, we assume a single bundle firm for each bundle. This bundle firm takes as given the total demand for its bundle, $E_{n,t}^j$ or $X_{n,t}$, and the sectoral composite prices, $\{p_n^j\}_{j\in\{a,m,s\}}$, and chooses the composite input mix and the bundle price to maximize profits. Following Baumol, Panzar, and Willig (1982), the bundle firm operates in a contestable market, where it faces the threat of free entry by competitors if profits are positive. Thus, the assembly firm prices its bundle, $P_{n,t}^{e,j}$, at average cost, ensuring zero profit. The optimal spending shares across sectoral composites are analogous to sectoral consumption expenditure shares in equation (7). To avoid repetition, we delegate these equations to Table G.1 in the appendix.

At the optimum, revenue equals total cost $\Omega_n^j$, which is (suppressing time subscripts):

$$P_n^{e,j} E_n^j \equiv \Omega_n^j(\mathbf{p_n}, E_n^j) = L_n \times \left( \sum_{k\in\{a,m,s\}} (\omega_{e,n}^{j,k})^{\sigma_e^j} (p_n^k)^{1-\sigma_e^j} \left(\frac{E_n^j}{L_n}\right)^{(1-\sigma_e^j)\varepsilon_e^{j,k}} \right)^{\frac{1}{1-\sigma_e^j}}, \tag{13}$$

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 with respect to scale $E_n^j$, the ratio of marginal to average cost, is given by:

$$\frac{\partial \Omega_n^j(\mathbf{p}_n, E_n^j)}{\partial E_n^j} \frac{E_n^j}{\Omega_n^j} = \sum_{k\in\{a,m,s\}} h_n^{j,k} \varepsilon_e^{j,k} \equiv \mathcal{E}_{e,n}^j, \tag{14}$$

where $h_n^{j,k}$ denotes the cost share of sector-$k$ composite in bundle $j$. The cost-share-weighted average of scale parameters, $\mathcal{E}_{e,n}^j$, represents the inverse of the returns to scale. In particular, if $\mathcal{E}_{e,n}^j > 1$, then there are decreasing returns to scale, so that the average cost (and bundle price) increases with the sector-$j$ scale. The opposite is true with $\mathcal{E}_{e,n}^j < 1$.

Differences in scale elasticities across composite inputs (e.g., $\varepsilon_e^{j,k} \neq \varepsilon_e^{j,k'}$) causes the returns to scale to vary over time and across countries due to variation in the cost shares, $h_n^{j,k}$. In contrast, if the bundling technology is homothetic (i.e., $\varepsilon_e^{j,k} = \bar{\varepsilon}_e^j$ for all $k$), then $\mathcal{E}_{e,n}^j = \bar{\varepsilon}_e^j$ and the returns to scale are invariant to changes in the cost shares and are identical across countries and over time. If $\bar{\varepsilon}_e^j$ is further restricted to 1, then $\mathcal{E}_{e,n}^j = 1$, indicating constant returns to scale and reducing the bundle technology to a standard CES aggregator.

## 3.3 Equilibrium

The model is summarized by time invariant parameters ($\beta$, $\sigma_c$, $\sigma_x$, $\sigma_e^j$, $\varepsilon_c^j$, $\varepsilon_x^j$, $\varepsilon_e^{j,k}$ $\omega_{c,n}^j$, $\omega_{x,n}^j$, $\omega_{e,n}^{j,k}$, $\nu_n^j$, $\theta^j$, $\alpha$, $\delta$, $\lambda$, $\eta$), time varying exogenous processes of sectoral productivities and trade costs $\{A_{n,t}^j,\ d_{n,i,t}^j\}$, the initial capital stock $K_{n,1}$, processes of labor endowment, discount factor shifters, and those controlling trade imbalances $\{L_{n,t}, \psi_{n,t}, \phi_{n,t}\}$. We now define the competitive equilibrium, with the corresponding conditions summarized in Table G.1.

**Definition.** A sequential equilibrium consists sequences of allocations $\{C_{n,t},\ X_{n,t},\ K_{n,t},\ c^j_{n,t},\ x^j_{n,t},\ k^j_{n,t},\ \ell^j_{n,t},\ E^j_{n,t},\ e^{j,k}_{n,t},\ \pi^j_{nit}\}$ and prices $\{P^c_{n,t},\ P^x_{n,t},\ P^{e,j}_{n,t},\ p^j_{n,t},\ R_{n,t},\ W_{n,t}\}$ that: (1) satisfy households' optimization, (2) satisfy all firms' optimization, and (3) clear markets.

The primary exogenous forces driving structural change are sectoral productivity and and trade costs, which operate through three channels: non-homothetic demand, price effects, and specialization. We provide an intuitive overview of how these interact in equilibrium. Consider first a closed economy with uniform productivity growth across sectors, homothetic bundling in investment and intermediates, and non-homothetic preferences. Here, relative prices remain constant, so sectoral expenditure and value-added shares evolve solely due to income-driven demand shifts: sectors with higher (lower) income elasticities gain (lose) expenditure and value-added shares over time.

Introducing SBTC alters this dynamic by changing relative prices. Faster productivity growth in a sector lowers its relative price, while gross complementarity shifts expenditure toward sectors with slower productivity growth. Under non-homothetic production structures, sectoral demand for intermediate and investment evolve in response to changes in production and investment. Moreover, returns to scale further influence relative prices: sectors with steeper supply curve (higher cost elasticities) experience rising relative price and expanding share in both final and intermediate expenditures.

Finally, international trade adds a global dimension. Trade, in and of itself, transmits SBTC across countries affecting relative prices. In addition, declining trade costs and evolving comparative advantages drive sectoral specialization and income growth. These forces amplify the transmission of foreign technological change, magnify scale effects, and shape relative prices. Sectors with steeper trade-cost declines undergo larger relative price reductions, reinforcing these effects. Moreover, countries gaining comparative advantage in manufacturing see rising manufacturing net exports, boosting manufacturing shares.

# 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 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.[14] 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 (E.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 premature 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.

[14]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.

The estimation of consumption demand parameters relies on the model-implied relationship between relative sectoral expenditures, relative prices and aggregate consumption—equation (7). The identification of elasticities comes from within-country variation over time, and the sector weights $\omega^j_{c,n}$ are constant 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.

### 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 aggregate consumption. We express the optimal sectoral expenditure and the total expenditure functions in terms of changes (see Appendix E 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

$$\frac{\widehat{p^j_{n,t}c^j_{n,t}}}{\widehat{p^m_{n,t}c^m_{n,t}}} = \left(\frac{\widehat{p}^j_{n,t}}{\widehat{p}^m_{n,t}}\right)^{1-\sigma_c} \left(\frac{\widehat{C}_{n,t}}{\widehat{L}_{n,t}}\right)^{(1-\sigma_c)(\varepsilon^j_c-\varepsilon^m_c)} + v^j_{n,t}, \qquad j \in \{a,s\} \tag{15}$$

$$\frac{\widehat{P^c_{n,t}C_{n,t}}}{\widehat{L}_{n,t}} = \left(\sum_{k\in\{a,m,s\}} \left(\frac{p^k_{n,t-1}c^k_{n,t-1}}{P^c_{n,t-1}C_{n,t-1}}\right) (\widehat{p}^k_{n,t})^{1-\sigma_c} \left(\frac{\widehat{C}_{n,t}}{\widehat{L}_{n,t}}\right)^{(1-\sigma_c)\varepsilon^k_c}\right)^{\frac{1}{1-\sigma_c}}. \tag{16}$$

The left-hand side of equation (15) 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 the sectoral expenditure share, depending on the observed changes in the relative price and the unobserved change in per-capita consumption.[15] The error between the predicted and observed sectoral expenditure share is $v^j_{n,t}$.[16] Had we observed $\widehat{C}_{n,t}$, we could estimate the elasticities directly by applying a non-linear least square regression. However, 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 (16), to infer $\widehat{C}_{n,t}$ from the observed changes in per-capita expenditure, sectoral spending shares in

[15] One advantage of expressing the estimating equation in terms of changes is that sector weights drop out, effectively being replaced by the observed sectoral spending shares over time. This simplification reduces the number of parameters to estimate in the nonlinear least squares optimization.

[16] The error term captures a combination of unmodeled preference shocks, potential measurement error in sectoral consumption or prices, and any deviations from the relationship implied by the model.

the prior year, and changes in sectoral prices, given a set of the elasticities.

As discussed in Hanoch (1975), the scale elasticities can be identified only up to a constant of proportionality using sectoral demand shares and prices, due to Engel aggregation. First, this constant is inconsequential for sector expenditure shares and for the estimated price elasticity. Second, this constant has no effect on consumption outcomes, as it affects only the cardinal utility, not the ordinal preferences. However, in the context of the production structure for assembly firms, the constant governs the degree of returns to scale. Given the well-known challenge in identifying sectoral returns to scale, we normalize the constant so that the average—across countries and time—returns to scale are one in each bundling technology. For consistency, we normalize scale elasticities in preferences analogously.

We use an iterative estimation procedure similar to the one in Deaton and Muellbauer (1980) to estimate AIDS demand models with non-homotheticities. We start with an initial guess of the elasticities $(\sigma_c, \varepsilon_c^a, \varepsilon_c^m, \varepsilon_c^s)$. Given these elasticities, we solve for $\widehat{C}_{n,t}$ using equation (16). With the implied values of $\widehat{C}_{n,t}$, we next estimate $(\sigma_c, \varepsilon_c^a/\varepsilon_c^m, \varepsilon_c^s/\varepsilon_m^a)$ via non-linear least squares using equation (15).[17] We then recover $\varepsilon_c^m$ such that the sample average of $\mathcal{E}_{c,n}^j$ in equation (14) is one. This yields an updated set of elasticities $(\sigma_c, \varepsilon_c^a, \varepsilon_c^m, \varepsilon_c^s)$. The procedure continues until convergence, yielding the final elasticity estimates. Lastly, we recover the associated $\widehat{C}_{n,t}$, which we utilize later on.

As noted above, we apply a similar procedure to estimate the elasticities for the investment bundle and the three intermediate input bundles. Table 1 reports the estimates. Each system involves estimating 4 parameters, pooling data across 3 sectors and 28 countries over 40 year-to-year changes (excluding ROW). Standard errors (in parentheses) are bootstrapped using 1000 resamples with replacement and errors are clustered at the country level.

We test our specification against a homothetic alternative ($\varepsilon^a = \varepsilon^m = \varepsilon^s$). The reported $F$ statistics reject the homothetic CES specification across all five systems. While non-homothetic consumption demand is a well-established feature in the structural change literature, non-homothetic structures for investment and intermediate inputs have received little attention. In what follows, we discuss the elasticity estimates for each system in turn.

**Consumption Bundle** The first column of Table 1 reports the results for the consumption demand. The price elasticity, $\sigma_c$, is 0.23, indicating sectoral composites are complements. This implies that consumption spending tends to shift to sectors with rising relative prices over time. The estimated scale elasticities vary significantly across sectors: services exhibit the highest scale elasticity, followed by manufacturing, with agriculture being the least scale elastic. This pattern implies that as the scale of consumption grows over time, expenditure

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

Table 1: Elasticity Estimates

| | Final demand | | Intermediate demand | | |
|---|---|---|---|---|---|
| | Cons | Inv | Agr | Mfg | Srv |
| **Price elasticities** | | | | | |
| $\sigma$ | 0.233 | 0.292 | 0.225 | 0.012 | 0.265 |
| | (0.046) | (0.075) | (0.042) | (0.003) | (0.054) |
| **Scale elasticities** | | | | | |
| $\varepsilon^a$ | 0.086 | 0.287 | 1.152 | 0.414 | 0.539 |
| | (0.004) | (0.031) | (0.107) | (0.040) | (0.087) |
| $\varepsilon^m$ | 0.860 | 0.955 | 0.917 | 1.112 | 0.833 |
| | (0.048) | (0.050) | (0.061) | (0.013) | (0.031) |
| $\varepsilon^s$ | 1.146 | 1.031 | 0.946 | 0.976 | 1.108 |
| | (0.020) | (0.026) | (0.054) | (0.038) | (0.016) |
| $R^2$ | 0.21 | 0.06 | 0.05 | 0.31 | 0.11 |
| $F_{(H_0\colon \varepsilon^j=1)}$ | 549.6 | 113.3 | 122.6 | 864.7 | 191.1 |

Notes: Each column reports the elasticity estimates for one of the five demand systems. For each system, we estimate four parameters to from 2240 observations using constrained NLS regressions. Within each demand system, the scale elasticities are identified relative to a constant, and then the constant is normalized so that the inverse-returns to scale for each bundle average to one in our sample: $\mathcal{E}^j = \sum_{n,t} h^j_{n,t}\varepsilon^j = 1$, where $h^j$ is sector's $j$'s demand share. 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 $\varepsilon^j = 1$). 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.

shifts towards services and away from agriculture.

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 Bundle** The results are reported in the second column of Table 1. As in the case of consumption demand, agriculture has the lowest scale elasticity, while services exhibit the highest scale elasticity in the investment bundle. The price elasticity $\sigma_x$ is 0.29, indicating a strong degree of complementary. Existing estimates of this elasticity in the literature, typically based on CES investment bundles without scale effects, span a wide wage. For example, Herrendorf, Rogerson, and Valentinyi (2021) estimate this elasticity to be 0 between goods and services using U.S. data, whereas García-Santana, Pijoan-Mas, and

Villacorta (2021) reports an estimate of 0.52 using data from for 49 countries. When we re-estimate our specification excluding scale effects, the resulting price elasticity is 0.38.

**Intermediate Bundle** We next describe the elasticity parameters for intermediate input bundles. As shown in the last three columns of Table 1, sectoral composites are complements in all three sectors' intermediate bundles with estimated price elasticities of $\sigma_e^a = 0.23$, $\sigma_e^m = 0.01$, and $\sigma_e^s = 0.27$. These low elasticities imply that as the relative price of manufacturing to services declines, the share of intermediate input spending shifts away from manufacturing and toward services in all sectors. This growing demand for services, driven by input-output linkages, mirrors the shift toward services in final consumption.

The estimated scale elasticities display two unique patterns. First, each sector's bundle displays the highest scale elasticity with respect to its *own-sector* composite input. For instance, in the agriculture bundle, the elasticity is highest for agriculture inputs; likewise, the manufacturing (services) bundle displays the highest elasticity for manufacturing (services) inputs. Second, among the *cross-sector* inputs, there is a consistent ranking: services inputs are the most scale elastic, followed by manufacturing, and then agriculture. Specifically, in the agriculture bundle, services' elasticity exceeds manufacturing's ($\varepsilon_e^{a,s} > \varepsilon_e^{a,m}$); in the manufacturing bundle, services' elasticity exceeds agriculture's ($\varepsilon_e^{m,s} > \varepsilon_e^{m,a}$); in the services bundle, manufacturing's elasticity exceeds agriculture's ($\varepsilon_e^{s,m} > \varepsilon_e^{s,a}$).

### 4.2.2 Calibration of Sectoral Demand Weights

We now explain the calibration of country-specific sectoral weight parameters for the consumption bundle; further details are in Appendix E. Given the estimated elasticities, we set the sector weights $\omega_{c,n}^j$ and the initial level of consumption $C_{n,1}$ to match observed sectoral expenditure shares and total expenditure in equations (7) and (16), respectively, for each country in 1971. With this calibrated $C_{n,1}$, we construct the time series of consumption $C_{n,t}$ using the estimated changes $\widehat{C}_{n,t}$ over time, along with $P_{n,t}^c$ for each country. The weights for the other systems are calibrated in a similar fashion. This approach also yields time series for investment $X_{n,t}$, sector-$j$ intermediate input demand $E_{n,t}^j$, and their associated price indices $P_{n,t}^x$ and $P_{n,t}^{e,j}$. The bundle firms set prices, $P_{n,t}^{e,j}$, based on the average cost for producing $E_{n,t}^j$ units of the intermediate bundle. Because the bundle technology exhibits returns to scale, the average cost $P_{n,t}^{e,j}$ depends on the normalization of scale elasticities. These price series lack direct empirical counterparts and are essential inputs for calibrating the productivity processes in Section 4.3.

### 4.2.3 Remaining Time-Invariant Parameters

We compute $\nu_n^j$ as the initial (1971) ratio of value added to gross output for each sector-country pair. Table 2 reports the cross-country average of this ratio for each sector, along with the $2.5^{\text{th}}$ and $97.5^{\text{th}}$ percentiles. On average, the services sector exhibits the highest ratio, while manufacturing shows the lowest. Following Simonovska and Waugh (2014), we set the trade elasticity in manufacturing to 4, and apply this value to all sectors. The elasticity of substitution between varieties within the composite good plays no quantitative role beyond satisfying $\eta < 1 + \theta^j$ (see Eaton and Kortum, 2002). Following the literature we set $\eta = 2$. The discount factor is set to 0.96 to target an annual real interest rate of 4% in the long run. We set capital's share in value added $\alpha$ at 0.33, as in Gollin (2002), and the annual depreciation rate $\delta$ at 6%, a standard value in macro models. The capital adjustment cost parameter, $\lambda$, is set at 0.83 to match a steady-state investment rate of 0.18.[18]

Table 2: Time-Invariant Parameters

| | | | |
|---|---|---|---|
| | $\nu^a$ | 0.60 | (0.40, 0.84) |
| Ratio of value added to gross output | $\nu^m$ | 0.39 | (0.26, 0.62) |
| | $\nu^s$ | 0.63 | (0.48, 0.80) |
| Trade elasticity | $\theta^j$ | 4 | |
| Discount factor | $\beta$ | 0.96 | |
| Capital share in value added | $\alpha$ | 0.33 | |
| Capital depreciation rate | $\delta$ | 0.06 | |
| Adjustment cost elasticity | $\lambda$ | 0.83 | |

Note: For $\nu_n^j$, we report the mean across countries, along with the $2.5^{\text{th}}$ and $97.5^{\text{th}}$ percentiles in parenthesis.

## 4.3 Time-Varying Exogenous Processes

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

We begin with labor endowments and capital stocks. For each sample country, the labor series $\{L_{n,t}\}$ is taken directly from the data and reflects the numbers of persons engaged across the three broad sectors. The initial capital stock is set to the 1971 value as reported

[18] In the steady state, the investment rate is $\alpha\delta/(\frac{1-\beta}{\lambda\beta} + \delta)$. Our estimated value for the adjustment cost is consistent with that used by Eaton, Kortum, Neiman, and Romalis (2016). Having $\lambda < 1$ proves useful to prevent counterfactually volatile capital stocks in the model. Relative to quadratic capital adjustment costs commonly used in the macro literature, this specification has the feature that investment is endogenously irreversible, which is desirable for two reasons. First, gross fixed capital formation is non-negative in the data. Second, the investment bundle is defined only for positive values in the model.

in the Penn World Table. Capital stocks for subsequent years are built using the investment series $X_{n,t}$, obtained in Section 4.2.2, and the capital accumulation equation (5). Based on the resulting capital stock series, we infer the rental rate of capital, which is then used in the calibration of fundamental productivities and trade costs, as described below.

We calibrate sectoral fundamental productivity series $\{A^j_{n,t}\}$ in two steps. First, we compute measured sectoral productivities using data on sectoral prices, wages, and rental rates. The latter two are calculated as the labor and capital shares of current-USD GDP, divided by employment and capital stock, respectively. Measured productivity is defined as

$$Z^j_{n,t} \equiv B^j_n (R^{\alpha}_{n,t} W^{1-\alpha}_{n,t})^{\nu^j_n} \left(P^{e,j}_{n,t}\right)^{1-\nu^j_n} \Big/ p^j_{n,t}, \tag{17}$$

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 sector-$j$ intermediate-bundle price $P^{e,j}_{n,t}$ is obtained as a by-product of the elasticity estimation in Section 4.2.2. As described in that section, the price of intermediate-input bundles depends on the chosen normalization of the scale elasticities. Hence, the inferred productivity series also varies with this normalization. Because relative prices are jointly determined by returns to scale and sectoral productivity, any change in one necessitates a compensating change in the other. Second, we back out fundamental *gross* productivity—fundamental productivity raised to share of value added in gross output: $(A^j_{nt})^{\nu^j_n}$—from the measured productivities $Z^j_{nt}$ as follows:

$$(A^j_{n,t})^{\nu^j_n} = \gamma^j Z^j_{n,t} \left(\pi^j_{n,n,t}\right)^{\frac{1}{\theta^j}}, \tag{18}$$

which adjusts for Ricardian selection effects, following Finicelli, Pagano, and Sbracia (2013).

Calibrated trade costs $\{d^j_{n,i,t}\}$ reconcile observed trade shares and price differences:

$$d^j_{n,i,t} = \left(\frac{\pi^j_{n,i,t}}{\pi^j_{i,i,t}}\right)^{-\frac{1}{\theta^j}} \left(\frac{p^j_{n,t}}{p^j_{i,t}}\right). \tag{19}$$

If $\pi^j_{n,i,t} = 0$ in the data, we set $d^j_{n,i,t}$ at $10^8$ to ensure that $\pi^j_{n,i,t} \approx 0$ in the model. If the implied cost is less than 1, we set $d^j_{n,i,t} = 1$.[19]

Finally, we calibrate the series for trade imbalances, $\phi_{n,t}$, and preference shifters, $\psi_{n,t}$. The trade imbalance $\phi_{n,t}$ is set at the ratio of net exports to GDP, such that there are no transfers from the global portfolio in the baseline.[20] The initial preference shifter $\psi_{n,1}$ is

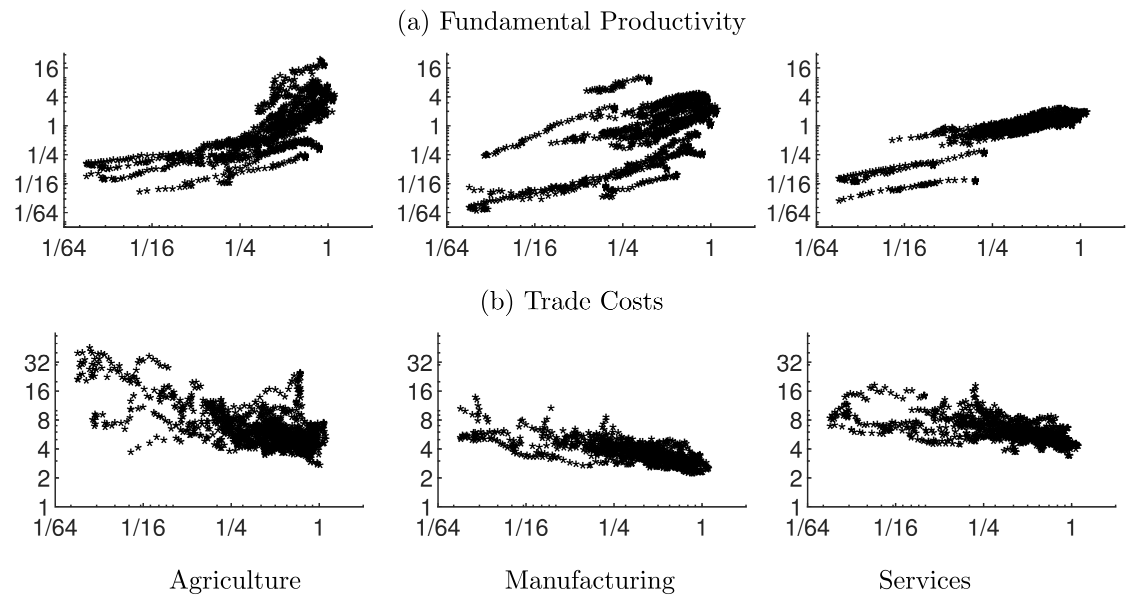
[19] Fewer than 1.2% of the implied trade cost parameters are less than 1. This may reflect the absence of cross-country demand shocks in the model or measurement error in bilateral trade shares or sectoral prices.

[20] In this setup, the current account is given by the exogenous $\phi_{n,t}$ process and the balancing condition of the global portfolio, rather than capital chasing the highest return. Consequently, real interest rates–representing marginal products of capital—may differ across countries, without arbitrage.

normalized to 1 for all countries in 1971. Subsequent shifters $\psi_{n,t+1}$ are chosen to reconcile observed consumption growth with the real rate of return to investment in equation (6).

We now present the estimated series for the two key exogenous drivers of structural change: sectoral fundamental gross productivities and trade costs. The top panel of Figure 5 plots sectoral fundamental gross productivity against income per capita, pooling data across countries and over time. In all three sectors, fundamental gross productivity is strongly positively correlated with income per capita. However, the degree of dispersion around this relationship varies across sectors: conditional on income, productivity variation is largest in manufacturing, followed by agriculture, and smallest in services.

Figure 5: Sectoral Fundamental Productivity and Trade Costs




Notes: The top panel plots sectoral fundamental gross productivity, $(A^j_{n,t})^{\nu^j_n}$, relative to each sector's median level in 1971, against income per capita. The bottom panel plots sectoral trade costs against income per capita. For each country, sectoral trade costs are computed as the weighted mean of export and import trade costs, where the weights correspond to each components share of total trade (the sum of imports and exports). Income per capita is relative to the 2011 US level.

We also examine the patterns of productivity growth over time and how these patterns shape manufacturing comparative advantage. Across the full sample period, the median growth rate is highest in agriculture, followed by manufacturing, and lowest in services.[21] However, the ranking of sectoral productivity growth differs across the income distribution and between time periods. In the pre-1990 period, manufacturing productivity growth ex-

[21]The top panel of Figure C.1 in the appendix illustrates these patterns over time. It also shows that agriculture and manufacturing display greater cross-country variation in productivity than services, as measured by the interquartile ratio in each year. This finding is consistent with Caselli (2005), Restuccia, Yang, and Zhu (2008), and Gollin, Lagakos, and Waugh (2014), and aligns with the Balassa-Samuelson hypothesis.

ceeds services for countries in both top and middle tertiles, while the opposite is true for the bottom tertile. In the post-1990 period, the growth gap between manufacturing and services closes for the bottom tertile, remains unchanged for the top tertile, and widens for the middle tertile. In terms of manufacturing comparative advantage, in 1971, it is weakest at the bottom tertile and strengthens with income per capita, reaching its peak in the top tertile. Over time, as the aforementioned sector-biased productivity growth unfolds, manufacturing comparative advantage weakens for the top tertile, and the disadvantage of the bottom tertile diminishes over time.

The lower panel plots the estimated sectoral trade costs against income per capita, pooling data across countries and over time. For each country, the sectoral trade cost is calculated as the bilateral trade cost average, weighted by the corresponding bilateral sectoral trade flows. Trade costs are generally lower in manufacturing than in agriculture and services. Furthermore, trade costs are negatively correlated with income per capita in all sectors, with this correlation being stronger in agriculture and manufacturing than in services.

Over time, trade costs decline across all sectors, with manufacturing experiencing the steepest reduction. Manufacturing also shows a faster decline in cross-country dispersion of trade costs over time.[22] While these trends reflect the broader process of global trade integration over the past half century, the experience varies across the income distribution. Bottom-tertile countries experience the sharpest decline in trade costs, particularly in the post-1990 period, whereas middle- and top-tertile countries see relatively consistent reductions across both the pre- and post-1990 periods.

## 4.4 Solution Method and Model Fit

With forward-looking households, we first specify the time paths of variables beyond the sample period. Specifically, we assume that each country's investment rate, measured in current prices, converges geometrically to a common value of 0.18 over a 25-year span (2012–2036).[23] Additionally, we hold post-2011 target moments constant at their 2011 values to infer parameters across all periods. We then solve the baseline model numerically, focusing on solving the sequences of capital stocks that satisfy the intertemporal Euler equations.[24] Lastly, we clarify an adjustment made to the model's GDP deflator, defined as a geometric average of sectoral prices weighted by sectoral expenditure shares on consumption and investment. While the model matches sectoral prices by construction, the model-implied GDP deflator

[22]The bottom panel of Figure C.1 in the appendix illustrates these patterns.

[23]Figure H.3 in the appendix depicts the paths of aggregate investment rates and capital-labor ratios for the sample countries. These projections do not impact the baseline results for 1971–2011.

[24]The solution approach follows Ravikumar, Santacreu, and Sposi (2019). See Appendix G for details.

may deviate from its empirical counterpart due to differences in aggregation methods and inaccuracies in model-implied expenditure weights. To reconcile this discrepancy, we introduce a "wedge" to align real income in the baseline model with the data.[25]

After obtaining the equilibrium, we assess the model fit against the data. We first recap which data moments are targeted and which are not. The calibration directly targets observed factor prices (or equivalently, aggregate income), sectoral output prices, and bilateral trade shares over time to identify the time-varying paths of sectoral productivities and bilateral trade costs. In addition, the sectoral weights $\omega_n^j$ are calibrated to match the observed sectoral shares in 1971 for each country. Beyond the initial year, each of the five non-homothetic CES systems specifies four elasticity parameters to fit 2240 data triplets (relative sectoral expenditure shares, relative sectoral prices, and total expenditure) over 40 years for 28 countries and 2 sectoral shares. While all moments are used, they cannot be matched one-for-one since the system is highly over-identified. The limited degrees of freedom requires the model to capture broad, systematic patterns in sectoral shares rather than relying on flexible, time-varying parameters to absorb idiosyncratic variation. This sparse parameterization imposes structure and discipline on the estimation, lending credibility to the functional form assumptions and the economic content of the estimated elasticities.

Since our ultimate goal is to evaluate sectoral value-added shares, it is important to recognize that the mapping from sectoral consumption, investment, and intermediate input shares into value-added shares depends on the ratio of value added to gross output in each sector, $\nu_n^j$. While these ratios vary over time in the data, our model assumes them to be constant. Thus, our model's ability to match sectoral value-added shares is inherently limited by the over-identification of elasticity parameters in the demand shares and the imposed constancy of these sectoral value added to gross output ratios.[26]

We now present the model's implications for sectoral value-added shares over time. The top row of Figure 6 compares the percentage changes in sectoral value-added shares predicted by the model (y-axis) with those observed in the data (x-axis).[27] The model closely tracks the observed pattern, with an average correlation of 0.73 between model-implied and empirical changes across three sectors. When examining sectoral value-added shares in levels, the average correlation rises to 0.93. The bottom row of Figure 6 contrasts the predicted paths for sectoral value-added shares over income per capita *within* a typical country, in both the data and the model. Clearly, the model successfully captures the observed patterns of

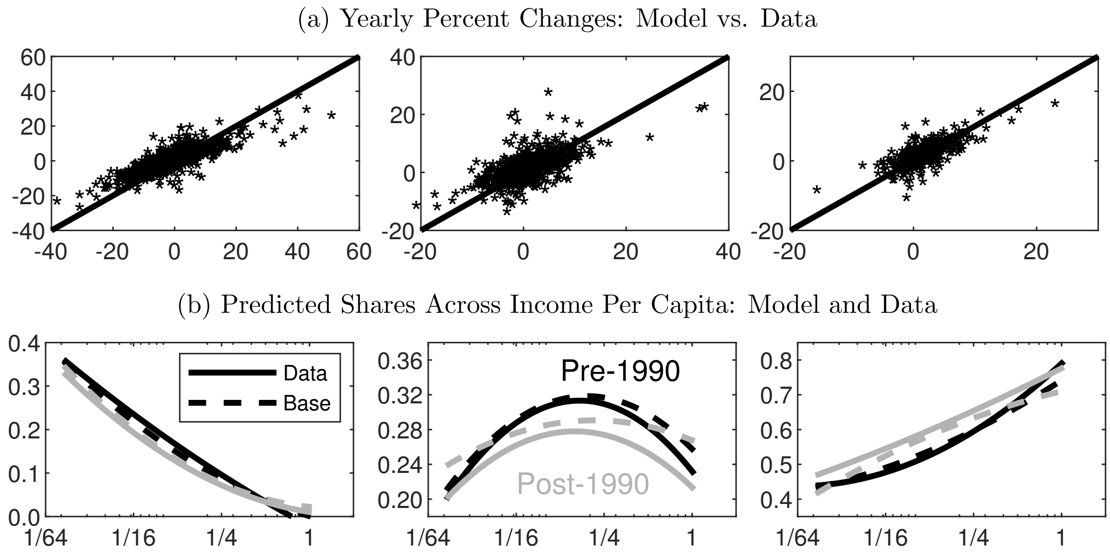
[25]This wedge does not affect equilibrium allocations. In counterfactual experiments, the wedge is held fixed, while the GDP deflator adjusts to accommodate changes in sectoral prices and expenditure weights.

[26]Allowing both the sectoral demand weights $\omega_n^j$ and the value added to gross output ratios $\nu_n^j$ to vary over time would enable the model to fully match the observed sectoral value-added shares.

[27]Percentage changes in agriculture are large due to some small value-added shares in this sector.

structural change, with the pre-1990 curve aligning more closely with the data than the post-1990 curve. Moreover, the model generates a decline of 2.6 percentage points in the peak share of the manufacturing hump from the pre-1990 to post-1990 periods—this corresponds to about three-quarters of the observed 3.5-percentage point decline in the data.

Figure 6: Baseline Model Fit: Sectoral Value-Added Shares

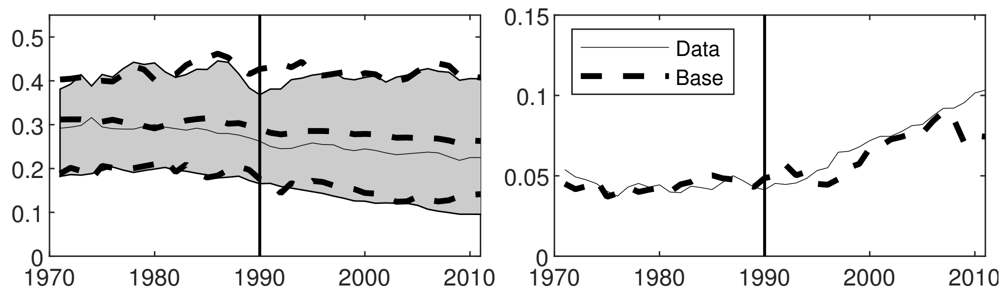



Agriculture Manufacturing Services

Note: The upper-row (a) 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 respective correlations (R-squared) between the model and data are 0.84 (0.71) for agriculture, 0.62 (0.38) for manufacturing, and 0.72 (0.52) for services. The bottom-row (b) 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 baseline model also replicates the pattern of industry polarization over time. The left panel of Figure 7 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 observed log-variance increased from and average of 0.043 to 0.074 from the pre-1990 period to the post-1990 period. Our baseline model yields an increase in the average log-variance from 0.043 to 0.064 across the two periods, so it explains more than two-thirds of industry polarization. Underpinning this result is the fact that trade integration over time increasingly reveals comparative advantage, thus leading to more specialization in manufacturing, and in other sectors. This generates diverse development trajectories widening the dispersion in value-added shares across countries. Similar results for agriculture and services are presented in Figure C.2 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 7: 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 $100^{\text{th}}$ 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). ROW is excluded from the calculations.

Finally, we demonstrate that the calibrated model effectively reproduces other key data moments well. Figure H.4 of the appendix compares sectoral prices, trade shares, consumption expenditure shares, investment shares and intermediate input shares in the model with data. The calibration targets sectoral prices and bilateral trade shares, resulting in a near-perfect fit in the upper two panels. The calibration also replicates well the data on sectoral shares of consumption, investment, and intermediate inputs in each sector. Appendix H reports statistics that summarize the model fit along these dimensions.

# 5 Quantitative Analysis

In this section, we quantify the impact of trade on premature deindustrialization and industry polarization. We will show that trade interacts closely with technological change to shape sectoral dynamics using both "subtractive" and "additive" approaches. In the subtractive approach, we begin with our baseline model where both trade and sector-biased technological change are active—the *SBTC-Trade scenario*. We then evaluate a counterfactual where trade is removed by setting trade costs prohibitively high, leaving each country in autarky—the *SBTC-Autarky scenario*. The difference in outcomes between these two scenarios illustrates the role of trade in the presence of sector-biased technological change.

Conversely, the additive approach begins from a scenario where both trade and sector-biased technological change are deactivated. We specifically deactivate sector-biased technological change by imposing two restrictions: (i) productivity growth is neutral across sectors but varying by country and time, with initial sectoral productivity levels are set at their calibrated 1971 levels, and (ii) bundle firms use homothetic technologies with unit scale elasticities, while household preferences remain non-homothetic.[28] Additionally, we remove international trade, ensuring sector-neutral technological progress occurs in closed economies—the *SNTC-Autarky scenario.* We then introduce trade integration alone by reinstating calibrated trade costs—the *SNTC-Trade scenario.* Comparing these two scenarios allows us to isolate the pure contribution of trade integration in the absence of sector-biased technological change.

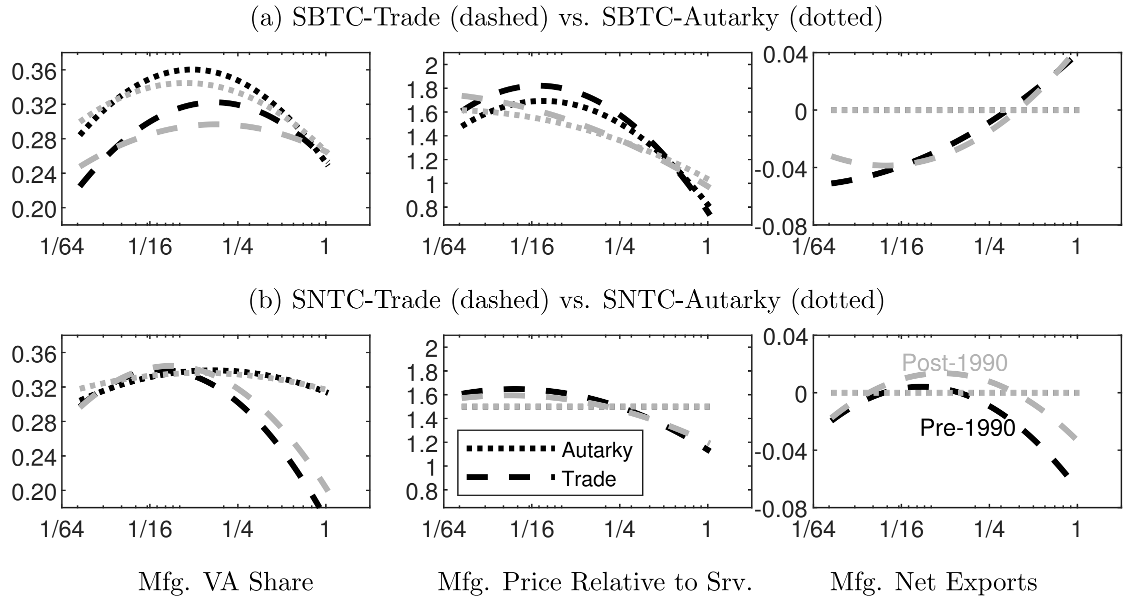
## 5.1 Premature Deindustrialization

We now turn to quantifying the contribution of trade to premature deindustrialization. To assess its role, we compare the SBTC-Autarky scenario to our baseline (SBTC-Trade), and we also compare the SNTC-autarky scenario to the SNTC-trade scenario. For each scenario, we apply regression (1) to the model-generated output to examine how three variables relate to income per capita across the pre-1990 and post-1990 periods: (i) the manufacturing value-added share; (ii) the relative price of manufacturing to services; and (iii) the ratio of manufacturing net exports to GDP. The latter two relationships help explain the first—the decline in the manufacturing hump over time. These relationships are shown in Figure 8, with dark (light) lines denoting the pre-1990 (post-1990) period. The key statistics are recorded in the first three columns of Table 3.

**Effects of Trade Under SBTC** The top panel of Figure 8 illustrates the subtractive approach by comparing the SBTC-Trade, our baseline, scenario (dashed lines) with the SBTC-Autarky scenario (dotted lines). As shown in the left column, a pronounced manufacturing hump and premature deindustrialization persist both with and without trade, although the decline in the hump is smaller under autarky. Specifically, the peak manufacturing share falls by 1.6 percentage points under autarky—approximately 60 percent of the decline in the baseline model. This comparison highlights that premature deindustrialization would have occurred even in the absence of trade, driven solely by sector-biased technological

[28] The sector-neutral productivity growth rate in each country is calculated as the value-added-weighted average of the growth rates of fundamental sectoral productivities. Unit scale elasticities yield constant returns to scale. Because fundamental productivity and returns to scale can not be separately identified, both SNTC scenarios impose constant-returns-to-scale bundle technologies so that the results are robust to the normalization of scale elasticities.

Figure 8: Role of Trade in Premature Deindustrialization




Notes: Dashed lines – Trade; Dotted lines – Autarky. Panel (a) illustrates the outcomes under trade or autarky with sector-biased technological change (SBTC). Panel (b) illustrates the outcomes under trade or autarky with sector-neutral productivity growth (SNTC). Each line plots the predicted value for a variable (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.

change. However, trade integration plays an important amplifying role, accounting for the remaining 40 percent of the overall decline in the baseline scenario.

Without trade, sector-biased technological change drives premature deindustrialization through its impact on relative price dynamics, as shown by the dotted lines in the middle column. As discussed in Section 4, manufacturing productivity grew more slowly than services productivity in the bottom income tertile, but more rapidly in the middle and top tertiles in the pre-1990 period. In the post-1990 period, manufacturing productivity growth continued to outpace services in the top and middle tertiles, while remaining on par with services in the bottom tertile. These patterns generate a hump-shaped relationship between the relative price and income in the pre-1990 period and a negative relationship in the post-1990 period. The cumulative effect of sustained manufacturing-biased productivity growth in the middle and top tertiles results in lower relative prices of manufacturing in the post-1990 period compared to pre-1990. Given the low elasticities of substitution, the lower relative price in the post-1990 period results in lower manufacturing value-added shares. Since net exports are zero under autarky, the manufacturing value-added shares mirror the dynamics of relative prices.

The relative price dynamics under trade (dashed lines) mirror those under autarky (dot-

Table 3: Results for Premature Deindustrialization and Industry Polarization

| | Peak Share (ppts.) | | | Avg. Log-Variance (ppts.) | | |
|---|---|---|---|---|---|---|
| | Pre-90 | Post-90 | Change | Pre-90 | Post-90 | Change |
| Data | 31.3 | 27.8 | −3.5 | 4.3 | 7.4 | 3.1 |
| Base Calibration | | | | | | |
| SBTC-Trade | 32.0 | 29.4 | −2.6 | 4.3 | 6.4 | 2.1 |
| SBTC-Autarky | 35.9 | 34.3 | −1.6 | 2.4 | 2.8 | 0.4 |
| SNTC-Trade | 33.8 | 34.3 | 0.5 | 4.7 | 7.7 | 3.0 |
| SNTC-Autarky | 33.6 | 33.3 | −0.3 | 2.7 | 2.3 | −0.4 |
| Re-Cal Closed Economy | | | | | | |
| Fully Homothetic | 32.8 | 31.7 | −1.1 | 2.9 | 2.8 | −0.1 |
| N-H Preferences | 32.3 | 30.8 | −1.5 | 2.8 | 2.7 | −0.1 |
| Fully N-H | 34.3 | 32.2 | −2.1 | 2.5 | 3.4 | 0.9 |

Note: In each scenario, the peak share corresponds to the manufacturing value-added share associated with the peak of the predicted value-added share curve based on regression 1. The average log-variance reports the mean value of the cross-country variance in log-manufacturing shares over time within each period. In the re-calibrated closed economies, "Fully Homothetic" refers to the version with homothetic bundle technologies, investment, and preferences. "N-H Preferences" refers to the version with homothetic bundle technologies and investment, and non-homothetic preferences. "Fully N-H" refers to the version with non-homothetic bundle technologies, investment, and preferences.

ted lines), indicating that sector-biased technological change is the key driver of the relationship between relative prices and income. However, trade amplifies the downward shift in relative price curves across most of the income range between the two periods. Declining trade costs increasingly reveal the underlying global structure of comparative advantage, allowing the cumulative effects of sector-biased technological change across all countries to influence domestic relative prices. In other words, each country's price dynamics reflect not only its own technological change, but also by that of its trading partners. Thus, the cumulated effects of technological change on the manufacturing relative price curve is stronger with trade than without it.

Complementing its impact on relative prices, the interaction between trade integration and sector-biased technological change shapes sectoral trade imbalances, further contributing to premature deindustrialization. As trade integration deepens, technological differences across countries lead countries to allocate resources more closely along lines of comparative advantage. This specialization drives manufacturing trade balances across income levels, generating a moderate deficit for countries in the bottom income tertile and a rising surplus for those in the top tertile, as shown in the right column. Relative to autarky, this pattern implies a manufacturing hump that tilts downward at low incomes and upward at high incomes. These forces also lead to a downward shift of the manufacturing net exports curve across the two periods for most countries. At income levels near the peak manufacturing value-added share (between 1/16 and 1/4 on the x-axis), the decline amounts to just below one percentage point of GDP, accounting for the majority of the interaction effect. By contrast, the SBTC-Autarky case, by construction, implies zero manufacturing net exports and no change across the two periods.

Through both sectoral relative prices and sector trade imbalances, trade interacts with sector-biased technological change to account for 40 percent of the premature deindustrialization. Later, we show that a recalibrated closed economy can replicate the relative price mechanism but not the trade-imbalance mechanism.

**Effects of Trade Under SNTC** The bottom panel of Figure 8 illustrates the additive approach, comparing the SNTC-Autarky scenario (dotted lines) with the SNTC-Trade scenario (dashed lines). In the SNTC-Autarky case, aggregate technological change within each closed economy raises income per capita over time at the same rate as in the baseline model. Because technological change is neutral across sectors, relative prices remain constant within each country (middle column). Moreover, since countries are closed, net exports are zero (right column). As a result, structural change in this scenario is solely driven by scale effects in consumption demand. As shown in the left column, the manufacturing value-added share displays only a modest hump-shaped pattern across income levels, and the curve remains unchanged across the two periods. This indicates that, in the absence of trade and sector-biased technological change, no premature deindustrialization occurs.

Trade integration under sector-neutral technological change—the SNTC-Trade scenario—also does not generate premature deindustrialization, as shown in the left column. This is because trade integration alone produces only an insignificant downward shift in the relative price curve between the two periods (middle panel). As discussed in Section 4, trade costs decline more rapidly in manufacturing than in services, however, this sectoral differential is only about half the magnitude of the corresponding differential in productivity growth. More importantly, trade costs affect only imports, which account for only about 15 percent of total spending, while domestic productivity affects the remaining 85 percent of expenditures. Consequently, the cumulative effect of asymmetric trade cost reductions—absence SBTC—is limited. What trade integration does achieve is a modest decline in manufacturing relative prices and the emergence of a hump-shaped relationship between manufacturing net exports and income. Since sectoral relative productivity is fixed in this scenario, these patterns are driven solely by differential changes in sectoral trade costs across income levels.

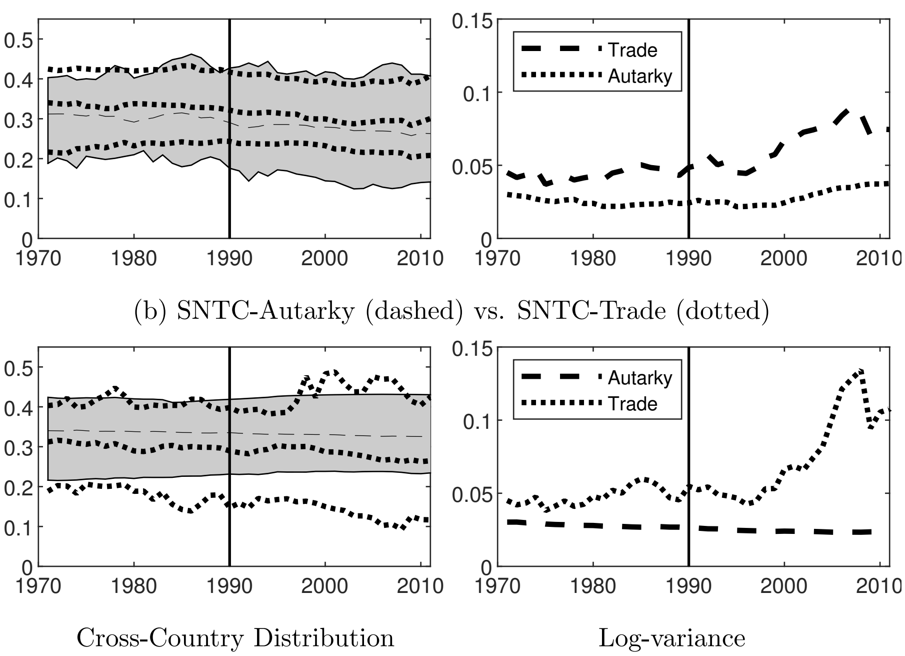
## 5.2 Industry Polarization

We now examine the implications for industry polarization. The key statistics are recorded in the last three columns of Table 3. The top panel of Figure 9 contrasts the baseline SBTC-Trade scenario (dashed lines) with the SBTC-Autarky scenario (dotted lines). The left column illustrates the cross-country distribution of manufacturing value-added shares over time, and the right column shows the variance of log manufacturing shares over time. When trade is removed, both the top and bottom percentiles remain relatively stable over time, and the increase in the log variance is modest, rising from an average of 0.024 in the pre-1990 period to an average of 0.028 in the post-1990 period – significantly less than in the baseline with trade. This indicates that sector-biased technological change alone cannot account for the rise in industry polarization.

Figure 9: Role of Trade in Industry Polarization

(a) SBTC-Trade (dashed) vs. SBTC-Autarky (dotted)

(b) SNTC-Autarky (dashed) vs. SNTC-Trade (dotted)




Notes: Dashed lines – baseline model; Dotted lines – counterfactuals. Panel (a) illustrates the outcomes of industry polarization under trade and autarky with sector-biased technological change (SBTC). Panel (b) illustrates the outcomes with sector-neutral productivity growth (SNTC). In the left column, 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. The right column reports the variance of the log manufacturing VA share across countries in each year (x-axis). ROW is excluded from each of the calculations.

The bottom panel compares the SNTC-Autarky scenario (dashed lines) with the SNTC-Trade scenario (dotted lines). In the SNTC-Autarky case, the distribution of manufacturing value-added shares remains nearly constant over time, as does the variance of their log shares. The variance actually declines slightly from 0.027 to 0.023. This again reflects the limited impact of sector-neutral technological change in the absence of trade on industry polarization. Once trade integration is introduced in the SNTC-Trade scenario, however, countries increasingly specialize according to comparative advantage. Consequently, the top manufacturing shares rise while the bottom shares fall, leading to a marked increase in cross-country variance—from 0.052 in the pre-1990 period to 0.108 in the post-1990 period—almost double the increase implied by the baseline model. Overall, the log variance increases from an average of 0.047 in the pre-1990 period to an average of 0.077 in the post-1990 period. This suggests that trade integration alone plays a major role in driving industry polarization. Note that this increase exceeds that of the baseline model, and is attributable to the fact that in the baseline, sector-biased technological change dampens comparative advantage over time. Levchenko and Zhang (2016) provide supporting evidence for this mechanism.

## 5.3 India, South Korea, and China, Revisited

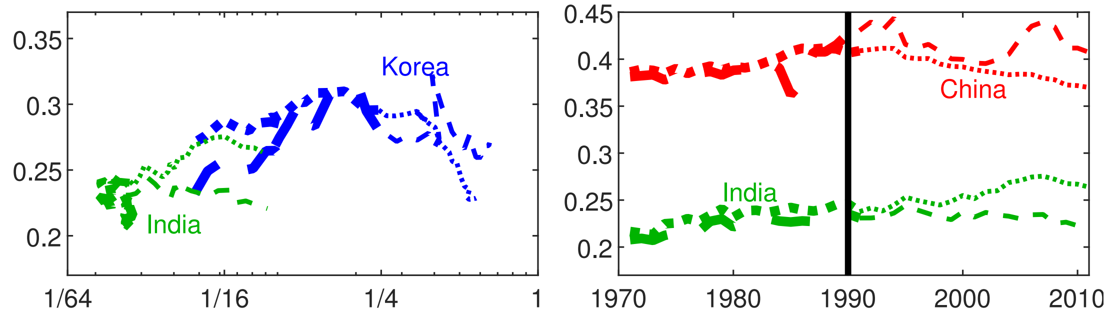
To further illustrate the role of international trade in premature deindustrialization and industry polarization, we return to the country examples—India, South Korea, and China—introduced in Section 2. In Figure 10 below, the dashed lines capture the baseline scenario (SBTC-Trade), and the dotted lines capture SBTC-autarky.

We begin with India and Korea, focusing on premature deindustrialization. The left column of panel (a) shows that for the baseline scenario, the model-implied peak in the manufacturing value-added share is 0.32 for Korea, and 0.24 for India, as compared to 0.36 and 0.26, respectively, in the data. In addition, in 2011, when India's income per capita relative to that of the U.S. reaches about $\frac{1}{11}$, the model-implied manufacturing value-added share is 0.22; when South Korea has that same income level in 1976, its model-implied manufacturing value-added share is 0.26; this gap of 4 percentage points is about half that in the data. Overall, the baseline scenario does a good job capturing the salient features of India's premature deindustrialization, especially in the context of Korea's structural change.

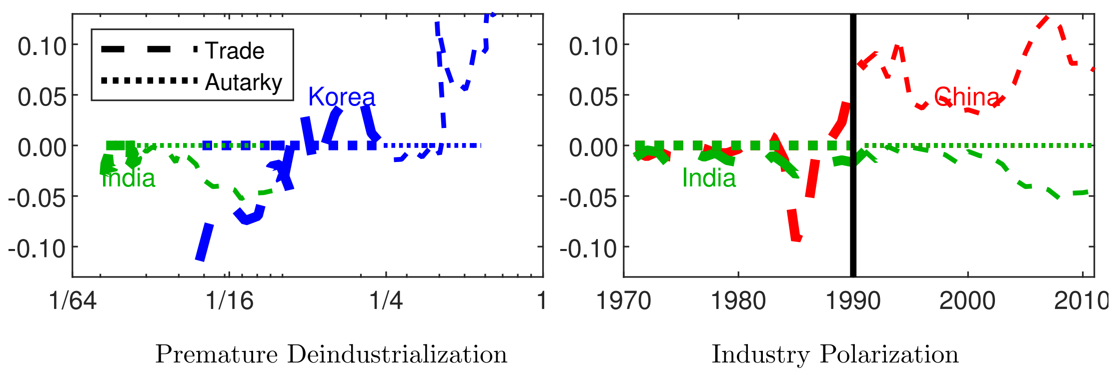
Moreover, much of the model-implied premature deindustrialization in India can be attributed to international trade. In the top left panel, focusing on the dotted lines for the autarky scenario, India's manufacturing value-added share (green line) is about 4 percentage points higher than in the baseline when income per capita is about 1/16, bringing its path close to South Korea's (blue line) at the same income level. The upward shift largely reflects the closed economy "forcing" India to produce more manufactured goods at home. Of course, the market mechanism leading to this higher production is higher relative prices of manufactured goods, stemming from slower productivity growth in manufacturing than in

Figure 10: Illustration: China, India, and South Korea

(a) Manufacturing Value-Added Share




(b) Manufacturing Net Exports/GDP




Notes: In the top panel, the y-axis represents the manufacturing value-added share, while in the bottom panel, it represents the ratio of manufacturing net exports to GDP. The x-axis corresponds to real income per capita at PPP prices relative to United States in 2011 in the left column, and time (year) in the right column. Dashed lines correspond to the SBTC-Trade scenario, and dotted lines to the SBTC-autarky scenario. Thick lines correspond to the pre-1990 period, and thin lines to the post-1990 period.

services. By contrast, in the baseline model with trade, India's relative price of manufacturing remains flat over time, reflecting the downward effect of trade on its relative price—and its comparative advantage in services.

For South Korea, the autarky path also deviates from the baseline, but in a more nuanced way: its manufacturing share is higher at income levels below about 1/8, yet lower at higher income levels. Overall, relative to the baseline, the autarky hump shifts clockwise. As seen in the bottom left panel, this pattern reflects how South Korea's initial comparative disadvantage in manufacturing generated trade deficits at low income levels, while its growing comparative advantage over time turned those deficits into surpluses. South Korea's autarky relative price of manufactured goods fell by more than 40 percent, driven by faster productivity growth in manufacturing relative to services, which under trade greatly improves its manufacturing comparative advantage. To summarize, the model captures premature deindustrialization for India and South Korea, and trade induced by comparative advantage is central to shaping their divergent paths.

Turning to industry polarization, the top right panel of Figure 10 depicts the paths for manufacturing value-added shares for India and China over time. Under autarky, India's share is higher than in the baseline and, after 1990, rises by 2 percentage points, rather than declining as it does in the baseline. By contrast, China's share under autarky is lower than in the baseline and declines by 5 percentage points after 1990. By 2011, the gap between their manufacturing value-added shares is only about 10.6 percentage points, compared with 18.7 percentage points in the baseline. The narrower gap under autarky highlights the role of international trade, specifically, China's comparative advantage in manufacturing and India's in services. These dynamics are evidence in their autarky relative prices: largely driven by relative productivity growth, India's relative price of manufacturing rises by 8 percent, while China's falls by 26 percent over this time period.

In the baseline, by 2011, China's manufacturing net export share exceeds India's by 11.9 percentage points, while under autarky that gap is zero. This divergence stems from both sectoral productivity differences and sharper declines in manufacturing trade costs—especially outward costs—in China relative to India. Between 1991 and 2011, China's outward trade costs fell from 4.5 to 1.6, a larger decline than in India. The net export share gap closely mirrors the 8.1-percentage-point difference in manufacturing share gaps between the two scenarios, underscoring how trade drives their widening divergence—and, ultimately, industry polarization—over time.

## 5.4 Further Analysis

When presenting the SBTC-Autarky result, we held non-trade related parameters fixed at their baseline values. To fully gauge the closed-economy's contribution, we now re-calibrate the parameters. We then compare the explanatory power of the re-calibrated closed-economy models with that of the baseline as they relate to premature deindustrialization and industry polarization. In addition, we evaluate how well they replicate the peak manufacturing value-added share across countries. These comparisons highlight trade's importance not only in driving premature deindustrialization and industry polarization—average patterns of structural change—but also in capturing cross-country variation. The key statistics are recorded in the bottom three rows of Table 3.

**Re-Calibrated Closed-Economy Models** We re-calibrate three closed-economy models to disentangle the roles of preferences, production structures, and sector-biased productivity growth in premature deindustrialization and industry polarization. The first is the

SBTC-Autarky model with sector-biased productivity, non-homothetic preferences, and non-homothetic production structures. The second retains sector-biased productivity growth and non-homothetic preferences but imposes homothetic production structures for intermediates and investment, closely mirroring standard closed-economy models of premature deindustrialization (e.g. Huneeus and Rogerson, 2024). In this literature, investment dynamics are typically omitted or, when included, assumed to be homothetic (e.g. García-Santana, Pijoan-Mas, and Villacorta, 2021; Herrendorf, Rogerson, and Valentinyi, 2021). The third adopts homothetic preferences and production structures, allowing us to isolate the contributions of non-homothetic preferences and sector-biased productivity growth.

To make the comparison across these specifications meaningful, we re-calibrate each model consistently. For the version with non-homothetic preferences and production structures, the baseline price and scale (income) elasticities are retained. For versions with homothetic production structures, we set $\varepsilon_x^j = \varepsilon_e^{k,j} = 1$ and re-estimate the price elasticities for the investment and three intermediate input bundles. For the version with homothetic preferences, we additionally set $\varepsilon_c^j = 1$ and re-estimate the price elasticity for consumption.[29] Across all three models, we separately re-calibrate the exogenous processes to match the same moments as in the baseline model, excluding trade-related moments.

We find that sector-biased productivity growth, non-homothetic preferences, and non-homothetic production structures are all crucial for capturing premature deindustrialization, yet none individually—or even combined—can generate industry polarization. Figure D.1 compares the three re-calibrated closed-economy models (dotted lines) with the baseline model (dashed lines). In each case, relative prices are matched by the calibration (second column) and manufacturing net exports are zero by construction (third column). The first column illustrates their implications for premature deindustrialization. With homothetic preferences and homothetic production structures (top panel), the peak share falls by only 1.1 percentage points, compared to 2.6 percentage points in the baseline. Adding non-homothetic preferences (middle panel) accentuates the premature deindustrialization slightly, yielding a 1.5-percentage-point decline. Including both non-homothetic preferences and non-homothetic production structures (bottom panel) brings the fit closer, with a 2.1-percentage-point decline, still short of the baseline's 2.6 percentage-points decline.

Figure D.2 compares industry polarization outcomes from the three closed-economy models (dotted lines) with those from the baseline model (dashed lines). All three of the re-calibrated closed-economy models fail to generate a meaningful increase in cross-country dispersion of manufacturing value-added shares post-1990. While their re-calibrated productivity processes account for trade's influences on relative prices, these closed-economy

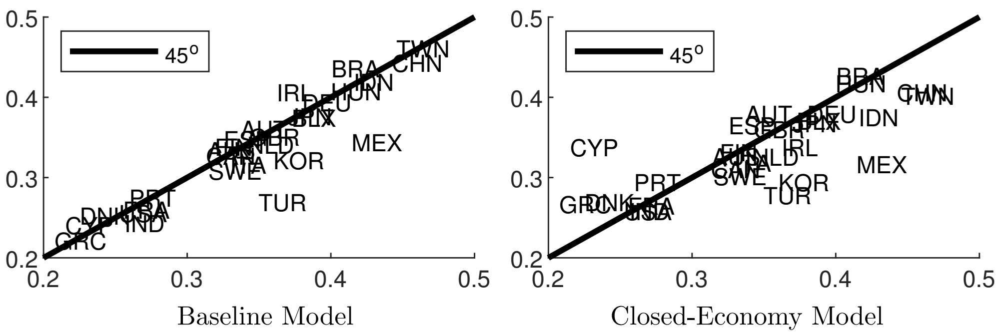
[29] The estimated homothetic price elasticities are $(\sigma_c, \sigma_x, \sigma_e^a, \sigma_e^m, \sigma_e^s) = (0.15, 0.38, 0.18, 0.18, 0.12)$.

models cannot capture sectoral specialization and trade imbalances arising from shifting comparative advantage. Thus, they are unable to replicate observed industry polarization.

**Cross-Country Heterogeneity in Peaks** We now assess the baseline model's ability to reproduce cross-country variation in manufacturing-value-added share peaks. Figure (11) plots the model-implied peak manufacturing share in the model (y-axis) against the observed counterpart (x-axis) across countries.

The left panel shows that the baseline model captures this heterogeneity well, achieving an $R^2$ value of 0.84. The right panel illustrates that the the re-calibrated SBTC-Autarky model—performs best among the three closed-economy models—still falls short, with an $R^2$ value of 0.57. For comparison, the $R^2$ value is 0.47 under both remaining closed-economy versions. These results underscore that, while closed-economy mechanisms explain part of the cross-country variation in manufacturing humps, trade is essential for replicating not only average structural change patterns—such as premature deindustrialization and industry polarization—but also the heterogeneity in the peak manufacturing share.

Figure 11: Peak Manufacturing Value-Added Shares: Model Versus Data




Notes: The left panel plots the peak manufacturing value added share in the baseline model (y-axis) against the data (x-axis); plots the peak manufacturing value added share in the re-calibrated closed-economy model with non-homothetic preferences, production, and investment (y-axis) against the data (x-axis); The R-squared is 0.57.

# 6 Conclusion

The main contribution of this paper is to quantify the role of international trade in driving premature deindustrialization and industry polarization. To address this question, we employ a dynamic, multi-country, three-sector trade model with non-homothetic CES demand structures for consumption, investment, and production. Our model is calibrated to the same set of countries used for our cross-country evidence. With the model we study the role of sector-biased technological change (SBTC) and increasing trade integration over time.

We highlight four main findings. First, the baseline model explains about three-fourths of premature deindustrialization (PD) and two-thirds of industry polarization (IP). Second, SBTC is a key driver of PD—explaining about 60 percent of the baseline PD. Third, while trade integration alone does not cause PD, it amplifies the effect of SBTC, accounting for the remaining 40 percent. Fourth, SBTC alone contributes little to the baseline IP, while trade integration alone explains over 100 percent of it. Overall, trade integration and SBTC complement each other in explaining PD, but play opposing roles in shaping IP.

Our counterfactuals illustrate the mechanisms behind these results. First, relative prices—jointly shaped by SBTC and trade integration—play a key role in conjunction with the "Baumol" elasticities of substitution. Faster technological progress in manufacturing, coupled with lower, and faster declining, trade costs in that sector, drives a persistent decline in manufacturing relative prices, which in turn reduces expenditure shares on manufacturing. Trade amplifies these effects by transmitting technological progress across borders, further lowering relative prices. PD arises largely from the cumulative impact of these relative price declines in the post-1990 period compared to the pre-1990 period. Second, sectoral trade imbalances are crucial for both PD and IP. As trade integration deepens, countries' comparative advantage are increasingly revealed, leading to larger manufacturing trade imbalances. This leads to greater dispersion, and a downward skew, in manufacturing value-added shares across countries. Finally, while a closed economy model could, in principle, "absorb" relative price dynamics, i.e., prices, it cannot accommodate sectoral trade imbalances, i.e., quantities. This limitation explains why the baseline model accounts for a great share of these two facts than even a re-calibrated closed-economy model.

Extending our production framework to allow for non-unitary elasticities of substitution between value-added and intermediates, as well as between capital and labor, would be a natural next step. Incorporating potential spillovers from trade integration to technology diffusion across countries could strengthen the interaction effect in our model, magnifying the role of trade integration. In addition, while our model treats current account imbalances as exogenous, making them endogenous could clarify whether the rise in global imbalances is connected to PD and IP. A deeper study of returns to scale would also be valuable, particularly for exploring the normative and welfare implications of PD.[30] Finally, since our sample focuses primarily on middle-income and advanced economies, extending the analysis to include low-income economies would shed light on how these dynamics unfold at earlier stages of development. We leave these and related extensions for future research.

[30] See Bartelme et al. (2025) for a recent example.

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# 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 United Nations Industrial Development Organization. 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 UK. 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 impute input-output shares and sectoral investment shares using the RAS method described in Appendix F. 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.

# Appendix B Robustness Check on Two Facts

This appendix illustrates that our baseline result of premature 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 deviations. 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 premature 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 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

Table B.1: Robustness of the Empirical Finding on Premature 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 $\xi^2$ | 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.

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 US PPP prices.[31] 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.

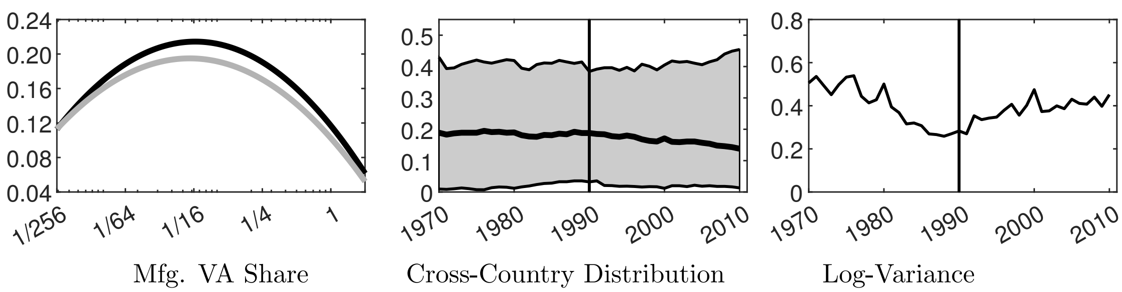
The countries are: Albania, Algeria, Andorra, Angola, Argentina, Australia, Austria, Belgium, Belize, Bhutan, Bolivia, Botswana, Brazil, Bulgaria, Cameroon, Canada, Chile, China,

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

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 premature 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: Robustness with 95 countries over 1970–2010



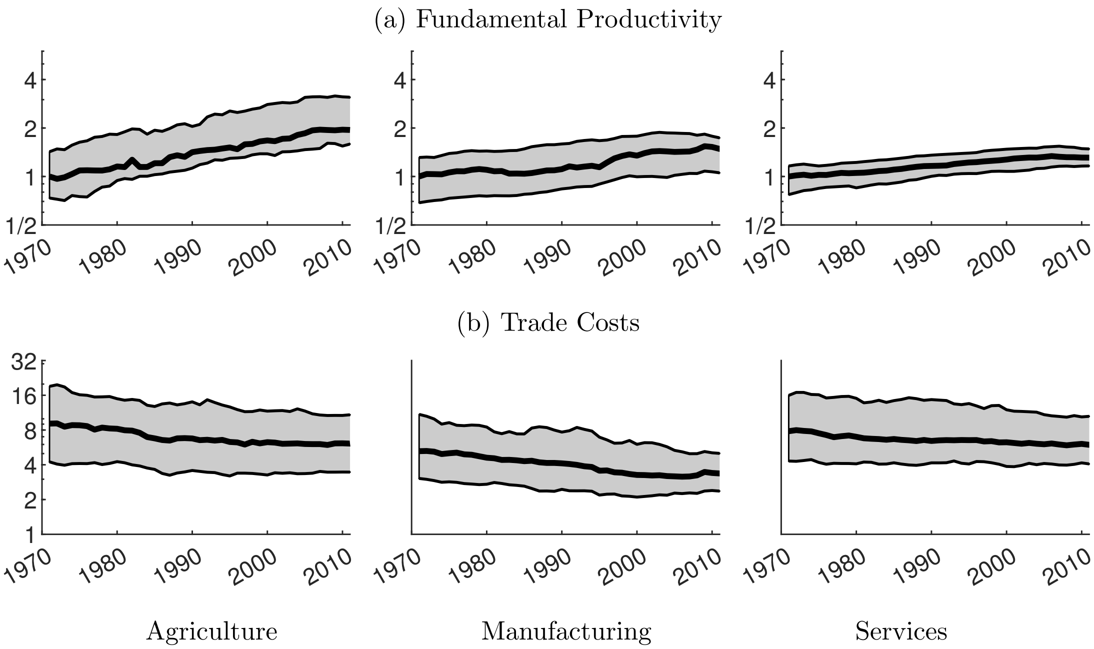

Notes: In the left panel, the fitted curves are based on regressions of sectoral manufacturing VA shares on income (y-axis), interacted with the two period dummies, and country fixed effects, over income per capita (x-axis). Dark (light) lines refer to pre-1990 (post-1990). In the center panel, the middle 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 $100^{th}$ 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).

Figure B.1 illustrates the patterns of premature 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 premature 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.

# Appendix C Secondary Results

Figure C.1 illustrates the evolution of the cross-country distribution of fundamental productivity over time. The solid line denotes the median value, and the ranges correspond to the 25$^{\text{th}}$ and 25$^{\text{th}}$ percentiles of the distribution.

Figure C.1: Sectoral Fundamental Productivity and Trade Costs Over Time

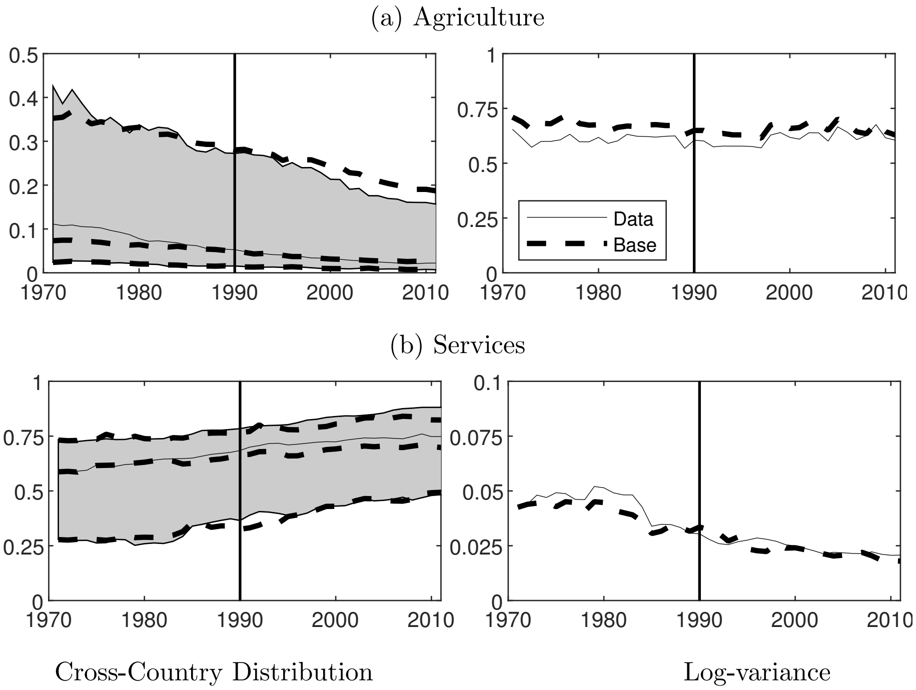



Notes: Each figure reports the cross-country distribution, where the solid line denotes the median value, and the ranges correspond to the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles of the distribution over time (x-axis). In the top panel, sectoral productivities across countries relative to the median in 1971.

The lower panel plots the cross-country distribution of the estimated trade costs for each sector over time. 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.

Figure C.2 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. The first column displays the median share as well as the 100$^{\text{th}}$ and 1$^{\text{st}}$ percentiles. The second column displays the log-variance in these shares over time. In the data, the log-variance of agriculture shares remains relatively stable, while the log-variance of services shares steadily declines over time. The baseline model replicates these patterns closely.

Figure C.2: Dispersion in VA Shares for Agriculture and Services

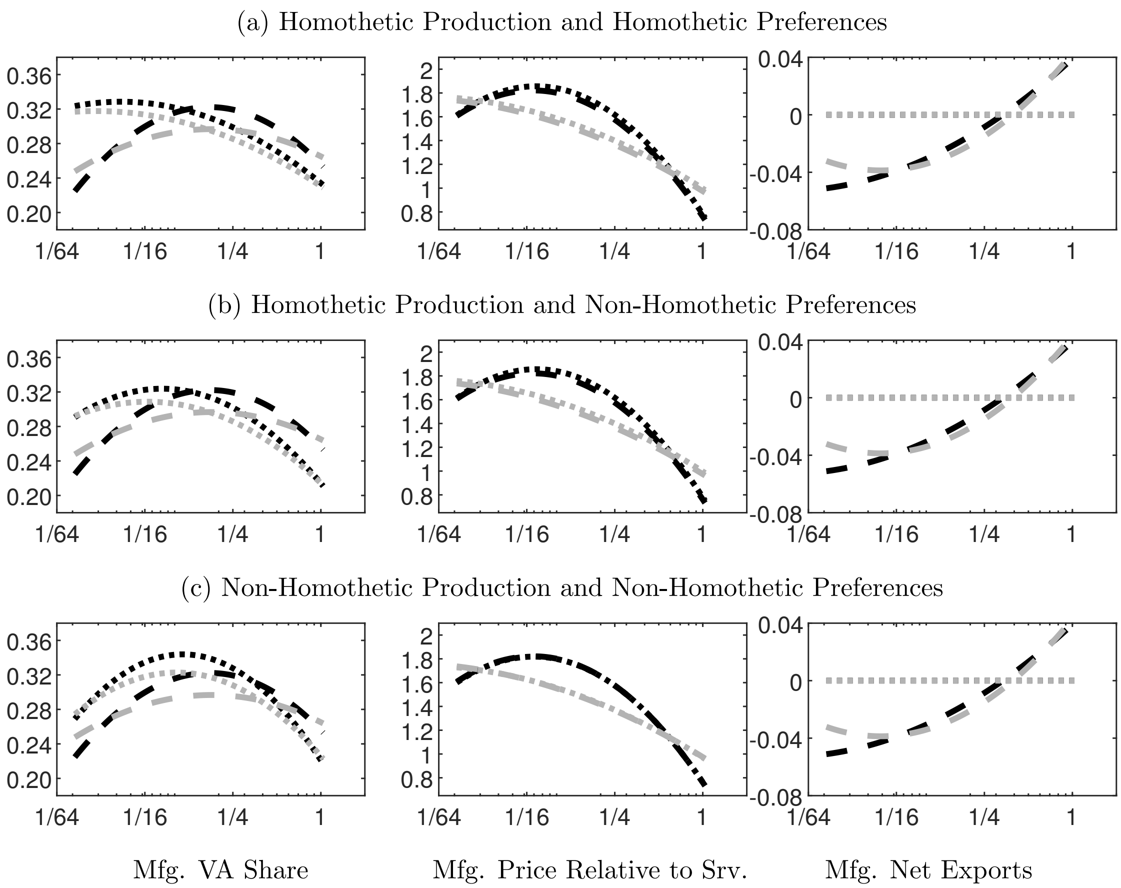



Notes: Solid lines – data; Dashed lines – baseline model. In the left panels, the middle line plots the median value of the manufacturing value-added shares across countries over time (x-axis), while the upper and lower bands correspond to the 100th and 1st percentiles, respectively. In the right panels,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

# Appendix D Re-calibrated Closed Economy Models

In this section of the appendix, we plot the resulting figures of the patterns of premature deindustrialization and industry polarization for the two versions of recalibrated closed economy models, discussed in Section 5.4.

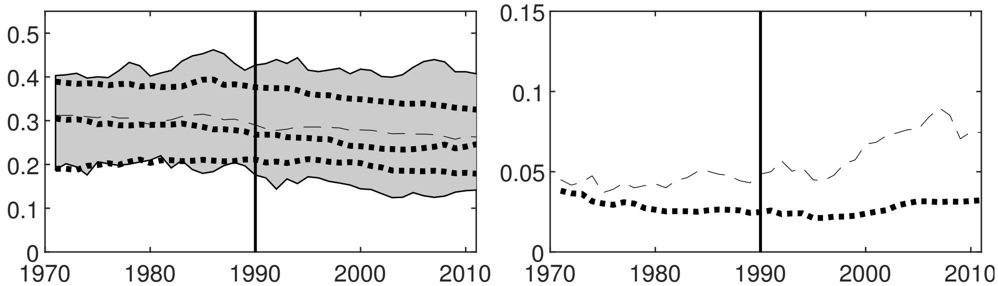
Figure D.1: Premature Deindustrialization in Re-calibrated Closed Economies



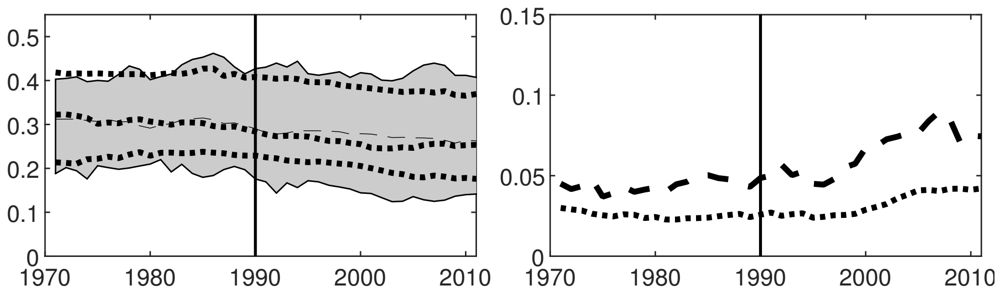

Dashed lines – baseline model; Dotted lines – re-calibrated models. Each line plots the predicted value-added share for a sector (y-axis), estimated from a balanced panel of 28 countries over 1971–2011 using equation (1) under the average country fixed effect and over the observed ranges of income per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

Figure D.2: Industry Polarization in Re-calibrated Closed Economies

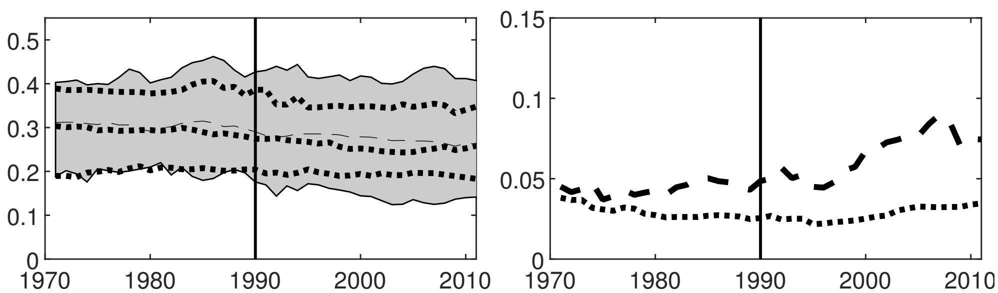
(a) Homothetic Production and Homothetic Preferences




(b) Homothetic Production and Non-Homothetic Preferences




(c) Non-Homothetic Production and Non-Homothetic Preferences




Cross-Country Distribution Log-variance

Notes: Dashed lines – baseline model; Dotted lines – re-calibrated models. 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.

# Appendix E 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 $\nu^j_n$ 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:

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

**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:

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

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

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

The gross change over time is:

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

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:

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

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:

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

**Lining Up Expenditure Shares in 1971** To do this we rearrange the first-order condition in equation (E.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:

$$
\begin{aligned}
1 &= \sum_{j \in \{a,m,s\}} \left( \left( \frac{p^j_{n,1} c^j_{n,1}}{P^c_{n,1} C_{n,1}} \right) \left( \left( \frac{p^j_{n,1}}{P^c_{n,1}} \right) \left( \frac{C_{n,1971}}{L_{n,1}} \right)^{\varepsilon^j_c - 1} \right)^{\sigma_c - 1} \right)^{\frac{1}{\sigma_c}} \\
C_{n,1} &= \frac{\text{Observed total expenditure in 1971}}{P^c_{n,1}} \\
\omega^j_{c,n} &= \left( \left( \frac{p^j_{n,1} c^j_{n,1}}{P^c_{n,1} C_{n,1}} \right) \left( \left( \frac{p^j_{n,1}}{P^c_{n,1}} \right) \left( \frac{C_{n,1}}{L_{n,1}} \right)^{\varepsilon^j_c - 1} \right)^{\sigma_c - 1} \right)^{\frac{1}{\sigma_c}}
\end{aligned}
$$

# Appendix F RAS to Impute Missing Shares

We now describe our procedure for imputing missing input-output 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 complete 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:

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

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

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

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

$$Con_i = Con^0_i e^{\lambda_i + \gamma_c} \tag{F.5}$$

$$Inv_i = Inv^0_i e^{\lambda_i + \gamma_x} \tag{F.6}$$

Using the constraints:

$$e^{\lambda_a}\left(IO^0_{aa}e^{\gamma_a} + IO^0_{ma}e^{\gamma_m} + IO^0_{sa}e^{\gamma_s} + Con^0_a e^{\gamma_c} + Inv^0_a e^{\gamma_x}\right) = GO_a - NX_a \tag{F.7}$$

$$e^{\lambda_m}\left(IO^0_{am}e^{\gamma_a} + IO^0_{mm}e^{\gamma_m} + IO^0_{sm}e^{\gamma_s} + Con^0_m e^{\gamma_c} + Inv^0_m e^{\gamma_x}\right) = GO_m - NX_m \tag{F.8}$$

$$e^{\lambda_s}\left(IO^0_{as}e^{\gamma_a} + IO^0_{ms}e^{\gamma_m} + IO^0_{ss}e^{\gamma_s} + Con^0_s e^{\gamma_c} + Inv^0_s e^{\gamma_x}\right) = GO_s - NX_s \tag{F.9}$$

$$e^{\gamma_a}\left(IO^0_{aa}e^{\lambda_a} + IO^0_{am}e^{\lambda_m} + IO^0_{as}e^{\lambda_s}\right) = GO_a - VA_a \tag{F.10}$$

$$e^{\gamma_m}\left(IO^0_{ma}e^{\lambda_a} + IO^0_{mm}e^{\lambda_m} + IO^0_{ms}e^{\lambda_s}\right) = GO_m - VA_m \tag{F.11}$$

$$e^{\gamma_s}\left(IO^0_{sa}e^{\lambda_a} + IO^0_{sm}e^{\lambda_m} + IO^0_{ss}e^{\lambda_s}\right) = GO_s - VA_s \tag{F.12}$$

$$e^{\gamma_c}\left(Con^0_a e^{\lambda_a} + Con^0_m e^{\lambda_m} + Con^0_s e^{\lambda_s}\right) = C \tag{F.13}$$

$$e^{\gamma_x}\left(Inv^0_a e^{\lambda_a} + Inv^0_m e^{\lambda_m} + Inv^0_s e^{\lambda_s}\right) = X \tag{F.14}$$

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 (F.1), (F.2), and (F.3).
- We then update $(\lambda^{(k)}, \gamma^{(k)})$ for $k = 1, 2, 3, ...$ as follows.
  - Using equations (F.7)-(F.8), we update $\lambda^{(k)}$ with $\gamma^{(k-1)}$.
  - Using equations (F.10)-(F.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 G Equilibrium Conditions

Table G.1 summarizes all the equilibrium conditions. The first three sets corresponds to the optimality conditions for production firms, retail firms, and assembly firms, respectively. The fourth set outlines the optimality conditions for households. The final set includes all market clearing conditions. Conditions (M1) and (M2) ensure capital and labor market clearing within each country. Condition (M3) requires that the use of the composite good (consumption demand by households and investment and intermediate input demand by assembly firms) equals its supply from both domestic and foreign sources at each sector-country level. Condition (M4) requires that the total value of output produced by production firms in each country-sector pair equals the total value of purchases made by retail firms worldwide from that country-sector pair. Condition (M5) imposes the aggregate resource constraint, requiring that the sum of net exports across sectors equals the value of net transfers by each country. Lastly, condition (M6) requires that the global portfolio's inflows must equal its outflows.

**Numerical Algorithm** Algorithm G.1 describes the methodology to compute the equilibrium. 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.

Table G.1: Equilibrium conditions

| | | |
|---|---|---|
| (VF1) | $R_{n,t}k^j_{n,t} = \alpha\nu^j_n p^j_{n,t}y^j_{n,t}$ | $\forall(n,j,t)$ |
| (VF2) | $W_{n,t}\ell^j_{n,t} = (1-\alpha)\nu^j_n p^j_{n,t}y^j_{n,t}$ | $\forall(n,j,t)$ |
| (VF3) | $P^{e,j}_{n,t}E^j_{n,t} = (1-\nu^j_n)p^j_{n,t}y^j_{n,t}$ | $\forall(n,j,t)$ |
| (CF1) | $(p^j_{n,t})^{-\theta^j} = \gamma^j \sum_{i=1}^{N} \left((A^j_{i,t})^{-\nu^j_i} u^j_{i,t} d^j_{n,i,t}\right)^{-\theta^j}$ | $\forall(n,j,t)$ |
| (CF2) | $u^j_{n,t} = \left(\frac{R_{n,t}}{\alpha\nu^j_i}\right)^{\alpha\nu^j_i} \left(\frac{W_{n,t}}{(1-\alpha)\nu^j_i}\right)^{(1-\alpha)\nu^j_i} \left(\frac{P^{e,j}_{n,t}}{1-\nu^j_i}\right)^{1-\nu^j_i}$ | $\forall(n,j,t)$ |
| (CF3) | $\pi^j_{n,i,t} = \frac{\left((A^j_{i,t})^{-\nu^j_i} u^j_{i,t} d^j_{n,i,t}\right)^{-\theta^j}}{\sum_{i'=1}^{N}\left((A^j_{i',t})^{-\nu^j_{i'}} u^j_{i',t} d^j_{n,i',t}\right)^{-\theta^j}}$ | $\forall(n,i,j,t)$ |
| (BF1) | $e^{j,k}_{n,t} = L_{n,t}(\omega^{j,k}_{e,n})^{\sigma^j_e}\left(\frac{p^k_{n,t}}{P^{e,j}_{n,t}}\right)^{-\sigma^j_e}\left(\frac{E^j_{n,t}}{L_{n,t}}\right)^{(1-\sigma^j_e)\varepsilon^{j,k}_e+\sigma^j_e}$ | $\forall(n,j,k,t)$ |
| (BF2) | $(P^{e,j}_{n,t})^{1-\sigma^j_e} = \sum_{k\in\{a,m,s\}}(\omega^{j,k}_{e,n})^{\sigma^j_e}(p^k_{n,t})^{1-\sigma^j_e}\left(\frac{E^j_{n,t}}{L_{n,t}}\right)^{(1-\sigma^j_e)(\varepsilon^{j,k}_e-1)}$ | $\forall(n,j,t)$ |
| (BF3) | $x^j_{n,t} = L_{nt}(\omega^j_{x,n})^{\sigma_x}\left(\frac{p^j_{n,t}}{P^x_{n,t}}\right)^{-\sigma_x}\left(\frac{X_{n,t}}{L_{n,t}}\right)^{(1-\sigma_x)\varepsilon^j_x+\sigma_x}$ | $\forall(n,j,t)$ |
| (BF4) | $(P^x_{n,t})^{1-\sigma_x} = \sum_{j\in\{a,m,s\}}(\omega^j_{x,n})^{\sigma_x}(p^j_{n,t})^{1-\sigma_x}\left(\frac{X_{n,t}}{L_{n,t}}\right)^{(1-\sigma_x)(\varepsilon^j_x-1)}$ | $\forall(n,t)$ |
| (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) | $(P^c_{n,t})^{1-\sigma_c} = \sum_{j\in\{a,m,s\}}(\omega^j_{c,n})^{\sigma_c}(p^j_{n,t})^{1-\sigma_c}\left(\frac{C_{n,t}}{L_{n,t}}\right)^{(1-\sigma_c)(\varepsilon^j_c-1)}$ | $\forall(n,t)$ |
| (H3) | $\frac{C_{n,t+1}/L_{n,t+1}}{C_{n,t}/L_{n,t}} = \beta\left(\frac{\psi_{n,t+1}}{\psi_{n,t}}\right)\left(\frac{R_{n,t+1}/P^x_{n,t+1}-\Phi_2(K_{n,t+2},K_{n,t+1})}{\Phi_1(K_{n,t+1},K_{n,t})}\right)\left(\frac{P^x_{n,t+1}/P^c_{n,t+1}}{P^x_{n,t}/P^c_{n,t}}\right)$ | $\forall(n,t)$ |
| (H4) | $P^c_{n,t}C_{n,t} + P^x_{n,t}X_{n,t} = (1-\phi_{n,t})(R_{n,t}K_{n,t}+W_{n,t}L_{n,t}) + T^P_t L_{n,t}$ | $\forall(n,t)$ |
| (H5) | $X_{n,t} = \Phi\left(K_{n,t+1},K_{n,t}\right) \equiv \delta^{1-\frac{1}{\lambda}}\left(\frac{K_{n,t+1}}{K_{n,t}}-(1-\delta)\right)^{\frac{1}{\lambda}}K_{n,t}$ | $\forall(n,t)$ |
| (H6) | $\Phi_1(K_{n,t+1},K_{n,t}) = \frac{\delta^{1-1/\lambda}}{\lambda}\left(\frac{K_{n,t+1}}{K_{n,t}}-(1-\delta)\right)^{(1-\lambda)/\lambda}$ | $\forall(n,t)$ |
| (H7) | $\Phi_2(K_{n,t+1},K_{n,t}) = \Phi_1(K_{n,t+1},K_{n,t})\left((\lambda-1)\left(\frac{K_{n,t+1}}{K_{n,t}}\right)-\lambda(1-\delta)\right)$ | $\forall(n,t)$ |
| (M1) | $K_{n,t} = \sum_{j\in\{a,m,s\}} k^j_{n,t}$ | $\forall(n,t)$ |
| (M2) | $L_{n,t} = \sum_{j\in\{a,m,s\}} \ell^j_{n,t}$ | $\forall(n,t)$ |
| (M3) | $Q^j_{n,t} = c^j_{n,t} + x^j_{n,t} + \sum_{k\in\{a,m,s\}} e^{k,j}_{n,t}$ | $\forall(n,j,t)$ |
| (M4) | $p^j_{n,t}y^j_{n,t} = \sum_{i=1}^{N} p^j_{i,t}Q^j_{i,t}\pi^j_{i,n,t}$ | $\forall(n,t)$ |
| (M5) | $\sum_{j\in\{a,m,s\}}\left(p^j_{n,t}y^j_{n,t} - p^j_{n,t}Q^j_{n,t}\right) = \phi_{n,t}(R_{n,t}K_{n,t}+W_{n,t}L_{n,t}) - L_{n,t}T^P_t$ | $\forall(n,t)$ |
| (M6) | $\sum_{n=1}^{N} L_{n,t}T^P_t = \sum_{n=1}^{N}\phi_{n,t}(R_{n,t}K_{n,t}+W_{n,t}L_{n,t})$ | $\forall(t)$ |

**Algorithm G.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 VF1, VF2, 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 CF1–CF3.
         D. Compute $P_{n,t}^x$ and $P_{n,t}^{e,j}$, using conditions BF4 and BF2, 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 H2 and H4.
         G. Compute $c_{n,t}^j$ and $x_{n,t}^j$, using conditions H1 and BF3, respectively.
         H. Compute $y_{n,t}^j$, $E_{n,t}^j$, $e_{n,t}^{j,k}$, and $Q_{n,t}^j$ using conditions VF3, BF1, M3 and M4.
         I. Compute factor demand $k_{n,t}^j$ and labor $\ell_{n,t}^j$ using conditions VF1 and VF2.
      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 $\Phi_2$ for every country using conditions H5, H6 and H7.
   (c) Return to step (a) and continue through period $T$.
3. Given sequences of prices and quantities, check the Euler condition H3. If it holds, stop. Otherwise, update $\boldsymbol{\rho}_t$ and return to step 2.

# Appendix H Additional Figures

This appendix presents additional figures mentioned in the main text.

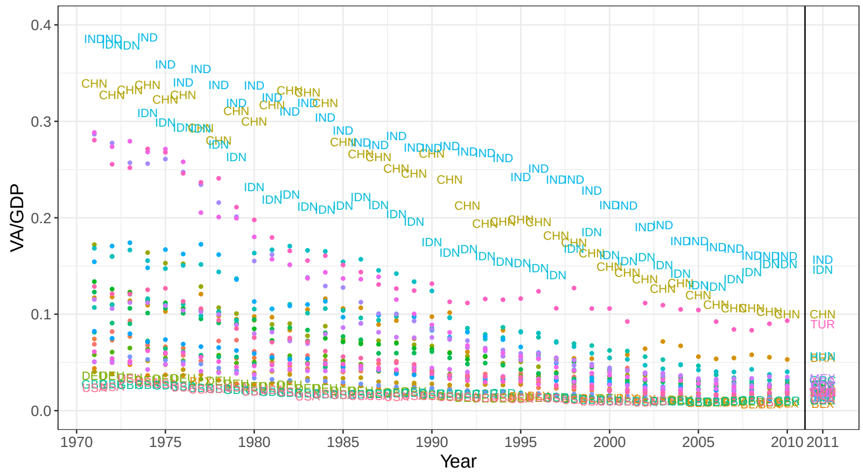
**Data Figures** Figures H.1 below showcases the dynamics of the cross-country distribution of each sector's value-added shares, agriculture in the top row, manufacturing in the middle row, and services in the bottom row. In each year, we have labeled the top three and bottom three countries in the distribution,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

**Calibration Figures** Figure H.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.

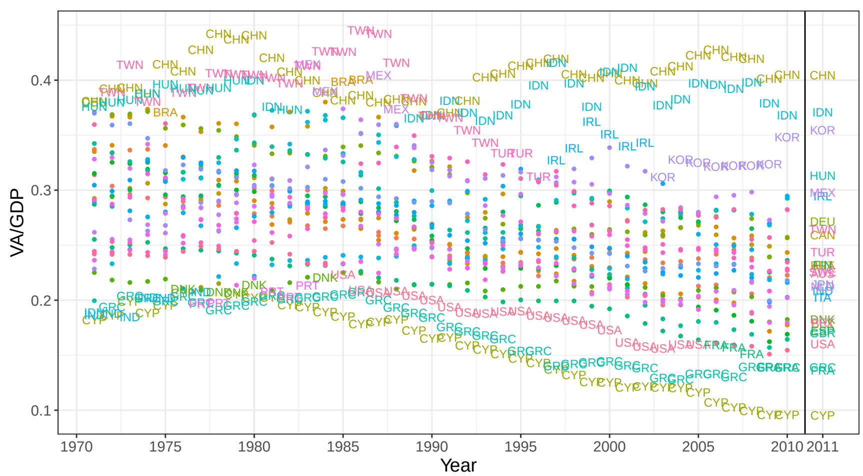
**Model Fit Figures** Figures H.4 and H.5 illustrate the fit of the calibrated baseline model (y-axis) with the data (x-axis). Figure H.4 evaluates the model's performance in targeting prices and bilateral trade shares across all three sectors, while Figure H.5 assesses its ability to match sectoral shares of consumption, investment, and intermediate inputs by sector. The correlations between the data and the model, pooled across all three sectors, for changes in sectoral expenditure shares, are 0.61 for consumption, 0.10 for investment, and 0.50, 0.61, 0.51 for intermediate spending by agriculture, manufacturing, and services, respectively.

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

(a) Agriculture




(b) Manufacturing




(c) Services

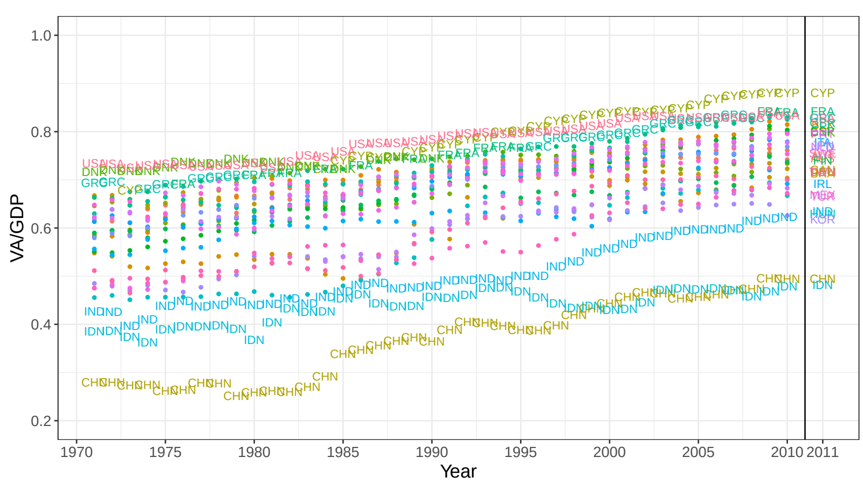
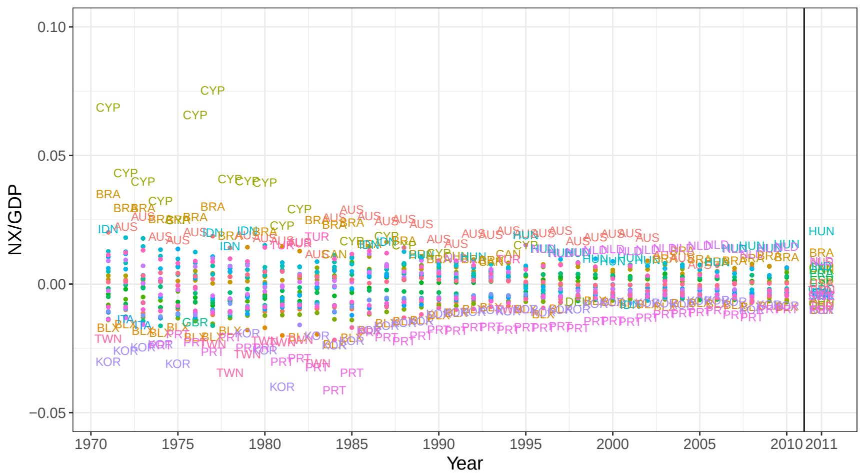
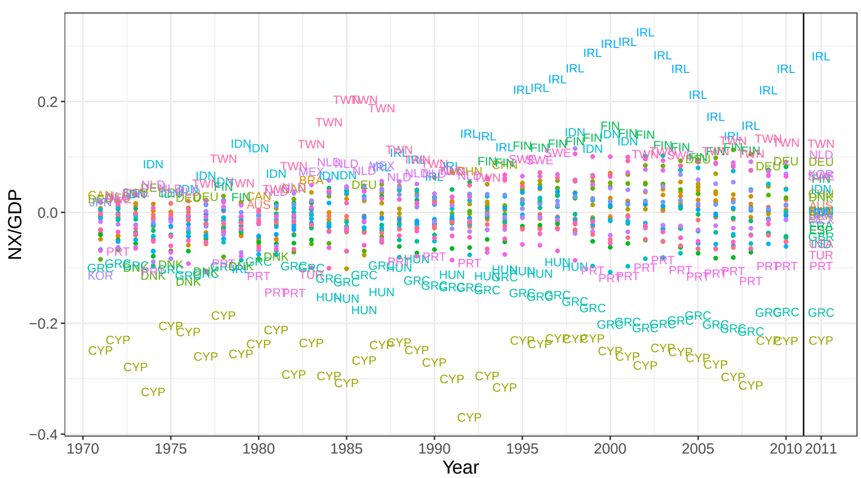


Figure H.2: World Distribution of Sectoral Net Export to GDP Ratios

(a) Agriculture




(b) Manufacturing




(c) Services

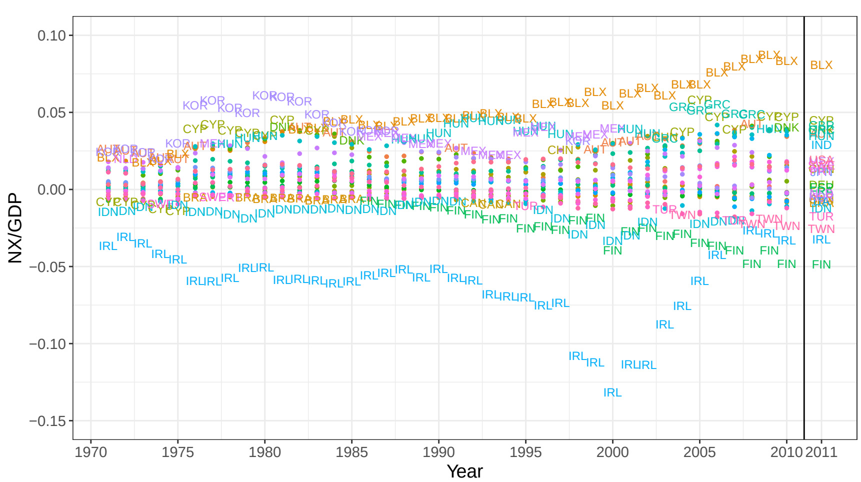
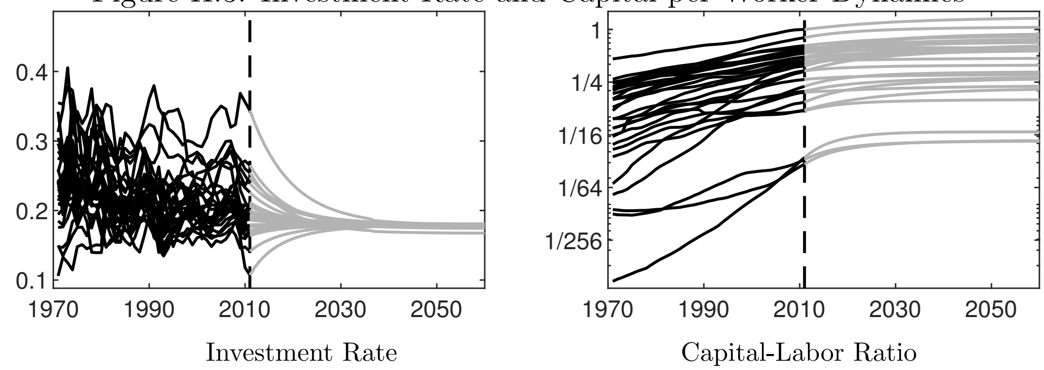
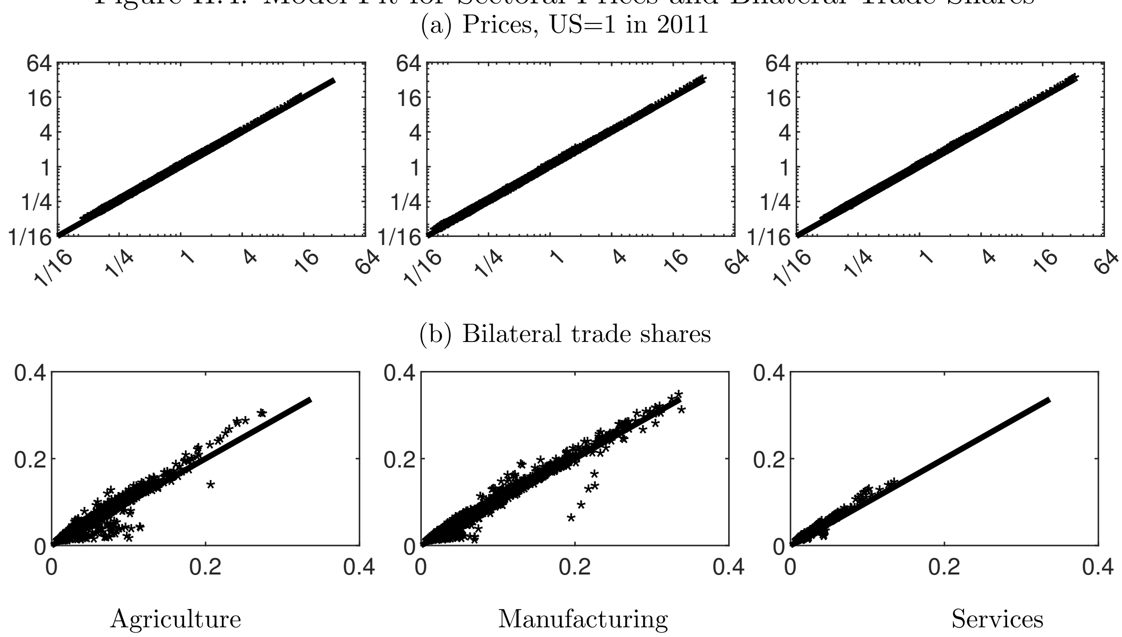


Figure H.3: Investment Rate and Capital per Worker Dynamics



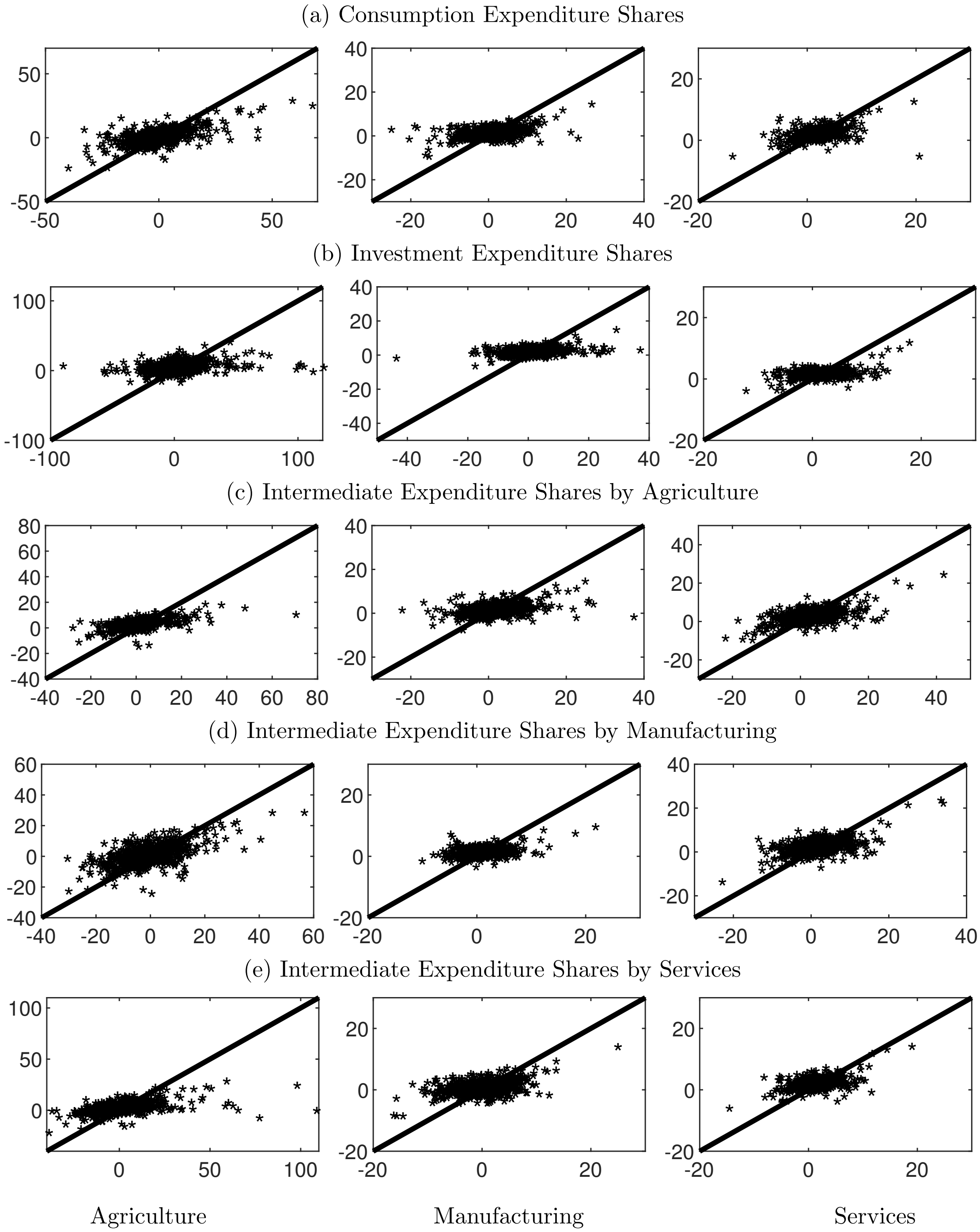

Notes: The dark lines are for the in-sample period, 1971-2011. The lighter lines are for the projection period, 2011-2060.

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




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, $\pi^j_{n,i,t}$.

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




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

# Appendix I Additional Analysis

This section analyzes three additional counterfactual scenarios: (i) holding trade costs constant at 1971 levels – the *Constant Trade Cost Scenario*, (ii) imposing balanced aggregate trade – the *Balanced Trade Scenario*, and (iii) removing discount factor shocks – the *Constant Discount Factor Scenario.*

**Balanced Aggregate Trade** Our baseline model differs from the SBTC-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 so as to match bilateral trade shares. Sectoral imbalances still emerge owing to comparative advantage, as in Uy, Yi, and Zhang (2013).

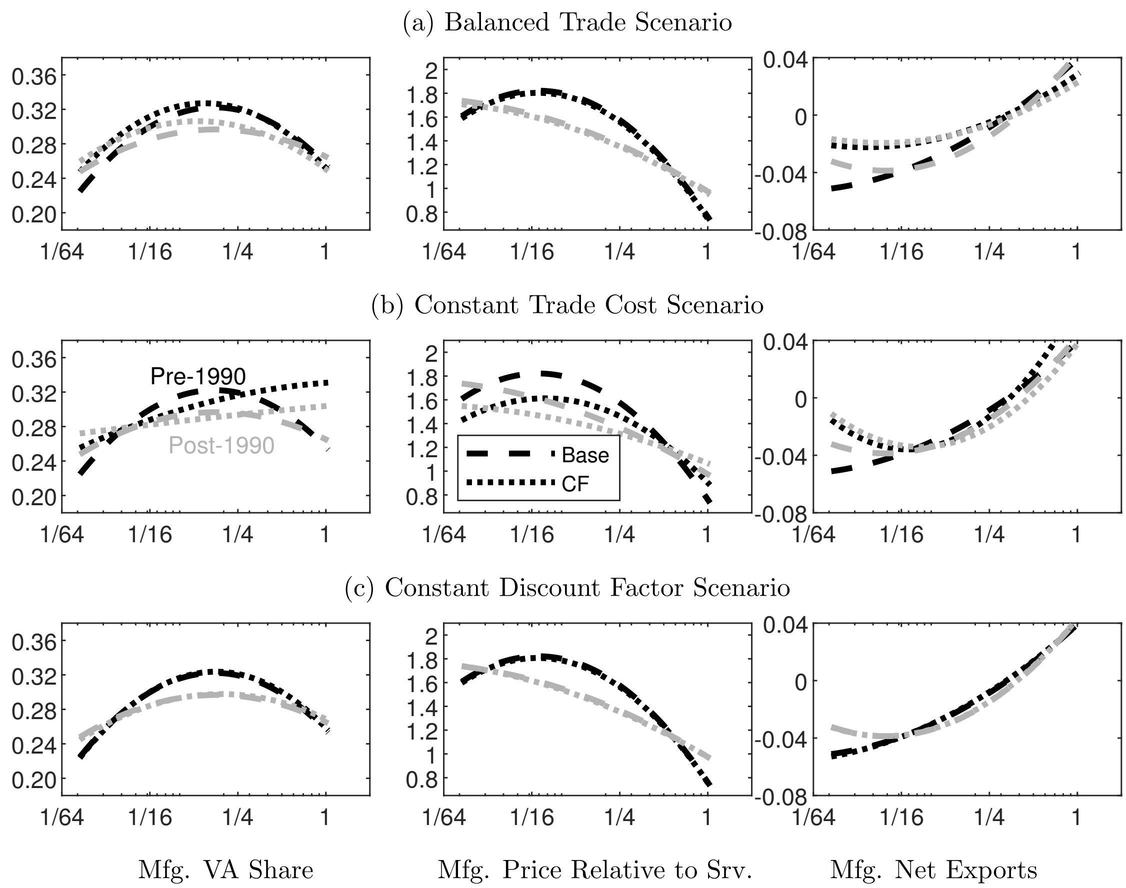
In this *balanced trade scenario*, the peak manufacturing value-added share declines by 2.1 percentage points across the two periods (first row in Figure I.1), compared to the 2.6 percentage point decline in the baseline model. Trade integration and sectoral trade imbalances matter for premature deindustrialization, as we have discussed above, but aggregate imbalances matter less.

However, aggregate trade imbalances do play a more substantive role in industry polarization. Without such imbalances, the log-variance in manufacturing value-added shares increases from an average of 0.030 in the pre-1990 period, to 0.038 in the post-1990 period (first row in Figure I.2). 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 0.043 to 0.064. 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 Trade Costs** Building on the balanced trade scenario described above, we now consider the effects of holding bilateral trade costs constant at their 1971 levels. In this setting, international trade persists but remains constrained by persistently high trade costs, preventing further trade integration. The consequences of this *constant trade cost scenario* for premature deindustrialization are shown in the second row of Figure I.1. The middle column illustrates that sector-biased technological change (SBTC) continues to operate, leading to a decline in the relative price curve from the pre- to post-1990 period. However, the upward-sloping net export curve reverses at lower income levels, since their strengthened comparative advantage in manufacturing is not fully realized to the same extent as in the baseline scenario. As a result, the value-added share hump is dampened, and its peak is not reached in either period.

Turning to industry polarization, the lack of trade integration means that comparative advantage is not revealed to the extent as in the baseline model, limiting the scope for sectoral specialization across countries. Consequently, the cross-country dispersion in manufacturing

Figure I.1: Robustness of Premature Deindustrialization



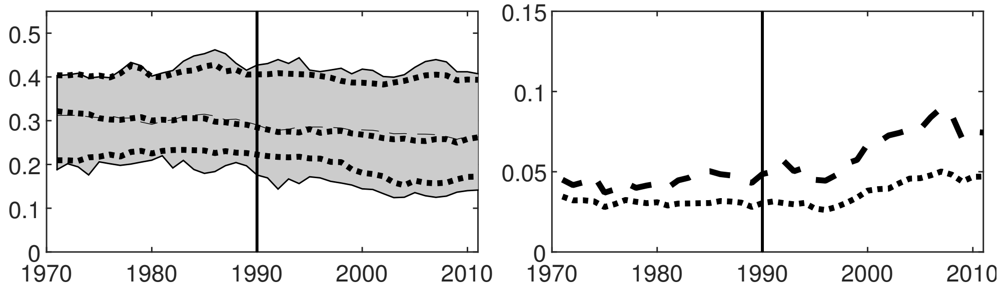

Notes: Dashed lines – baseline model; Dotted lines – re-calibrated models. The fitted curves are based on regressions of the variable of interest on income (y-axis), interacted with the two period dummies, and country fixed effects, over income per capita (x-axis). The dashed lines refer to the baseline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

value-added shares largely unchanged over time (Figure I.2); the log-variance in manufacturing value-added shares remains at 0.03 both pre-1990, and post-1990. Countries that would typically run rising manufacturing trade deficits due to comparative disadvantage in the baseline end up importing less manufacturing under this counterfactual. Consequently, they retain larger manufacturing value-added shares. This is reflected in the upward shift of the dotted line relative to the dashed line at the lower end of the distribution in the left panel.

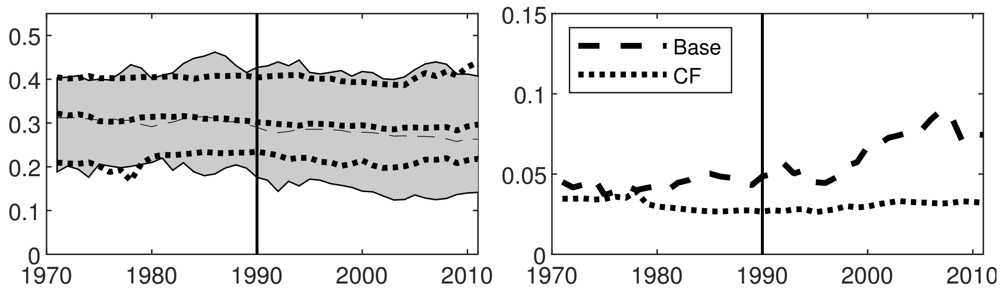
**Constant Discount Factor** We finally consider the importance of matching the aggregate saving rate. In the baseline model, the saving rate is matched to the data by choosing a sequence of country-specific discount factor "shocks", $\psi_{n,t+1}$. In the long-run steady state, this sequence settles 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.

Figure I.2: Robustness of Industry Polarization

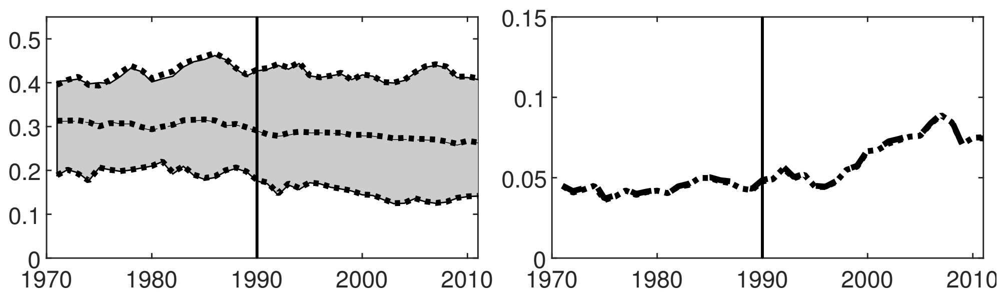
(a) Balanced Trade Scenario




(b) Constant Trade Cost Scenario




(c) Constant Discount Factor Scenario



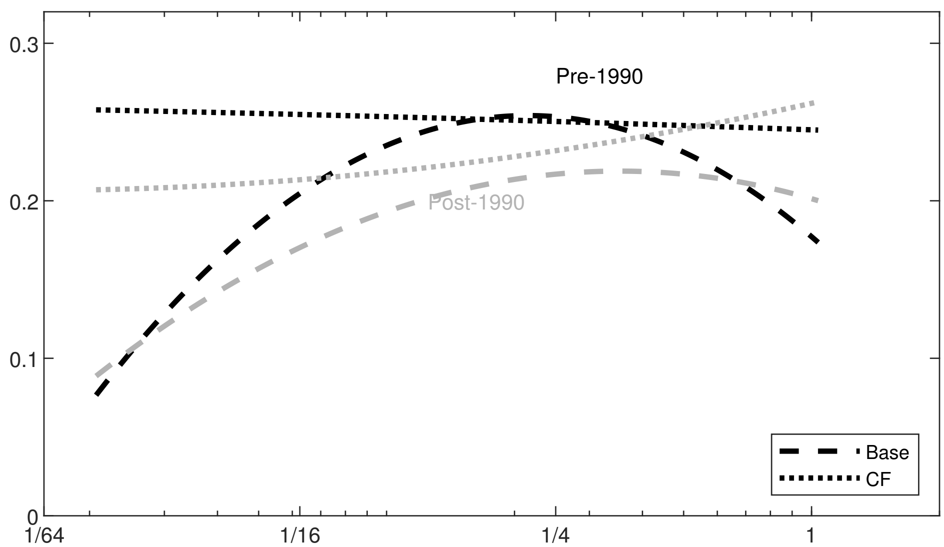

Cross-Country Distribution　　　　Log-variance

Notes: Dashed lines – baseline model; Dotted lines – counterfactuals. 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.

This *constant discount factor scenario* 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 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. Figure I.3 plots the predicted relationship between the aggregate investment rate and income per capita, using regression 1, for both the pre-1990 and post-1990 periods. It shows the predicted paths emerging from both the baseline model and from the Constant-Discount-Factor scenario.

As a result, the hump shape for the manufacturing value-added share becomes flatter (bottom row in Figure I.1). 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 I.3 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 premature deindustrialization is dampened: the peak manufacturing value-added share declines by 2.6 percentage points in this scenario, same as in the baseline model.

Figure I.3: Predicted Investment Rate Across Income per Capita




Notes: Dashed lines – baseline model; Dotted lines – re-calibrated models. 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). Dashed lines refer to the baseline model, and dotted lines refer to the constant discount factor scenario. Dark (light) lines refer to pre-1990 (post-1990).