Deindustrialization and Industry Polarization*

Michael Sposi† Kei-Mu Yi‡ Jing Zhang§

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Abstract

We add to recent evidence on deindustrialization and document a new pattern: increasing industry polarization over time. These facts can be explained by a dynamic, multi-sector, multi-country model of structural change in which the two primary driving forces are sector-biased productivity growth and trade integration. We find that sector-biased productivity growth is important for deindustrialization, and trade integration is important for industry polarization through specialization. The interaction of these two forces is also essential. The key transmission channel is the declining relative price of manufacturing goods to services over time.

JEL Classifications: F11, F43, O41, O11

Keywords: Structural change; international trade; sector biased productivity growth

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†Southern Methodist University; 3300 Dyer Street, Dallas, TX 75275. msposi@smu.edu

‡University of Houston, Federal Reserve Bank of Dallas, and NBER; 3623 Cullen Blvd, McElhinney 223E, Houston, TX 77204. kyi3@central.uh.edu

§Federal Reserve Bank of Chicago, Research Department, 230 S. LaSalle St., Chicago, IL 60604. jing.zhang@chi.frb.org

1 Introduction

The key patterns of structural change have been well-known since the pioneering work of Kuznets. As countries develop, the agriculture share of total employment or value-added decreases, while the services share increases, and the share of industry or manufacturing rises and then falls, i.e., follows a "hump" pattern. These patterns are so well-established they would seem to be immutable. Recent research has shown that the patterns are not immutable, however. Rodrik (2016) was the first to show systematically that countries are "deindustrializing". At similar levels of development, countries today have a smaller share of total value-added, and employment, devoted to manufacturing than countries several decades ago. In particular, the peak of the manufacturing hump is lower than in the past.

Moreover, in this paper, we document a new fact: industry polarization. Compared to several decades ago, the cross-country dispersion of the manufacturing share of total value-added is higher. These new facts demonstrate that the nature of structural change is itself evolving in a process occurring over decades.

To investigate the sources of, and reasons for, this evolution, we develop, calibrate, and simulate a dynamic open economy model of structural change. In our model, we focus on two driving forces – sector-biased productivity growth and sectoral trade integration. These two forces interact with key model mechanisms – relative price effects, income effects, comparative advantage, and capital accumulation – to cause structural change. For the model to generate deindustrialization and industry polarization, the driving forces, mediated through the model's mechanisms, must evolve over time. Our calibration approach is a global one, including more than two dozen countries, commensurate with generating implications that can be assessed against the two facts. We find that sector-biased productivity growth and trade integration have evolved over time in a way to quantitatively explain virtually all of deindustrialization and industry polarization.

Our main data analysis uses a balanced panel of 28 countries covering 1971 – 2011. We split the sample into pre-1990 and post-1990 periods and run a panel regression of the sectoral value added share on per capita income and per capita income squared together with country fixed effects. We find that, as in Rodrik (2016), the estimated hump-shaped relationship between the manufacturing value added share and income per capita shifts down over time. The peak of the manufacturing hump in the post-1990 period is 3.4 percentage points lower than in the pre-1990 period. Hence, our findings are consistent with the idea 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 unconditional variance of these shares more than doubles between the pre-1990 and post-1990 periods. We control for variation owing to income per capita; the conditional variance of manufacturing valued-added shares is non-monotonic over time, but during the post-1990 period, it also doubles.

Our open economy model of structural change embodies the main driving forces and mechanisms from the structural change literature: non-homothetic preferences, in which income effects lead to shifts in sectoral demands; sector-biased TFP growth, which engenders relative price changes inducing shifts in sectoral demands; and comparative advantage-based international trade, which generates sectoral reallocation directly through sectoral trade imbalances and indirectly through its impact on relative prices and income effects. Our model also features endogenous capital accumulation and input-output linkages.

Each of the two driving forces, sector-biased TFP growth and trade integration, mediated through the model's mechanisms, will have implications for sectoral output and factor demand, which, in turn, affects the sectoral allocation of value-added and of factors of production. For example, a decline in trade costs will affect sectoral value-added shares through at least three channels. First, the decline in these costs will increase specialization, which will directly affect the composition of sectoral production, and correspondingly, sectoral factor demands (mediated through input-output linkages within and across sectors). Second, to the extent the specialization leads to a more efficient allocation of resources, real income will increase, which, owing to non-homothetic preferences, will engender differential changes in sectoral output demand with corresponding effects on sectoral factors of production (again, with input-output linkages playing a role). Third, to the extent that trade costs decline faster in manufacturing than in other sectors, the relative price of manufacturing's output will decline, thereby shifting final expenditure away from manufacturing and into services.

To facilitate a careful comparison with our empirical findings, we calibrate our model to the same set of countries and time frame as in our main data analysis. This global approach is needed because, at a narrow level, industry polarization is a second-moment fact, and thus we need a large sample of countries, and at a broader level, the two data patterns we seek to explain our global patterns. In our calibration, agriculture is income inelastic, while services is more income elastic than manufacturing. In addition, the elasticities of substitution between sectoral goods in consumption, investment, and intermediate input demand are all less than one. We calibrate the time series of sectoral fundamental TFP and trade costs for each country to match data on sectoral prices and trade flows. The median growth rate of fundamental TFP is the highest in agriculture, followed by manufacturing, and then services. The rate of decline of trade costs is the highest for manufacturing, followed by agriculture, and then services.

Our baseline model successfully replicates both deindustrialization and industry polarization over time. When we run the same regression with the model outcomes as we did with the actual data, the model implies a decline in the peak manufacturing value-added share of 3.4 percentage points from the pre-1990 period to the post-1990 period, the same magnitude of decline as in the data. The baseline model also implies a doubling in the unconditional variance and a 33 percent increase in the conditional variance of the manufacturing value-added share between the two periods. Thus, sector-biased productivity growth and trade integration can rationalize the changing nature of structural change over time.

To assess how and why these two driving forces can lead to deindustrialization and industry polarization over time, we conduct three counterfactual exercises. In the first exercise, we remove declining trade costs and implement autarky. The only driving force is sector-biased productivity growth. In the second exercise, we remove sector-biased productivity growth and implement identical productivity growth across the three sectors (for each country), i.e., we have constant relative productivity. In the third exercise, both driving forces are removed. For each exercise, we solve the model, and then fit the relationship between sector value-added shares and per capita income with the model-implied "data".

Our counterfactual exercises reveal that sector-biased productivity growth alone can explain about 60 percent of deindustrialization, but is insignificant for industry polarization. In addition, trade integration alone explains virtually all of industry polarization, but is insignificant for deindustrialization. We also find that non-linear interaction between sector-biased productivity growth and trade integration is essential for understanding deindustrialization. Our interpretation is that trade integration allows countries to, in effect, "import" sector-biased TFP growth from other countries.

The declining relative price of manufacturing to services over time is the key channel driving deindustrialization and industry polarization. We show that this declining relative price stems primarily from higher productivity growth in manufacturing relative to services across a large swath of countries. Trade integration has also contributed, because trade costs have fallen more quickly in manufacturing than in services. Hence, by the post-1990s period, the cumulative effect of these forces was a low relative price of manufactured goods, and countries more specialized in manufactured goods, compared to the pre-1990s. The relatively low price of manufactured goods, coupled with the "Baumol" elasticities, i.e., elasticities of substitution in final demand and production that are less than one, meant that the global market for manufactured goods has been smaller in recent decades. Thus, there have have been fewer opportunities for recently industrializing countries to reach the industrial heights of economies like Taiwan and S. Korea in the pre-1990s – deindustrialization. Put differently, early industrializers encountered a relatively high price and high demand for manufacturing, and hence, all else equal, a greater share of the factors of production freed from agriculture joined manufacturing. Later industrializers, at the same level of income, have faced relatively low prices and demand for manufacturing, and hence, are more likely to bypass manufacturing and join services. Related, increased specialization in manufacturing has led to more countries relying on imports for their manufactured goods. Hence, they have had lower shares of manufacturing value-added; this, in conjunction with the high shares of manufacturing value-added in the countries specializing in manufacturing has led to industry polarization.

We also conduct an accounting decomposition to assess the role of sectoral and aggregate expenditure, as well as input-output, channels as transmission mechanisms. We find that shifts in sectoral consumption shares and input-output linkages account for four-fifths of deindustrialization and industry polarization. For both channels, the declining relative price of manufactured goods, in conjunction with the "Baumol" elasticities of substitution in both consumption and production, play a key role.

We note that while non-homothetic preferences have been shown to be an important mechanism for structural change, they have only a small role as a channel for deindustrialization and industry polarization. This is almost by definition, because the two facts are conditioned on income. For example, deindustrialization is about the declining peak manufacturing output share *controlling for per capita income* (and per capita income squared).

The starting point for our paper is Rodrik (2016), which was the first to document deindustrialization in a wide swath of countries. Recently, Felipe, Mehta, and Rhee (2019) provide further evidence for deindustrialization in a large sample of countries. In terms of models, Huneeus and Rogerson (2020) argue, using a benchmark, closed economy model of structural change, that heterogeneous paths of agricultural productivity across countries can result in deindustrialization. A related recent paper by Fujiwara and Matsuyama (2020) explains deindustrialization in terms of technology gaps.

In addition, our paper relates to three strands of the structural change literature. The first 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), Święcki (2017), Betts, Giri, and Verma (2017), Teignier (2018), and Matsuyama (2019). The second is the research on investment and structural change, and includes Kehoe, Ruhl, and Steinberg (2018), Herrendorf, Rogerson, and Valentinyi (2020), and García-Santana, Pijoan-Mas, and Villacorta (2021). The third is research on input-output linkages and structural change, and includes Sinha (2019) and Sposi (2019). None of these papers focuses on deindustrialization or industry polarization.

Our paper also relates to the literature on multi-country trade models with capital accumulation, and includes Eaton et al. (2016), Alvarez (2017), Ravikumar, Santacreu, and

Sposi (2019), Anderson, Larch, and Yotov (2020), and Mix (2021). These papers do not study structural change.

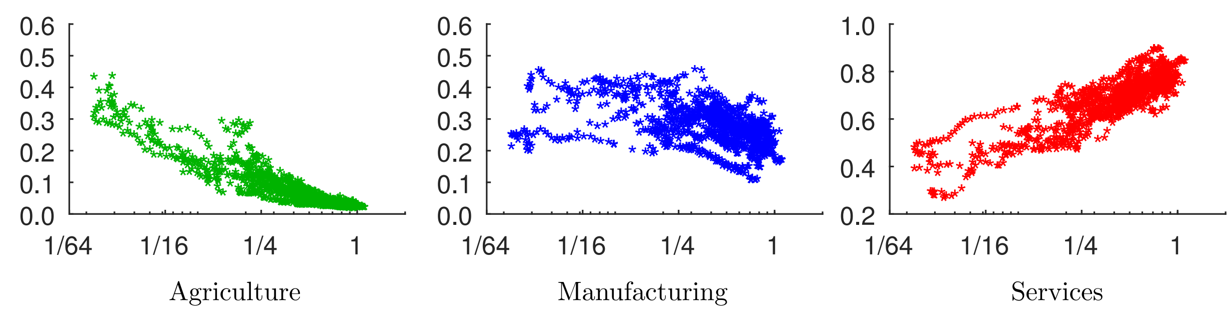
The paper is organized as follows. Section 2 presents the established and new stylized facts about structural change. Section 3 lays out our model while section 4 describes the model calibration. Section 5 presents our results, and the final section concludes.

2 Evidence on Deindustrialization and Industry Polarization

In this section, we document two sets of facts. We first add to the body of evidence on deindustrialization. We then show that the manufacturing value added shares across countries have become more dispersed over time, a feature we call *industry polarization*.

Figure 1 plots the sectoral value added share against real income per capita in PPP terms (normalized by the 2011 US income per capita), using a balanced panel of 28 countries over the period 1971–2011.[1] The figure shows the well known fact that as countries develop the agriculture value added share declines, the services value added share increases, and the manufacturing value added share follows a "hump" pattern. Similar patterns hold for the sectoral employment shares. Also, these patterns are robust when we extend the sample to an unbalanced one covering 95 countries over the period 1970–2010, which is presented in the Appendix.

Figure 1: Sectoral Value Added Shares: 1971–2011



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

We then examine whether the relationship between the sectoral value added shares and income changes over time. To do this, we estimate the relationships for the pre-1990 and post-1990 periods using OLS regressions of a quadratic specification using country fixed

[1] See Appendix A for list of countries and details on our data sources.

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:

$$\mathrm{va}_{n,t}^{j} = \alpha_n^j + \sum_{\mathrm{pd}\in\{\text{pre, post}\}} \left(\beta_{0,\mathrm{pd}}^{j} + \beta_{1,\mathrm{pd}}^{j} y_{n,t} + \beta_{2,\mathrm{pd}}^{j} y_{n,t}^{2}\right) \mathbb{1}_{t\in\mathrm{pd}} + \epsilon_{n,t}^{j}, \tag{1}$$

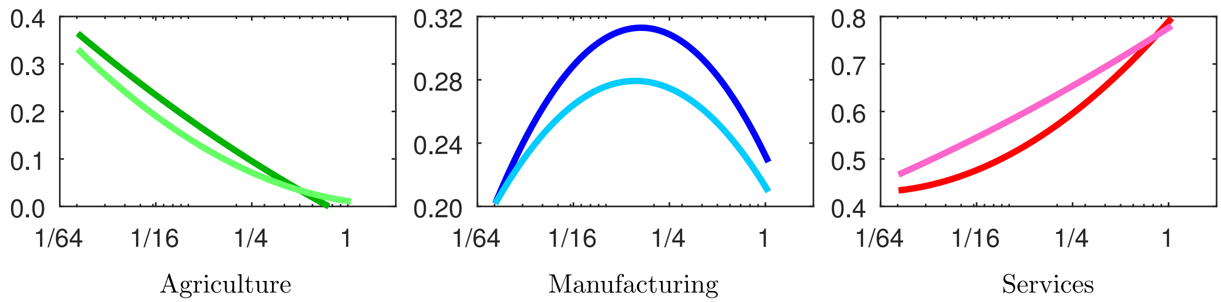
where $\mathrm{va}_{n,t}^{j}$ denotes the value added share of sector j in country n and year t, and y denotes log income per capita. The sample is split into two periods: pd $\in$ {pre-90, post-90}, and the indicator function $\mathbb{1}_{t=\mathrm{pd}}$ takes the value of one when year t is in period pd and zero otherwise. Country fixed effects α_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 changes over time, so we allow for the coefficients (β_0^j, β_1^j, β_2^j) of the quadratic function of income per capita to vary across the two periods.

Given that the specification is quadratic in income per capita, we use a figure to present the estimation results visually and transparently. For each period, using the coefficient estimates from (1), we construct the relationship between sectoral value added shares and income per capita for a "typical" country. This typical country has the average country fixed effects. Hence, we calculate the predicted sectoral value added shares for every level of income per capita experienced by this country in the pre-1990 and post-1990 periods. Figure 2 plots the relationship in each sector for both periods. The figure shows the central facts of structural change in each period. The figure also shows that for countries at the same low levels of income, the agriculture value added share is lower, but the services share is higher, in the post-1990 period than in the pre-1990 period. Most important, the Manufacturing panel shows deindustrialization: the hump-shaped relationship shifts down substantially between the pre-1990 and post-1990 periods, with the peak share of the hump declining by 3.4 percentage points, from 0.313 to 0.279.[2]

In addition to the average sectoral value added shares—the first moment—across income levels and time periods, we also examine the variance of the sectoral value added share—the second moment—over time. Figure 3 shows that the cross-country dispersion in manufacturing value added shares. The shaded area displays the 1$^{\text{st}}$ to 99$^{\text{th}}$ percentiles, with the median plotted as the dark solid line. The median share declines consistently over time, while the cross-country variance of manufacturing value added shares rises. In particular, the share at the 99$^{\text{th}}$ percentile has remained stable at about 40 percent, but the share at

[2] An F-test rejects the null hypothesis that the coefficients are the same across the two periods. The p-value is significantly less than 0.0001 for each sector.

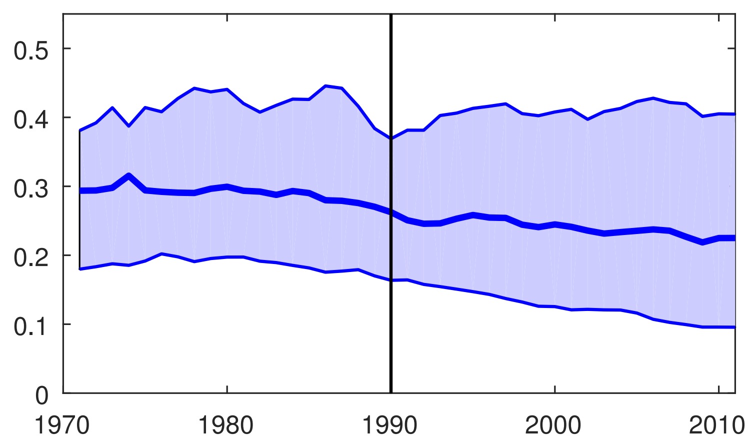
Figure 2: Deindustrialization: Sectoral Value Added Shares Pre-90 vs. Post-90



Notes: In the top row, 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). Lines in the darker (lighter) color are for the pre-1990 (post-1990) period.

the 1st percentile has fallen since 1990. Thus, the manufacturing value added share has been increasingly polarized since 1990.

Figure 3: Distribution of Manufacturing Value Added Shares

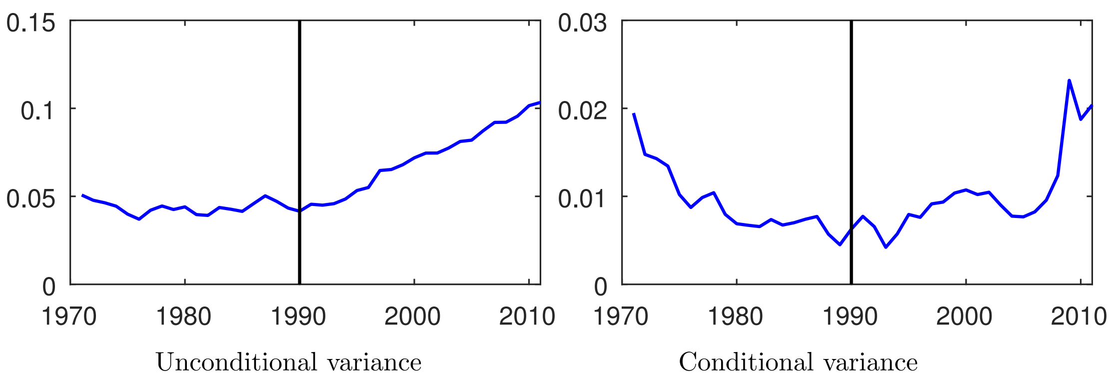


Notes: The solid line denotes the median value across countries in each year, while the upper and lower bands correspond to the 99th and 1st percentiles, respectively.

We quantify the degree of polarization over time using two measures. The first measure is the raw variance of the log sectoral value added share, which we refer to as the "unconditional variance". This variance describes the average squared percentage deviation from the mean value of each period. The second measure is the mean squared percentage prediction errors, which we refer to as the "conditional variance". This measure removes the variation due to cross-country time-invariant differences (country fixed effects) and that due to income differences over time from the unconditional variance. Alternatively speaking, this variance describes the variation that is unexplained by either country fixed effects or by income.

Figure 4 reports these two measures. The conditional variances are substantially smaller in magnitude than the unconditional variances, which shows that cross-country and income variations are important drivers behind the unconditional variances. The unconditional variance of the manufacturing value added share more than doubled from around 0.05 in the pre-1990 period to 0.11 in 2011. The conditional variance in manufacturing displays a U-shape over time. It declined by more than half from 1971 to 1990, and then more than doubled from 1991 to 2011. A simple accounting for this increased industry dispersion in the post-1990 period is the contrasting experiences across countries. Latin American countries (e.g. Brazil and Mexico) have much lower manufacturing value added shares than Asian economies (e.g. South Korea and Taiwan), conditional on the same level of income (e.g., Sinha, 2021) in the post-1990 period.

Figure 4: Industry Polarization
Cross-country Variance of Manufacturing Value Added Shares



Notes: Unconditional variance reports the log-variance of the manufacturing VA share across countries in each year. Conditional variance reports the mean squared difference between the log observed VA share and the log predicted VA share from regression (1) across countries in each year.

We conduct robustness checks on the main facts of deindustrialization and polarization in a large sample of 95 countries over 1970-2010 in the appendix.[3] We find in this large sample that the relationship between income per capita and the manufacturing value added share shifts down over time. The peak of the manufacturing-income curve declines by 2 percentage points from 0.214 in the pre-1990 period to 0.195 in the post-1990 period. Moreover, both unconditional and conditional cross-country variances of the manufacturing value added share display a U-shape pattern over time, declining from 1970 to 1990 and rising from 1990 to 2010. Thus, our main empirical findings of deindustrialization over time and polarization since 1990 are robust in a larger sample.

[3]We thank the authors of Felipe, Mehta, and Rhee (2019) for sharing their data.

Summary We have provided further confirmation of deindustrialization; countries that have developed more recently have tended to experience a greater share of resources effectively "bypassing" manufacturing and going directly from agriculture to services. Moreover, the dispersion of the manufacturing shares around this relationship has increased since 1990, reflecting heightened industry polarization across countries in the post-1990 period. The joint dynamics of deindustrialization and industry polarization are key features of the evolving global patterns of structural change.

3 Model

In this section, we describe the model used to study the evolving global structural change patterns. Along the lines of Uy, Yi, and Zhang (2013), Świecki (2017), and Sposi (2019), we employ a three-sector, multi-country, Ricardian model of trade. A novel departure from the existing open economy structural change models is the introduction of endogenous capital accumulation. There are N countries and three sectors: agriculture, industry, and services. Time is discrete and infinite, and agents have perfect foresight. In each country, there is a representative household with nonhomethetic preferences and firms with constant returns to scale technology. Countries can produce and trade a continuum of varieties in each sector, and trade is subject to "iceberg" trade costs. Time-varying and country-specific sectoral productivity and trade costs are the two key drivers of structural change in the model.

3.1 Households

A representative household in each country owns the raw factors of production (capital and labor) and decides on consumption and investment over time and also on final demand allocations across the three sectors. Lifetime utility of the representative household is defined over a discounted stream of population-weighted period utility, which is the logarithm of per-capita aggregate consumption:

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

where $C_{n,t}$ denotes aggregate consumption in country n and time t, $L_{n,t}$ denotes total labor, and $\beta < 1$ is the constant discount factor. The term $\psi_{n,t}$ is an exogenous shock to the discount factor, capturing the impact on investment dynamics of forces outside of the model—time-varying demographics, capital taxes, and other distortions at the country level.

In each period aggregate consumption is defined as a generalized, non-homothetic, CES aggregate over the three sector composite goods, along the lines of Comin, Lashkari, and Mestieri (2015)[4] . It is implicitly defined as:

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

where $c^j_{n,t}$ denotes consumption of the sector-j good. The term $\sigma_c > 0$ governs the elasticity of substitution across sectors (price elasticity), and ε^j governs the income elasticity for each sector.[5] Finally, $\omega^j_{c,n}$ denotes the relative weight of the sector-j good within the bundle, with $\sum_j \omega^j_{c,n} = 1$. We allow $\omega^j_{c,n}$ to be country-specific to capture any time-invariant factors that affect sectoral consumption allocations across countries, such as taste, geography, or institutions, but are unrelated to income per capita and relative prices. When the income elasticity ϵ^j is set at one for all sectors, equation (3) gives the standard CES consumption aggregation over sectoral goods. When the elasticity of substitution σ_c is also set to one, equation (3) becomes Cobb-Douglas.

The representative household chooses consumption and investment over time to maximize utility specified by equations (2)–(3), subject to budget constraints and the law of motion for capital stocks. In each period, the expenditure on consumption and investment across the three sectors equates to income:

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

The left hand side of equation (4) accounts for the expenditure on consumption $c^j_{n,t}$ and investment $x^j_{n,t}$ in each sector j at price $p^j_{n,t}$. Just as $C_{n,t}$ denotes aggregate consumption, $X_{n,t}$ denotes aggregate investment, which is specified as a CES aggregate of sectoral investment $x^j_{n,t}$:

$$X_{n,t} = \left(\sum_{j\in\{a,m,s\}} \omega^j_{x,n} \left(x^j_{n,t}\right)^{\frac{\sigma_x-1}{\sigma_x}}\right)^{\frac{\sigma_x}{\sigma_x-1}},$$

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

[5] The income elasticities are technically elasticities with respect to instantaneous utility, but we use the term income elasticity to align with existing literature. Only the difference in the income elasticities matters for allocations. Changing the levels, holding the difference fixed, affects only the cardinal properties of the utility function.

where σ_x is the elasticity of substitution across sectors, and $\omega_{x,n}^j$ controls the weight of sector j in aggregate investment spending. The price indices for aggregate consumption and investment are denoted by $P_{n,t}^c$ and $P_{n,t}^x$, respectively.

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

The law of motion for capital stocks specifies that aggregate investment augments the existing stock of capital subject to depreciation and adjustment costs:

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

where δ is the depreciation rate, and $\lambda \in [0,1]$ governs the adjustment cost. To see this transparently, we rewrite equation (5) as an investment function:

$$X_{n,t} \equiv \Phi\left(K_{n,t+1}, K_{n,t}\right) = \delta^{1-\frac{1}{\lambda}}\left(\frac{K_{n,t+1}}{K_{n,t}} - (1-\delta)\right)^{\frac{1}{\lambda}} K_{n,t}. \tag{6}$$

When $\lambda = 1$ there is no adjustment cost, and when $\lambda = 0$ adjustment costs are infinite.

3.2 Firms

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

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

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

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

where η is the elasticity of substitution between varieties, which is constant across countries, sectors, and time. The term $q^j_{n,t}(v)$ is the quantity of variety v used by country n at time t to construct the sector-j composite good. Each variety can be sourced from any location, i.e., variety-v goods are perfect substitutes across origin locations. The resulting composite good, $Q^j_{n,t}$, is the quantity of the sector-j composite good available in country n to use as an intermediate input or for final consumption or investment.

Individual varieties Each individual variety can be produced using capital, labor and intermediate (composite) goods from each sector. The technology for producing variety v in sector j and country n is given by:

$$y^j_{n,t}(v) = a^j_n(v) \left(A^j_{n,t} k^j_{n,t}(v)^\alpha \ell^j_{n,t}(v)^{1-\alpha}\right)^{\nu^j_n} E^j_{n,t}(v)^{1-\nu^j_n}. \tag{7}$$

Production is a Cobb-Douglas aggregate of value added and intermediate inputs. The parameter $\nu^j_n \in [0,1]$ denotes the share of value added in total output that is constant over time and $E^j_{n,t}$ denotes the intermediate input index used in sector j. Value added is a Cobb-Douglas aggregate of capital $k^j_{n,t}(v)$ and labor $\ell^j_{n,t}(v)$ with a capital share of α that is constant across countries, sectors, and time. For intermediates, sectoral inputs are combined in a more general CES fashion:

$$E^j_{n,t}(v) = \left(\sum_{k\in\{a,m,s\}} \omega^{j,k}_{e,n} e^{j,k}_{n,t}(v)^{\frac{\sigma^j_e - 1}{\sigma^j_e}}\right)^{\frac{\sigma^j_e}{\sigma^j_e - 1}}, \tag{8}$$

where $e^{j,k}_{n,t}(v)$ denotes country n's use of composite good k in the production of sector j's variety v and $\omega^{j,k}_{e,n}$ denotes the corresponding weights in total spending on intermediates by sector j, with $\sum_l \omega^{j,k}_{e,n} = 1$ for all (n,j). The weights are country-specific and constant over time. σ^j_e denotes the elasticity of substitution across sectoral composite intermediate inputs.

Country- and sector-specific value-added productivity, $A^j_{n,t}$, varies over time. The term $a^j_n(v)$ 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 shape parameters θ^j, with c.d.f.s given by $F^j_{n,t}(a) = \exp(-a^{-\theta^j})$. Without loss of generality, we assume the idiosyncratic productivity draws are constant over time.

Given prices of output and inputs and factor prices, the firms maximizes profit given by:

$$p^j_{n,t}(v) y^j_{n,t}(v) - r_{n,t} k^j_{n,t}(v) - w_{n,t} \ell^j_{n,t}(v) - P^{e,j}_{n,t} E^j_{n,t}(v),$$

where $P^{e,j}_{n,t} E^j_{n,t}(v) = \sum_{k \in \{a,m,s\}} p^k_{n,t} e^{k,j}_{n,t}(v)$ is the total spending on intermediates by firms in sector j. $P^{e,j}_{n,t}$ denotes the cost index of sector-j's intermediate input bundles.

3.3 Trade

Varieties are traded internationally subject to physical iceberg costs. Country n must 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 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:

$$\pi^j_{n,i,t} = \frac{\left((A^j_{i,t})^{-\nu^j_i} u^j_{i,t} d^j_{n,i,t}\right)^{-\theta^j}}{\sum_{i'=1}^{N} \left((A^j_{i',t})^{-\nu^j_{i'}} u^j_{i',t} d^j_{n,i',t}\right)^{-\theta^j}}, \tag{9}$$

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

$$u^j_{i,t} = \left(\frac{R_{i,t}}{\alpha \nu^j_i}\right)^{\alpha \nu^j_i} \left(\frac{W_{i,t}}{(1-\alpha)\nu^j_i}\right)^{(1-\alpha)\nu^j_i} \left(\frac{P^{e,j}_{i,t}}{1-\nu^j_i}\right)^{1-\nu^j_i}. \tag{10}$$

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

$$p^j_{n,t} = \gamma_j \left[\sum_{i=1}^{N} \left((A^j_{i,t})^{-\nu^j_i} u^j_{i,t} d^j_{n,i,t}\right)^{-\theta^j}\right]^{-\frac{1}{\theta^j}}, \tag{11}$$

where γ^j is a constant.

3.4 Equilibrium

The model economy is summarized by time invariant parameters (β, ϵ^j, σ_c, σ_x, σ^j_e, θ, δ, λ, η, α, ν^j_n, $\omega^j_{c,n}$, $\omega^j_{x,n}$, $\omega^{j,k}_{e,n}$), time varying exogenous processes of sectoral productivities and trade costs $\{A^j_{n,t}, d^j_{n,i,t}\}$, the initial capital stock K_{n0}, processes of labor endowment $\{L_{n,t}\}$, and processes controlling trade imbalances $\{\phi_{n,t}\}$ and discount factors $\{\psi_{n,t}\}$. We first define and then characterize the competitive equilibrium of the model.

Definition. A competitive equilibrium of this model consists sequences of allocations $\{C_{n,t}$, $X_{n,t}$, $K_{n,t}$, $c^j_{n,t}$, $x^j_{n,t}$, $k^j_{n,t}$, $l^j_{n,t}$, $E^j_{n,t}$, $e^{j,k}_{n,t}$, $\pi^j_{nit}\}$ 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 satisfy the following conditions: (1) the representative household maximizes utility taking prices as given, (2) firms maximize profits taking prices as given, (3) each country purchases each variety from the least costly supplier/country, and (4) markets clear.

3.4.1 Households' optimization

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

$$\frac{C_{n,t+1}/L_{n,t+1}}{C_{n,t}/L_{n,t}} = \beta \left(\frac{\psi_{n,t+1}}{\psi_{n,t}}\right) \left(\frac{\frac{R_{n,t+1}}{P^x_{n,t+1}} - \Phi_2\left(K_{n,t+2}, K_{n,t+1}\right)}{\Phi_1\left(K_{n,t+1}, K_{n,t}\right)}\right) \left(\frac{P^x_{n,t+1}/P^c_{n,t+1}}{P^x_{n,t}/P^c_{n,t}}\right), \tag{12}$$

where Φ_1 and Φ_2 denote the first derivative of the investment function with respect to the first and second arguments, respectively.[7]

The intratemporal decisions are characterized by the first order conditions as well. Investment across sectors follows the standard CES demand:

$$x^j_{n,t} = (\omega^j_{x,n})^{\sigma_x} \left(\frac{p^j_{n,t}}{P^x_{n,t}}\right)^{-\sigma_x} X_{n,t}, \tag{13}$$

where the price index for investment is given by:

$$P^x_{n,t} = \left(\sum_{j\in\{a,m,s\}} (\omega^j_{x,n})^{\sigma_x} (p^j_{n,t})^{1-\sigma_x}\right)^{\frac{1}{1-\sigma_x}}.$$

Given the nonhomothetic CES preferences, consumption allocations across sectors depend on not only the relative prices, but also aggregate consumption (instantaneous utility):

$$c^j_{n,t} = L_{n,t}(\omega^j_{c,n})^{\sigma_c} \left(\frac{p^j_{n,t}}{P^c_{n,t}}\right)^{-\sigma_c} \left(\frac{C_{n,t}}{L_{n,t}}\right)^{\varepsilon^j(1-\sigma_c)+\sigma_c}, \tag{14}$$

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

where the price index for consumption is given by:

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

When $\epsilon^j = 1$ for all sectors, equation (14) becomes the standard CES demand function. With non-unitary income elasticities, changes in income also impact sectoral consumption allocations. Specifically, as income rises, households consume more goods from a sector with a higher income elasticity. The magnitudes of the price and income effects are governed by the price elasticity σ_c and the income elasticities ϵ^j, respectively. These two effects also drive the consumption expenditure share of sector j:

$$\frac{p^j_{n,t} c^j_{n,t}}{P^c_{n,t} C_{n,t}} = (\omega^j_{c,n})^{\sigma_c} \left(\frac{p^j_{n,t}}{P^c_{n,t}}\right)^{1-\sigma_c} \left(\frac{C_{n,t}}{L_{n,t}}\right)^{(\varepsilon^j-1)(1-\sigma_c)}. \tag{15}$$

3.4.2 Firms' optimization

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

$$\begin{aligned} R_{n,t} k^j_{n,t} &= \alpha \nu^j_n p^j_{n,t} y^j_{n,t}, \\ W_{n,t} \ell^j_{n,t} &= (1-\alpha) \nu^j_n p^j_{n,t} y^j_{n,t}, \\ P^{e,j}_{n,t} E^j_{n,t} &= (1-\nu^j_n) p^j_{n,t} y^j_{n,t}, \end{aligned}$$

where the cost index of intermediate inputs used in sector j is

$$P^{e,j}_{n,t} = \left(\sum_{k\in\{a,m,s\}} (\omega^{j,k}_{e,n})^{\sigma^j_e} (p^k_{n,t})^{1-\sigma^j_e} \right)^{\frac{1}{1-\sigma^j_e}}. \tag{16}$$

Intermediate inputs acquired from sector k by sector j are given by

$$e^{j,k}_{n,t} = (\omega^{j,k}_{e,n})^{\sigma^j_e} \left(\frac{p^k_{n,t}}{P^{e,j}_{n,t}}\right)^{-\sigma^j_e} E^j_{n,t}. \tag{17}$$

3.4.3 Feasibility

We begin by describing the domestic market clearing conditions:

$$
\begin{aligned}
K_{n,t} &= \sum_{j\in\{a,m,s\}} k^j_{n,t}, \\
L_{n,t} &= \sum_{j\in\{a,m,s\}} \ell^j_{n,t}, \\
q^j_{n,t} &= c^j_{n,t} + x^j_{n,t} + \sum_{k\in\{a,m,s\}} e^{k,j}_{n,t}.
\end{aligned}
$$

The first two conditions impose capital and labor market clearing in country n. The third condition requires, in each sector-country, that the use of the composite good equals its supply. Its use consists of consumption and investment by the representative household, and of intermediate input use by firms in all sectors. Its supply is the quantity of the composite good, which consists of an aggregation of both domestically- and foreign-produced varieties.

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

$$
p^j_{n,t} y^j_{n,t} = \sum_{i=1}^{N} p^j_{i,t} Q^j_{i,t} \pi^j_{i,n,t}. \tag{18}
$$

Finally we impose an aggregate resource constraint that requires the sum of net exports across sectors to equal the value of net transfers in each country:

$$
\sum_{j\in\{a,m,s\}} \left(p^j_{n,t} y^j_{n,t} - p^j_{n,t} Q^j_{n,t} \right) = \phi_{n,t}(R_{n,t}K_{n,t} + W_{n,t}L_{n,t}) - L_{n,t}T^P_t. \tag{19}
$$

The left-hand side is the value of gross production minus gross absorption. The right-hand side is the difference between income and spending, i.e., transfers or net exports. Table C.1 summarizes all of the equilibrium conditions.

4 Calibration

In this section, we calibrate our dynamic trade model, which will then be used to investigate the forces that drive the two evolving patterns of structural change over time. To facilitate comparing out model to our empirical patterns, our quantitative analysis includes the same 28 countries as in our empirical analysis, plus a rest-of-world aggregate, from 1971 to 2011. We will discuss first the calibration of the time-invariant parameters and then that of the time-varying processes of the model. This section concludes with the model fit. For details on data sources used in the calibration see Appendix A.

4.1 Time invariant parameters

We start with the preference parameters. The discount factor is set at 0.96 to target an annual real interest rate of 4%. The preference elasticities are recovered from the model-implied relationship between relative sectoral expenditure, relative prices and aggregate consumption in the logged form:

$$\ln\left(\frac{P^j_{n,t}C^j_{n,t}}{P^m_{n,t}C^m_{n,t}}\right) = \sigma_c \ln\left(\frac{\omega^j_{c,n}}{\omega^m_{c,n}}\right) + (1-\sigma_c)\ln\left(\frac{P^j_{n,t}}{P^m_{n,t}}\right) + (1-\sigma_c)(\varepsilon^j - 1)\ln\left(\frac{C_{n,t}}{L_{n,t}}\right), \tag{20}$$

for $j = a$ and s. We observe sectoral expenditure, sectoral prices and total labor in the data. If we had a model-consistent measure of $C_{n,t}$, we would simply recover $\{\omega^j_{c,n}, \sigma_c, \epsilon^j\}$ from an OLS regression by pooling countries and sectors (agriculture and services) with country×sector fixed effects and normalizing $\varepsilon^m = 1$. Specifically, the estimated country×sector fixed effects reveal the country-sector specific weights, $\omega^j_{c,n}$, and the income and price elasticities are identified through how changes in sectoral expenditures co-move with income and relative prices over time at the country level. However, we do not observe $C_{n,t}$, so we conduct the following iterative estimation procedure, as in Lewis et al. (2020). We first guess parameters $\{\omega^j_{c,n}, \sigma_c, \epsilon^j\}$. Then we compute $C_{n,t}$ as a solution to the expenditure function

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

where total consumption expenditure on the left hand side is taken from the data. With the constructed $C_{n,t}$ in hand, we estimate preference parameters $\{\omega^j_{c,n}, \sigma_c, \epsilon^j\}$ using the OLS regression (20). We then use the estimated parameters to construct a new measure of $C_{n,t}$, and re-estimate equation (20). We iterate this process until the preference parameters $\{\omega^j_{c,n}, \sigma_c, \epsilon^j\}$ converge.

Three caveats are worth noting. First, because our sample contains only a few low income countries, we over-sample India, China, and Indonesia in order to obtain more precise estimates of the income elasticities.[8] Second, confidence intervals are constructed using a bootstrap procedure where, for each country, years are independently sampled with replace-

[8] Each observation for India, China, and Indonesia are included four times, while all other countries' observations are included once.

ment so that the bootstrap samples each have the same number of country observations as the data sample. Third, we impose a constraint on the estimate of $\sigma_c > 0$. This constraint does not bind in our sample. However, it does bind in some of the bootstrap iterations.

Table 1 reports the estimation results. The estimated price elasticity σ_c is 0.06, and the income elasticities $(\varepsilon_a, \varepsilon_m, \varepsilon_s)$ are $(0.45, 1.00, 1.34)$. These values imply that sectoral composites are complements in final consumption demand, and the services (agriculture) composite has the highest (lowest) income elasticity among the three sectors, which is broadly consistent with those in Comin, Lashkari, and Mestieri (2015). Our price elasticity is lower than their range of estimate (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. In a two-sector model, Lewis et al. (2020) estimate this parameter to be 0.16 using expenditure shares.

Table 1: Time Invariant Parameters

Income elasticity	$\varepsilon^a,\ \varepsilon^m,\ \varepsilon^s$	0.45	1.00	1.34
		(0.41, 0.48)		(1.27, 1.43)
Price elasticity	σ_c	0.06		
		(0.01, 0.12)		
	σ_x	0.29		
		(0.16, 0.40)		
	$\sigma_e^a,\ \sigma_e^m,\ \sigma_e^s$	0.48	0.06	0.01
		(0.43, 0.53)	(0.01, 0.13)	(0.01, 0.01)
Value added share in output (mean)	$\nu^a,\ \nu^m,\ \nu^s$	0.57	0.36	0.61
Discount factor	β	0.96		
Capital share in value added	α	0.33		
Capital depreciation rate	δ	0.06		
Adjustment cost elasticity	λ	0.75		
Trade elasticity	θ^j	4		

Notes: The income and price elasticities are estimated using constrained OLS regressions with positive price elasticities. The 95% confidence intervals (in parentheses) are bootstrapped with 1000 iterations where years are independently sampled with replacement for each country, so each bootstrap sample has the same number of observations as the data sample.

To estimate the elasticity across sectors within investment, we run the following constrained ($\sigma_x > 0$) OLS regression with country×sector fixed effects, implied by the optimality condition of the model:

$$\ln\left(\frac{P^j_{n,t}X^j_{n,t}}{P^m_{n,t}X^m_{n,t}}\right) = \sigma_x \ln\left(\frac{\omega^j_{x,n}}{\omega^m_{x,n}}\right) + (1-\sigma_x)\ln\left(\frac{P^j_{n,t}}{P^m_{n,t}}\right), \tag{21}$$

for $j = a$ and s. Our estimate for the price elasticity of sectoral investment demand σ_x is 0.29. This value indicates a strong degree of complementary, in line with estimates in the literature.

For example, Herrendorf, Rogerson, and Valentinyi (2020) estimate this parameter to be 0 between goods and services for the United States.

We next describe the production parameters. We implement an analogous estimation procedure for sector-level intermediate-input spending as we did for sector-level investment spending. We obtain $\sigma_e^a = 0.48$ and $\sigma_e^m = 0.06$. For the services sector, the unconstrained estimate of σ_e^s is negative; hence, the constraint $\sigma_e^s > 0$ is binding in our sample, and in each bootstrap iteration, resulting in an estimate of $\sigma_e^s = 0.01$ with the standard error being zero. Intermediate inputs are complementary in all three sectors, particularly in the services sector. This implies that intermediate input demand shifts away from manufacturing and toward services in response to a declining relative price of manufacturing to services over time. Moreover, given the gradual rise of services in final demand, the steady increase in the relative price of services amplifies the indirect demand for services through the input-output structure.

We compute ν_n^j as the average ratio—from 1971 to 2011—of value added to gross output for each sector j and country n. Table 1 reports the average ratio across countries for each sector. Not surprisingly, the services sector has the highest ratio of value added to gross output, and manufacturing, the lowest.

The remaining production parameters are taken from the literature. Capital's share in value added α is 0.33, as in Gollin (2002). The depreciation rate δ is set at 6%, a standard value in macro models using annual data. The adjustment cost parameter λ is set to 0.75, based on Eaton, Kortum, Neiman, and Romalis (2016).[9] Simonovska and Waugh (2014) estimate the trade elasticity for manufacturing to be 4. We apply this estimate to all sectors: $\theta^j = 4$ for all j. The elasticity of substitution between individual goods within the composite good plays no quantitative role in the model other than satisfying a technical condition: $1 + \frac{1}{\theta^j}(1-\eta) > 0$. Following the literature we set $\eta = 2$.

4.2 Time-Varying Exogenous Processes

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

We first describe the calibration of labor endowments and capital stocks. For each sample country, the labor series $\{L_{n,t}\}$ is directly taken from the data: the numbers of persons engaged across the three broad sectors. The initial capital stock is taken directly from data of 1971. The capital stocks in subsequent years are constructed using data on investment

[9]When $\lambda = 1$ there is no adjustment cost and when $\lambda = 0$ capital cannot be adjusted.

along with the law of motion for capital. While the capital stock in our model is endogenous, the data construct is used for imputing other moments, like the rental rate for capital, as described below.

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

$$Z^j_{n,t} \equiv \frac{u^j_{n,t}}{p^j_{n,t}} = B^j_n \frac{(R_{n,t})^{\alpha\nu^j_n}(W_{n,t})^{(1-\alpha)\nu^j_n}}{p^j_{n,t}} \left(\sum_{k\in\{a,m,s\}} (\omega^{j,k}_{e,n})^{\sigma^j} (p^k_{n,t})^{1-\sigma^j} \right)^{\frac{1-\nu^j_n}{1-\sigma^j}}, \tag{22}$$

where $B^j_n = (\alpha\nu^j_n)^{-\alpha\nu^j_n} ((1-\alpha)\nu^j_n)^{-(1-\alpha)\nu^j_n} (1-\nu^j_n)^{-(1-\nu^j_n)}$. The wage rate is nominal GDP in USD times the labor share in GDP divided by the number of workers: $W_{n,t} = \frac{(1-\alpha)\text{GDP}_{n,t}}{L_{n,t}}$. The rental rate of capital is imputed using the capital-labor ratio and the wage rate. For sectoral prices, we gross up the data on sectoral value added prices. The second step is to compute the fundamental productivity, A^j_{nt}, from the measured productivity, Z^j_{nt}, using data on sectoral home trade shares:

$$A^j_{n,t} = \left(\gamma^j Z^j_{n,t} \left(\pi^j_{n,n,t}\right)^{\frac{1}{\theta^j}} \right)^{\frac{1}{\nu^j_n}}. \tag{23}$$

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

We then calibrate the series of bilateral trade costs $\{\pi^j_{n,i,t}\}$. Through the lens of the model, the bilateral trade barrier between two countries is a wedge that reconciles the observed pattern of trade and relative price difference:

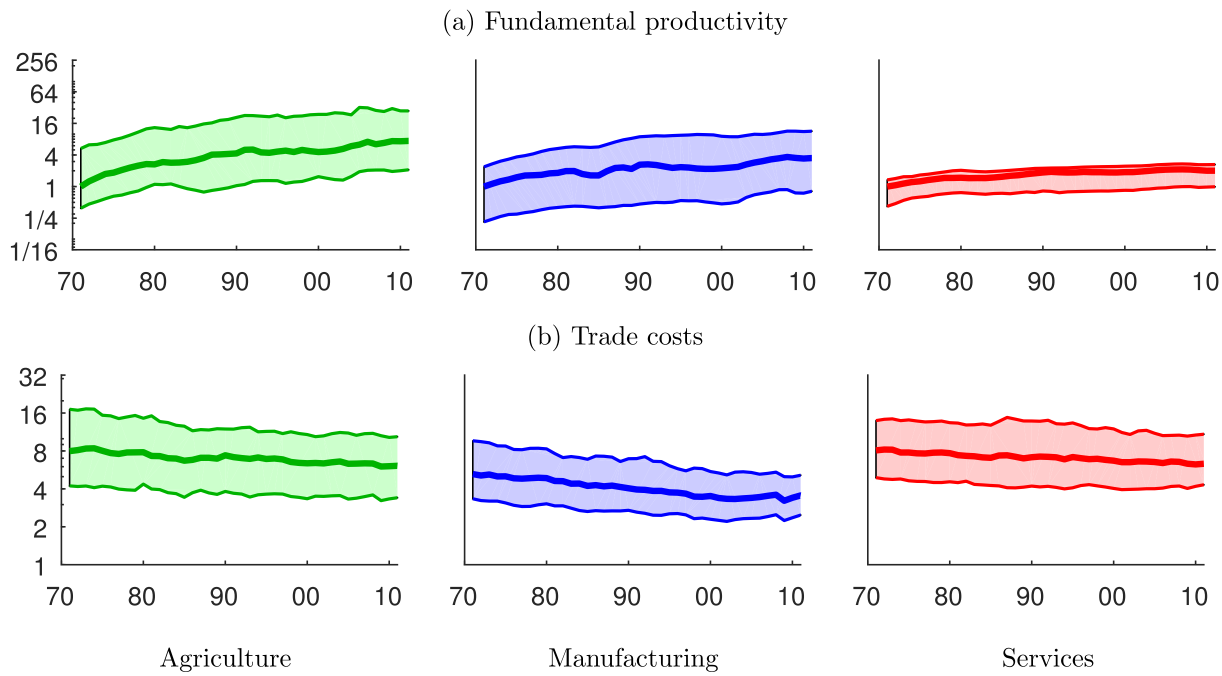
$$d^j_{n,i,t} = \left(\frac{\pi^j_{n,i,t}}{\pi^j_{i,i,t}} \right)^{-\frac{1}{\theta_j}} \left(\frac{p^j_{n,t}}{p^j_{i,t}} \right). \tag{24}$$

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

Finally, we calibrate the series for the trade imbalances and preference shifters. For every country n, the series $\phi_{n,t}$ is set at the ratio of net exports to GDP in every year. The series of preference shifters $\psi_{n,t}$ is pinned down as residual that relates per-capita consumption growth to the real rate of return to investment, as in equation (12), with $\psi_{n,1} = 1$.

We now present the estimated series of the two key exogenous driving forces of structural change: sectoral productivities and trade costs. The top panel of Figure 5 plots the interquartile range of the cross-country productivity distribution for each sector. The annual growth

Figure 5: Sectoral fundamental productivity and trade barriers



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

rate of the world median fundamental productivity is 5.4% in agriculture, 3.4% in manufacturing, and 1.8% in services.[10] The ranking across sectors is common to most—especially advanced—economies and consistent with that in Herrendorf, Rogerson, and Valentinyi (2013). Among the three sectors, agriculture shows the greatest cross-country variation in productivity, (consistent with Caselli, 2005; Restuccia, Yang, and Zhu, 2008; Gollin, Lagakos, and Waugh, 2014), and services shows the least (in line with the Balassa-Samuelson hypothesis). Finally, the cross-country variation is stable over time in all three sectors.

The lower panel plots the cross-country distribution of the estimated trade costs for each sector over time. Clearly, trade costs are generally lower in manufacturing than in the other two sectors at any point in time. Although trade barriers decline in all sectors, they decline at a faster rate in the agriculture and manufacturing sectors than in the services sector. The agriculture and manufacturing sectors also display more rapidly declining cross-country variation over time. The findings are the manifestation of global trade integration over the past half a century.

4.3 Solution method and model fit

The calibration sets the time-invariant parameters and the time-varying processes to best align the model with the observed data. To complete the description of the dynamic model with forward-looking capital decisions, we need to specify the time-varying processes subsequent to the sample period. We assume that the data targets remain constant at their 2011 values and infer the parameters in all periods given this assumption. We next solve the baseline model numerically. The key is to solve for the series of capital stocks during the transition path that satisfy the intertemporal Euler equations in all countries.[11]

After solving the calibrated model to obtain the equilibrium, we check the model fit with respect to the data. We first check on the model implications on patterns of structural change over time. As shown in the upper panel of Figure 6, the sectoral value added shares in the model (y-axis) are very close to those in the data (x-axis). Hence, it is not surprising that our estimation of the relationship between model-implied sectoral value added shares and model-implied income reproduces the patterns of deindustralization, as shown in the bottom panel of Figure 6. Specifically, the model implies a decline in the peak share of the hump-shaped relationship between the manufacturing value added share and income by 3.4 percentage points from the pre-1990 to post-1990 periods – just as in the data.

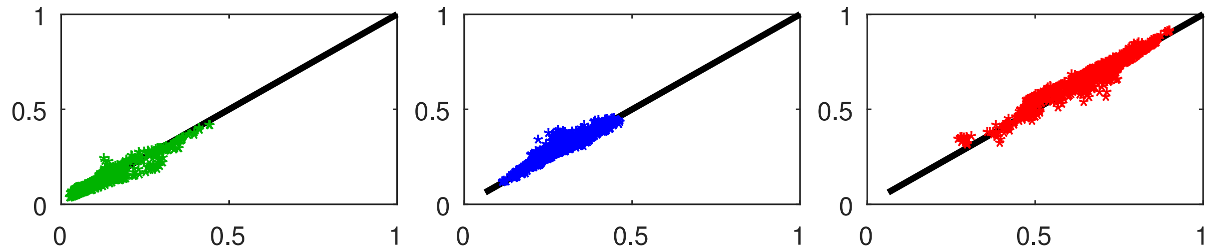
The baseline model also replicates the pattern of industry polarization over time. Figure

[10] Regarding *measured* productivity, we find that the median growth rate across countries is 5.5% in agriculture, 3.9% in manufacturing, and 1.9% in services.

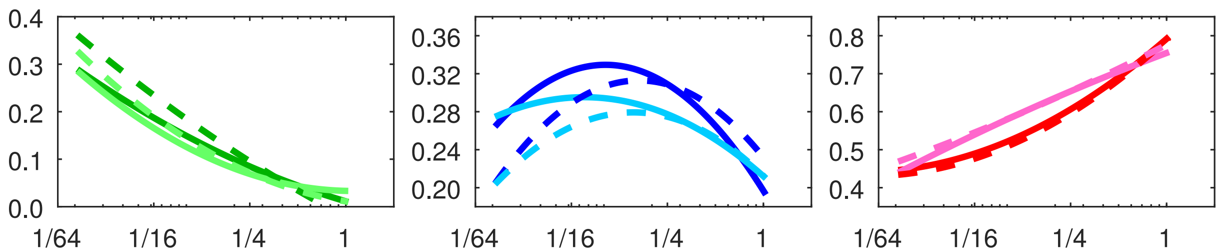
[11] Our method is based on Ravikumar, Santacreu, and Sposi (2019). For details see Appendix C.

Figure 6: Baseline Model Fit: Sectoral Value Added Shares

(a) Model vs. Data



(b) Predicted Shares across Income Per Capita: Model and Data



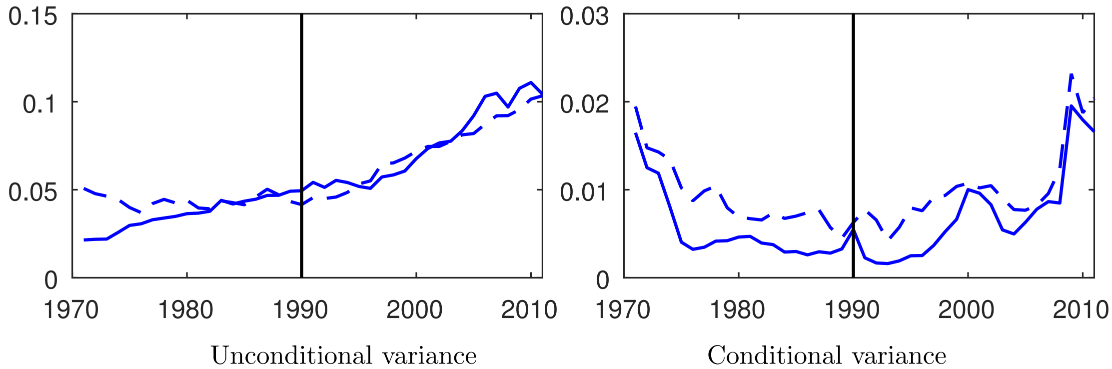
Agriculture Manufacturing Services

Note: The upper-row scatter plots have model value added shares on the y axis and data shares on the x axis with the 45^o line on the diagonal. The bottom-row line plots depict the implied share based on regression (1) on the y axis over income per capita on the x axis. The regression is applied separately to the actual data and to the model-generated data. Dashed lines - data; Solid lines - model. Dark lines - pre 1990; Light lines - post 1990.

7 compares the cross-country unconditional and conditional variances of manufacturing value added shares in the model and in the data. The left panel shows that the baseline model reproduces the rising unconditional variance in the data, particularly in the post-1990 period. The right panel illustrates that though it produces a smaller magnitude of the conditional variance than the data, the baseline model generates a U-shape pattern of the conditional variance over time, similar to that in the data. The baseline model also reproduces well the declining dispersion of services value added shares in terms of both unconditional and conditional variances over time. For the agriculture sector, the baseline model matches well for the unconditional variances, which is relatively flat over time. For the conditional variance, the model replicates the flat dispersion over time pre-1990, and under-predicts the rise post-1990. The results are plotted in Figure D.3 of the Appendix.

Finally, we show that the calibrated model replicates other key data moments well. The scatter plots in Figure D.1 of the Appendix compare sectoral prices, trade shares, consumption expenditure shares, investment shares and intermediate input shares in the model with those in the data. The calibration targeted sectoral prices and bilateral trade

Figure 7: Industry Polarization: Baseline Model and Data



Notes: Dashed lines - data; Solid lines - model. Unconditional variance reports the log-variance of the manufacturing VA share. Conditional variance reports the mean squared difference between the log VA share and the log predicted VA share using regression (1) across countries in each year.

shares, which explains the almost perfect fit between the data and the model in the upper two panels. The remaining panels show that the calibration also replicates well the data on sectoral shares of consumption, investment, and intermediate inputs in each sector. The correlation between the data and the model is close to 1 for sectoral value added shares, and 0.99 for sectoral consumption and investment shares. The model also fits the intermediate input shares well: the correlation between model and data is 0.92, 0.97 and 0.99 for sectoral intermediate input shares in agriculture, manufacturing and services, respectively.

By construction, our model matches nominal GDP. In addition, our model matches well the sector shares in GDP as well as spending shares in final demand (consumption and investment). To line up real GDP in the model and in the data, we need to construct the model GDP deflator to be consistent with that in the data. For details see Appendix C.

5 Quantitative Analysis

This section conducts counterfactual exercises to quantify the contribution of the two driving forces – sector-biased productivity growth and trade integration – on the global patterns of deindustrialization and industry polarization. We carry out three counterfactual scenarios. In the first counterfactual, declining trade costs is removed, and countries stay in autarky throughout. We call this *the autarky scenario*. Second, sector-biased productivity growth is removed, and productivity growth is set equal across the three sectors of a country in a period. We call this *the constant-relative-productivity (CRP) scenario*. In the third scenario, both driving forces are removed: countries stay in autarky and have the same productivity growth rate in the three sectors every period. This is called *the autarky-CRP scenario.* In the latter two, the country-specific productivity growth rate is constructed to deliver the same paths for each country's income per capita as in the baseline model.

For each counterfactual scenario, we first compute the associated model equilibrium for the world economy. We then fit the relationship between sectoral value added shares and income per capita implied by each counterfactual, over two sample periods, pre-1990 and post-1990, using regression (1).

We also conduct accounting exercises that facilitate a better understanding of the model linkages from the driving forces to deindustrialization and industry polarization. The two drivers work through five channels to impact sectoral value added shares: sectoral consumption shares, sectoral investment shares, sectoral IO shares, sectoral net export shares, and aggregate consumption or investment shares.

Section 5.1 briefly describes the implications of our counterfactual analyses for global patterns of structural change. Section 5.2 discusses the implications for deindustrialization and investigates the mechanisms behind deindustrialization, and Section 5.3 assesses the driving forces for the dynamics of industry polarization. Section 5.4 presents the accounting exercise.

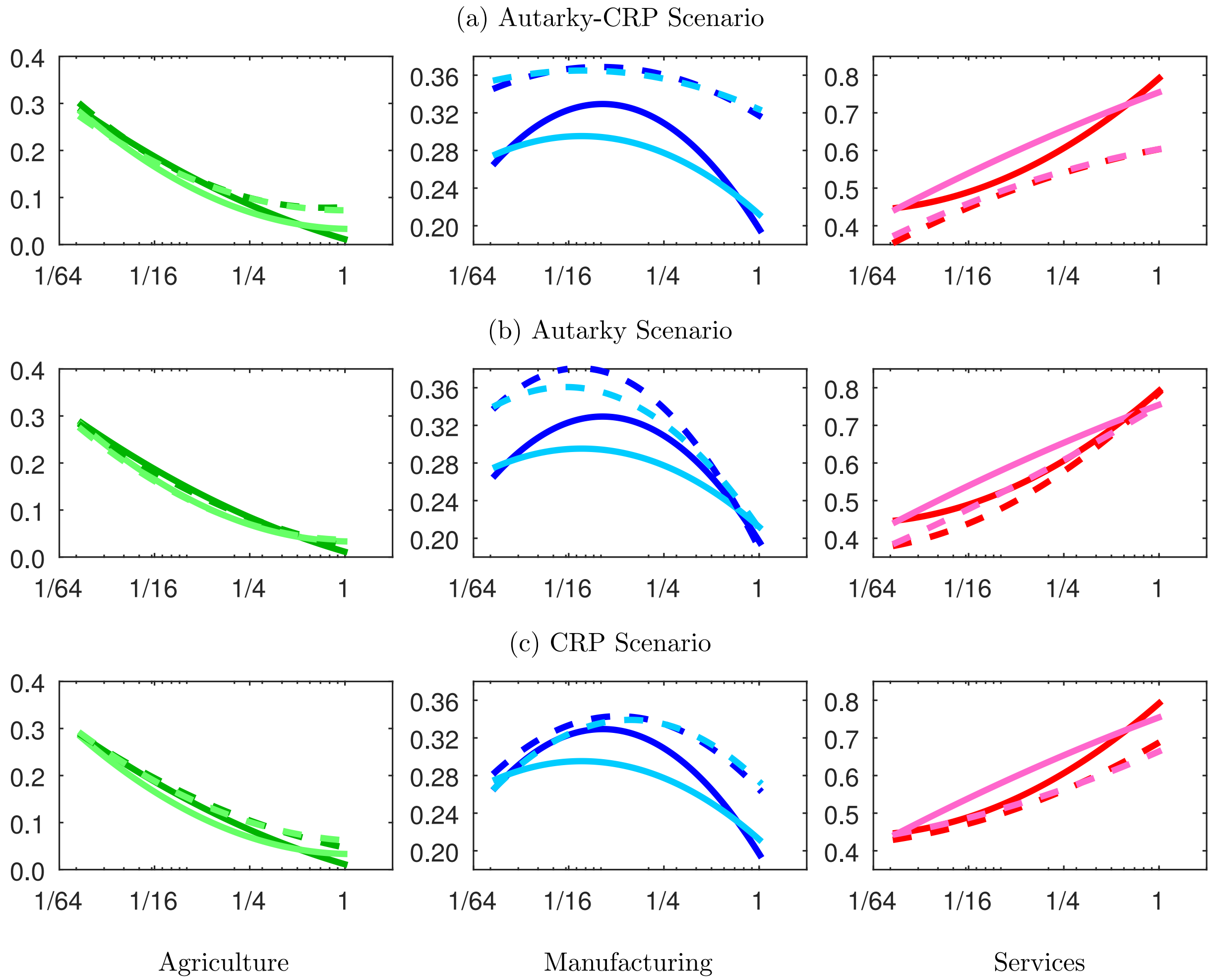
5.1 Global Patterns of Structural Change

Figure 8 plots the fitted relationship as dashed lines for each sector in each counterfactual. To facilitate our evaluation, we also plot the corresponding relationship from our baseline model (shown with solid lines). The darker lines are for the pre-1990 period, and the lighter lines are for the post-1990 period.

We first consider the **autarky-CRP** scenario, in which the common sectoral productivity growth of these closed economies leads to higher income over time without changing relative prices across sectors. As a result, the main operating mechanism of sectoral reallocation is the income effect in final consumption demand. As countries get richer, their agriculture share decreases, and their services share increases. These patterns are illustrated by the dashed lines in the upper panel of Figure 8. The income effect alone apparently accounts well for the observed pattern in the agriculture value added share in both periods. On the other hand, the model's implications for manufacturing shares are too high, and for services shares are too low, compared to the data. It also fails to produce a pronounced hump shape of the manufacturing value added share across income levels.

We next consider the **autarky** scenario, in which sector-biased productivity growth operates. Thus, in addition to the income effect mentioned above, the price effect is also at

Figure 8: Predicted Sectoral Value Added Shares across Income Per Capita



Notes: The fitted curves are based on regressions of sectoral VA shares on income, interacted with the two period dummies, and country fixed effects. Solid (dashed) lines refer to the baseline model (counterfactuals), and dark (light) lines refer to pre-1990 (post-1990).

work, because movements in relative sectoral productivity change relative prices over time. Productivity generally grows faster in manufacturing than in services, particularly in rich countries: productivity in manufacturing relative to services grows by 2.1% per year in countries at the top tertile of income compared to 1.1% in countries at the bottom tertile. This implies declining manufacturing prices relative to services over time, particularly in high income countries, which brings the value added shares in manufacturing and services closer to the data and the baseline model. The manufacturing value added share of rich countries is 7.5 percentage points lower in the autarky counterfactual than in the autarky-CRP counterfactual. On the other hand, the value added shares in the manufacturing sector are still well above those in the data and the baseline model for poor countries, and, to a lesser degree, middle income countries in both periods.

We finally analyze the **CRP** scenario, in which trade integration occurs, but relative sectoral productivity is constant over time. This counterfactual generates sectoral value added shares much closer to the data, particularly at the low end of the income distribution. It also generates a hump pattern in manufacturing, albeit "shallower" than in the baseline model. Compared to the other scenarios, trade integration lowers the manufacturing value added shares, especially at the two ends of the income distribution.[12]

In sum, our three counterfactual exercises reveal that neither sector-biased productivity growth nor trade integration alone can fully account for the hump-shape pattern of the manufacturing value added share across income. Sector-biased productivity is critical in matching the manufacturing value added shares in rich countries, while trade integration is critical for matching these shares in poor countries. Both driving forces are necessary in characterizing the full hump shape pattern across income levels.

5.2 Deindustrialization

The impact of the two driving forces on deindustrialization can be seen clearly through the changes in the peak of the income curve of the manufacturing value added share across the two periods in each counterfactual. As shown in Figure 8, the peak manufacturing value added share declines by 3.4 percentage points from the pre-1990 to post-1990 periods in the baseline model, which is the same amount observed in the data. In other words, trade integration and sector-biased productivity growth together explain all of the observed decline in the peak of the manufacturing value added share across the two periods.

Now, we look at the effects of each counterfactual exercise on deindustrialization. When both driving forces are absent in the autarky-CRP counterfactual, there is essentially no change in the peak share. Essentially, the income effect alone does not alter the relationship between the manufacturing VA share and income across the two periods. That is, there is no sign of deindustrialization over time from the income effect alone. By contrast, sector-biased productivity alone – the autarky counterfactual – generates a decline in the peak share by 2.0 percentage points, which is 59 percent of the decline in the data.

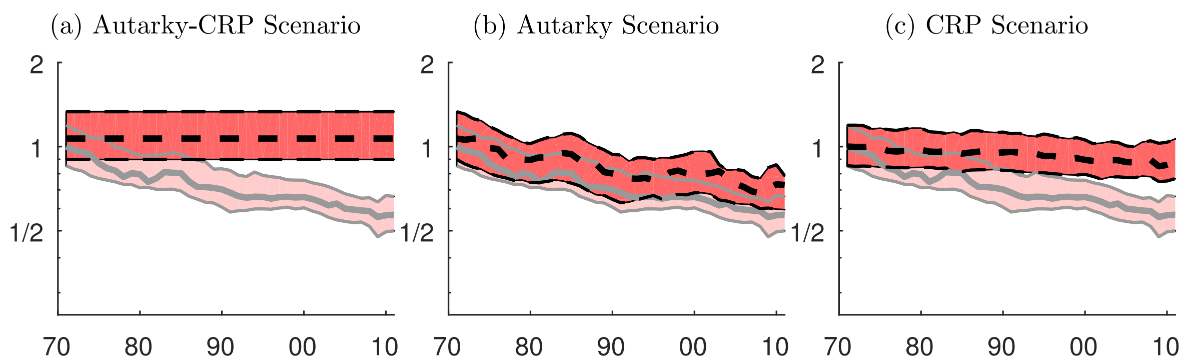
Finally, trade integration alone – the CRP counterfactual – also generates no decline in the peak share. We can infer from these scenarios, as well as our baseline model, that non-linear interaction effects from trade integration and sector-biased productivity growth are also important – accounting for almost two-fifths of the decline in the manufacturing

[12] Compared to the autarky-CRP case, trade lowers the manufacturing value added share by 5.1 percentage points for the bottom tertile, 2.6 percentage points for the middle tertile, and by 3.5 percentage points for the top tertile.

peak value added share across the two periods.

The key to understanding deindustrialization is the declining manufacturing price relative to services over time, as the decline in manufacturing value added share between the two periods goes hand-in-hand with the increase in the services share between the same periods. Figure 9 illustrates how the relative price of manufacturing to services evolves in each counterfactual scenario compared to the declining path in the baseline. In the baseline model with both sector-biased technical change and trade integration, relative prices across the world decrease substantially by about one-half from 1971 to 2011. The primary force behind the declining relative manufacturing price is asymmetric technological progress between manufacturing and services. As shown in the left panel, the relative price in the autarky-CRP counterfactual is constant at the 1971 level in every country, which explains why the manufacturing value added shares are much higher than the baseline manufacturing value added shares and are essentially unchanged across the two periods.

Figure 9: Relative Price of Manufacturing to Services



Notes: Solid lines refer to the baseline model and dashed lines refer to the counterfactuals. The relative manufacturing prices are normalized by the cross-country median value in 1971. The upper and lower bands correspond to the 75th and 25th percentiles across countries in each year.

When sectoral productivity evolves asymmetrically over time in the autarky scenario, the median relative price of manufacturing declines substantially by 33%, from 1971 to 2011, because productivity growth is higher in manufacturing. As shown in the middle panel, this scenario generates a decline in the manufacturing relative price of about two-thirds of the decline in the manufacturing relative price in the baseline case. In the right panel with trade integration alone, the relative price of manufacturing declines over time because trade costs declined more rapidly in manufacturing than in services. However, this driving force leads to a decline in relative prices of only 13% over time. Trade integration matters more in combination with sector-biased productivity growth. When both forces are present, trade integration amplifies the impact of sector-biased productivity growth on the manufacturing relative price, because trade permits a country to access foreign technologies and "import" asymmetric productivity growth even if it itself has constant relative productivity.

How does the declining relative price of manufacturing to services shift the income path of the manufacturing value added share? As a country's income grows, say, owing to technological progress, its agriculture sector sheds productive factors that then move to manufacturing and services. Which of these two sectors receives more of these factors depends on the relative demand or price between the two sectors. Early industrializers faced a high relative demand or price of manufacturing at a given level of income, so more production shifted out of agriculture to the manufacturing sector. Later industrializers, at the same level of income, are facing a lower relative price or demand of manufacturing, so more production has migrated to the service sector, lowering the manufacturing value added share.

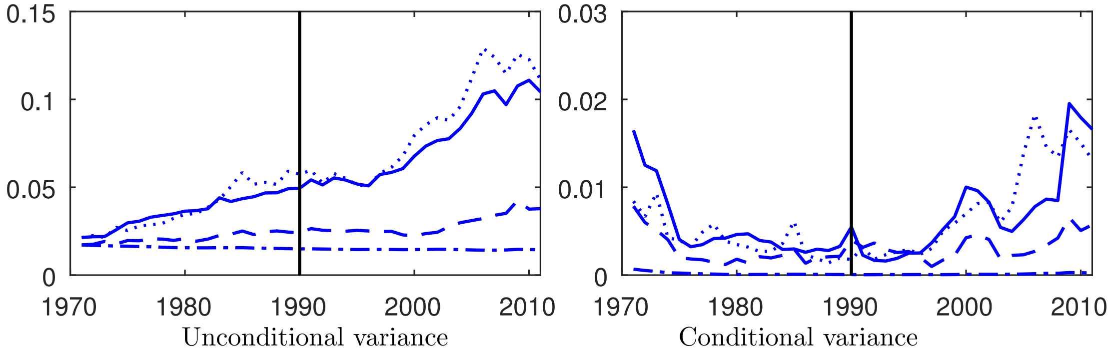
As indicated above, we find that asymmetric productivity growth alone yields a sharp decline in the relative price of manufacturing along with a 2.0 percentage point decline in the peak manufacturing value added share across the two periods. At the same time, trade integration alone, with constant relative productivity growth, yields only a mild decline in the relative price and the peak manufacturing value added share essentially is unchanged acrss the two periods. However, the presence of trade amplifies the impact of sector biased productivity growth, and the two forces together fully account for the observed 3.4 percentage point decline in the peak share. This highlights that the non-linear interaction of the two forces is crucial in explaining deindustrialization.

5.3 Industry Polarization

This subsection highlights the implications of the two driving forces on the patterns of industry polarization over time. Figure 10 illustrates the evolution of industry polarization, i.e., the unconditional and conditional variances in manufacturing value added shares, for the three counterfactuals. For the ease of comparison, we also plot the cross-country variances in the baseline model with solid lines. In the baseline model, the unconditional variance increases by 8 percentage points from 0.025 in 1971 to 0.105 in 2011, and the conditional variance declines by 1.4 percentage points from 0.018 in 1971 to 0.004 in 1990 and then rises by 1.6 percentage points to 0.02 in 2010. Thus, industry polarization across countries rises in the post-1990 period under both measures.

We now examine the dynamics of industry polarization in each counterfactual. We start with the autarky-CRP scenario, plotted with dotted-dashed lines. In this scenario, both the unconditional and conditional variances are low and unchanged over time. Notably, the conditional variance is effectively zero in every period, because the only force operating

Figure 10: Predicted Industry Polarization – Baseline and Counterfactuals



Notes: Unconditional variance reports the log-variance of the manufacturing VA share. Conditional variance reports the mean squared difference between the log simulated VA share and the log predicted share. Top panel: Solid lines – baseline model; Dotted lines – CRP scenario; dashed lines – autarky scenario; dotted-dashed lines – autarky-CRP scenario.

in this scenario is the income effect. Next, consider the autarky scenario, illustrated with dashed lines. Both variances are uniformly lower than in the baseline. The unconditional variance increases only slightly by 2 percentage points from 0.02 in 1971 to 0.04 in 2011. This is only one-fourth of the increase in the baseline model. Although the conditional variance displays a U shape over time, the magnitude of the decline and the rise is only around 0.5 percentage points, about only one-third of the changes in the baseline. Hence, sector-biased productivity growth alone leads to a substantially muted increase in industry polarization post-1990, compared to the baseline case. Lastly, we present the CRP scenario with dotted lines. Both unconditional and conditional variances closely follow those in the baseline case over time, suggesting that trade integration alone drives most of the dynamics of industry polarization.

In our baseline model, we allow for aggregate trade imbalances. However, in our autarky counterfactual, because trade flows are zero, aggregate trade balances are also zero, of course. This difference in the way aggregate trade balances are modeled across the scenarios could potentially matter, because manufacturing is responsible for the lion's share of trade flows and trade imbalances for many countries. To provide an alternative comparison of the autarky scenario to the baseline model, we construct a baseline in which balanced trade is imposed for each country and every time period.[13] We find that both the unconditional and conditional variances in manufacturing value-added shares are slightly lower than in the baseline, and the increase over time post-1990 is slightly attenuated. Thus, aggregate

[13]To achieve this, we set $\phi_{n,t} = 0$ for every country and time period. All other parameters, including bilateral trade costs, remain at the calibrated values. Note that in this case, sectoral imbalances still emerge owing to comparative advantage, as in Uy, Yi, and Zhang (2013). Results are reported in Figure D.4 of the Appendix.

trade imbalances contribute to the cross-country dispersion in manufacturing value added shares by allowing further specialization. On the other hand, even with balanced trade, both variances remain about 75% of those in the baseline in the post-1990 period. That is, intratemporal trade under balanced trade alone accounts for about three-quarters of the increased polarization over time.

In sum, trade integration is the key to understanding increased industry polarization since 1990. This result is more transparent when looking at the unconditional variance.[14] Without trade, the cross-country dispersion of the industry share hardly changes over time, as shown in the autarky and autarky-CRP counterfactuals. Only when trade integration is introduced, the cross-country dispersion substantially increases post 1990. This result captures the fundamental impact of trade—allowing countries to specialize in their comparative advantage sectors—which increases dispersion in the manufacturing VA shares across countries.

5.4 Importance of Final Demand and Input-Output Channels

In this section we implement a reduced-form accounting method to measure the importance of aggregate and sectoral final demand channels, as well as input-output channels, as transmission mechanisms between our driving forces and deindustrialization and industry polarization.[15] Our approach distinguishes between investment and consumption, and is applied to model-generated data, rather than observed data. Omitting country and time subscripts, we have the following accounting identity for each country in each period:

$$\begin{bmatrix} \mathrm{va}^a \\ \mathrm{va}^m \\ \mathrm{va}^s \end{bmatrix} = \begin{bmatrix} 1-\xi^{a,a} & -\xi^{m,a} & -\xi^{s,a} \\ -\xi^{a,m} & 1-\xi^{m,m} & -\xi^{s,m} \\ -\xi^{a,s} & -\xi^{m,s} & 1-\xi^{s,s} \end{bmatrix}^{-1} \begin{bmatrix} \nu^a & 0 & 0 \\ 0 & \nu^m & 0 \\ 0 & 0 & \nu^s \end{bmatrix} \begin{bmatrix} \rho_c\zeta_c^a + \rho_x\zeta_x^a + \rho_n\zeta_n^a \\ \rho_c\zeta_c^m + \rho_x\zeta_x^m + \rho_n\zeta_n^m \\ \rho_c\zeta_c^s + \rho_x\zeta_x^s + \rho_n\zeta_n^s \end{bmatrix}, \quad (25)$$

where va^j denotes sector j's share in value added. ρ_c, ρ_x and ρ_n denote the shares of aggregate consumption, investment and net exports in GDP and sum to one. ζ_c^j, ζ_x^j, and ζ_n^j denote sector j's share in final consumption, investment and net exports with $\sum_j \zeta_b^j = 1$ for each $b \in \{c, x, n\}$. As a reminder, ν^j is the ratio of value added to gross output in sector j. Finally, $\xi^{j,k} = (1-\nu^j)\nu^k(\nu^j)^{-1}\mu_e^{j,k}$ captures both the direct and indirect contributions of sector j's value added to sector k's final demand, and $\mu_e^{j,k}$ denotes sector k's share in intermediate

[14] Conditional variance is a bit more intricate, because it is the residual after cleansing out the variation due to the country fixed effects and due to the income per capita. The decline in conditional variance from 1970-1975 occurs even in the presence of trade integration, then remains flat and then rises throughout the post-1990 period.

[15] Our method follows that of Berlingieri (2014), Sposi (2019), and Sinha (2021)

input spending by sector j.

This accounting identity describes the sectoral value added shares as the product of the inverse of the input-output-share matrix and the final demand vector. We decompose final demand into three main components: aggregate consumption, investment and net exports, and further decompose each component into sectoral shares.[16]

In the baseline model, all of these shares are endogenous and are solved for. In our accounting exercise, we allow one component to vary, and hold the other components constant at their 1990 values and then compute the implied sectoral value added shares using equation (25). Hence, we construct "synthetic" paths for the manufacturing value added share in the pre-1990 and post-1990 periods, and re-run regression (1). We repeat this exercise for each of the other components. We then examine the impact on the peak of the manufacturing VA share across income, as well as the cross-country variance in manufacturing value added shares, over the two periods. Table 2 summarizes the contribution from each component or channel to the change in the peak manufacturing value added share and the change in the variance of those shares from the pre-1990 period to the post-1990 period.

Table 2: Contribution of Each Channel to Deindustralization and Polarization

	Peak Manufacturing Share			**Unconditional variance**		
	Pre-1990	Post-1990	Change	Pre-1990	Post-1990	Change
All channels	0.329	0.295	−0.034	0.039	0.077	0.038
Sectoral cons shares	0.317	0.299	−0.018	0.037	0.059	0.022
Sectoral inv shares	0.270	0.269	−0.001	0.046	0.048	0.002
Sectoral IO shares	0.295	0.286	−0.009	0.043	0.051	0.008
Aggregate inv rate	0.265	0.264	−0.001	0.050	0.047	−0.003

Notes: We allow one channel to vary over time as in the baseline model, holding all other channels constant at 1990 values, and compute reduced-form counterfactual VA shares using equation (25). Peak refers to the peak predicted manufacturing VA share based on regression (1) with the median country fixed effect. Unconditional variance reports the log-variance of the manufacturing VA share.

Consider first each channel's contribution to deindustrialization. Table (2) shows that if only the sectoral consumption channel operates, the peak manufacturing value added share declines by 1.8 percentage points, more than half of the total decline in the baseline model of 3.4 percentage points. The sectoral input-output channel contributes about a quarter of

[16] The decomposition allows us to disentangle the role of sectoral shares in consumption and investment from that of their component shares in GDP. For example, with aggregate shares fixed, changes in sectoral demand shares feed directly into sectoral value added shares. Alternatively, with sectoral demand shares fixed, changes in the investment share in GDP alter sectoral value added shares because investment is more manufacturing intensive than consumption is.

the total decline in the peak. The investment channel, in terms of both sectoral shares and the aggregate investment rate, has little impact on the decline of the peak.

The importance of the input-output channel merits a brief discussion. As final demand shifts toward services over time, the fact that services use itself intensively in the production creates an amplification as discussed in Sposi (2019). What is novel here is that this intermediate demand channel is strengthened because service inputs are complementary to goods inputs. As the relative price of services rises, this amplification mechanism grows stronger. Therefore, countries that industrialize later will use services inputs more intensively than their predecessors and thus, at a given level of income, will expend more resources on services than on manufacturing not only in final demand, but also in intermediate demand.

For industry polarization, we focus on the unconditional variance, averaging across the pre-1990 period and the post-1990 period. In the baseline model with all channels operating, the variance doubled from 0.039 to 0.077 between the two periods. When we change only sectoral consumption shares, the cross-country variance increased by 0.022, well over half of the increase in the baseline case. The sectoral investment channel alone yields about 5 percent, while the input-output channel alone generates over 20 percent, of the increase in the unconditional variance over the two periods. Finally, the aggregate investment channel actually contributes negatively to the change in variance between the two periods.

Summary Summarizing section 5, we find that sector-biased productivity is the key driver of deindustrialization, and trade integration is the key for industry polarization. In addition, their interaction is important for a complete understanding of both phenomena. These two forces generate the declining relative price of manufacturing to services over time, which, via the "Baumol" elasticities, lead to services, rather than manufacturing, absorbing a larger share of resources exiting from agriculture over time. In addition, trade integration facilitates comparative advantage and specialization, leading to industry polarization. Finally, the sectoral consumption shares and input-output linkages are the transmission mechanisms linking our driving forces to deindustrialization and industry polarization.

6 Conclusion

In this paper, we first present evidence that the nature of structural change has evolved over time. We re-confirm recent evidence by Rodrik (2016) on deindustrialization, and also demonstrate a new pattern in the data – industry polarization. Over time, the peak of the manufacturing value-added share "hump" has declined by 3.4 percentage points, and the cross-country dispersion in the manufacturing value-added share of total value-added has almost doubled. To explain these patterns, we employ a structural change framework with non-homothetic preferences, international trade, input-output linkages, and capital accumulation. With our framework, we focus on the role of two driving forces, sectoral TFP growth and declining trade costs.

Our calibrated model can account for most of the deindustrialization and all of the industry polarization. To further understand the underlying sources and mechanisms, we conduct several counterfactual exercises. These exercises reveal the importance of sector-biased TFP growth in driving deindustrialization, and of declining trade costs in driving industry polarization. High productivity growth in manufacturing decreases the relative price of manufactured goods, which, coupled with sectoral consumption and sectoral investment elasticities of substitution that are less than one, leads to declining expenditure and value-added shares in manufacturing. Declining trade costs in manufacturing leads some countries to increasingly specialize in that sector, and other countries to reallocate their resources to other sectors, thus inducing increased dispersion of cross-country manufacturing value-added shares. Our counterfactual exercises also point to the importance of non-linear interaction effects between sector-biased TFP growth and declining trade costs. Sector-biased TFP growth has a larger effect when it occurs in conjunction with trade integration, and vice versa. In other words, each driving force leads to reallocation across sectors, and, together, the reallocation effects are multiplied.

The primary mechanism underlying the reallocation behind deindustrialization is relative prices. Both driving forces, especially the sector-biased TFP growth, lead to lower relative prices of manufactured goods. Over time, then, newly industrialized countries, facing lower prices of manufactured goods, have more limited opportunities to specialize in that sector, which then limits the peak of their manufacturing hump. This, in a nutshell, is the story for deindustrialization.[17]

In our framework, agents have perfect foresight about the paths of the sectoral TFP and trade costs. Allowing for these paths to be treated as shocks would be a useful exercise. In addition, current account imbalances are effectively exogenous in our model; treating them as endogenous could give more insight into whether the increase in global imbalances over time is connected to deindustrialization and industry polarization. Buera and Kaboski (2012) We leave these and other exercises for future research.

[17]We note that the importance of relative prices for deindustrialization does not mean that income effects and non-homothetic preferences are not important for structural change. In our framework, they are important, but they do not play a key role in the *evolving* nature of structural change over time.

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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 International Historical Statistics. For bilateral trade in agriculture and manufacturing, we use the UN Comtrade Database and the IMF's Direction of Trade Statistics. For services imports, we use World Development Indicators from the World Bank. For aggregate investment, we use the Penn World Table 9.1. Due to the limited availability of bilateral services import shares prior to 1995, we impute them using their averages over 1995–1997.

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

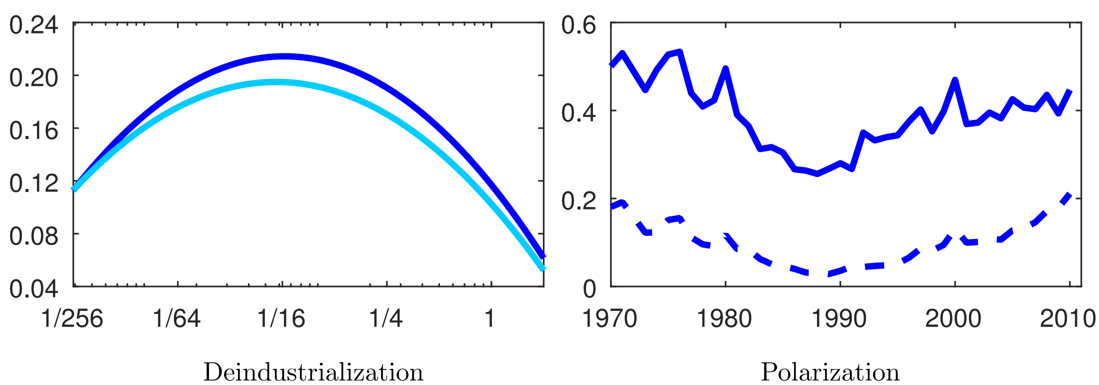
We construct real data using the corresponding price indexes to deflate nominal data. The price indexes for aggregate income and investment are from the Penn World Table 9.1. We obtain sectoral value-added price indexes by dividing value added at current prices by value added at constant prices using 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.

Appendix B Robustness Check on Two Facts

To examine the robustness of our empirical findings, we study a large 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 is above $1,000 over the sample period, in terms of 2010 U.S. PPP prices.[18] This larger sample includes many low and middle income countries; the average ratio of per-capita income of the richest to the poorest across periods is 317. In comparison, our baseline sample has this average ratio of 23. We cannot include the extended sample in the quantitative analysis, however, because complete data for other variables is not available.

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

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



Notes: In the left panel each line plots the predicted manufacturing value added share (y-axis), estimated from a balanced panel of 95 countries over 1970–2010 using equation (1) under the average country fixed effect and over the observed ranges of income per capita (x-axis). Lines in the darker (lighter) color are for the pre-1990 (post-1990) period. In the right panel, the solid (dashed) line denotes the unconditional (conditional) variance of manufacturing value added shares. Unconditional variance reports the log-variance of the manufacturing VA share across countries in each year. Conditional variance reports the mean squared difference between the log observed VA share and the log predicted VA share from regression (1) across countries in each year.

Figure B.1 illustrates the patterns of deindustrialization and polarization for this large

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

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

Appendix C Algorithm and Equilibrium Conditions

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

Algorithm C.1 Numerical Solution

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

Table C.1: Equilibrium conditions

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

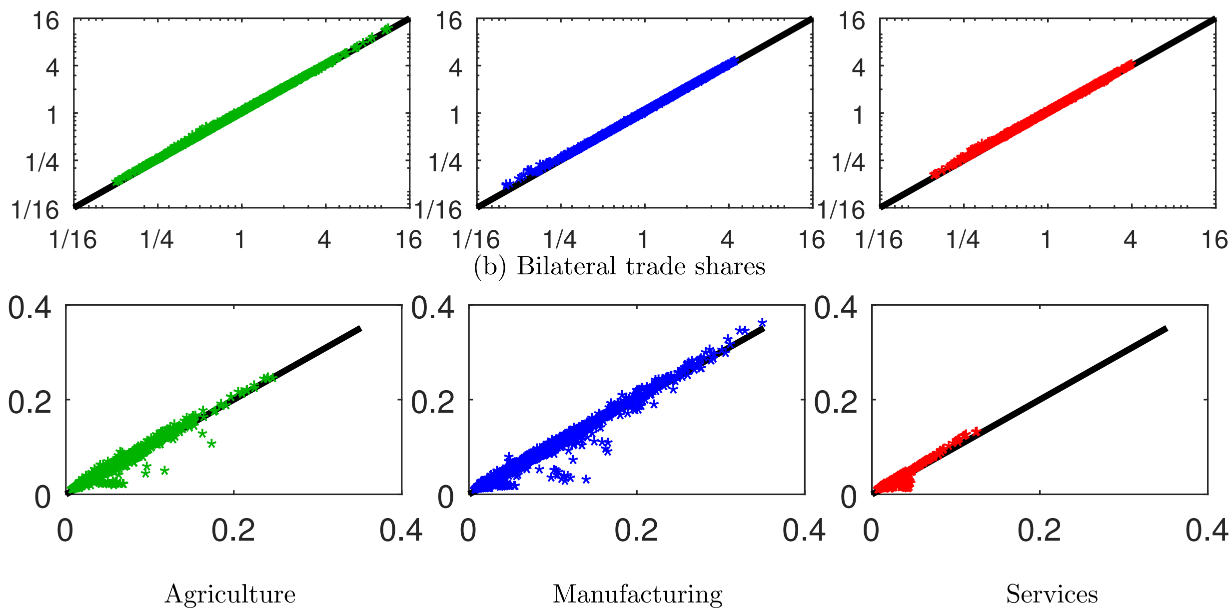
Appendix D Additional Figures

This appendix presents additional figures mentioned in the main text. Figures D.1 and D.2 illustrate the fit of the calibrated baseline model (y-axis) with the data (x-axis). Figure D.1 shows the overall performance of the calibration in terms of targeting sectoral prices and bilateral trade shares for all three sectors. The correlation between the model and the data is one for sectoral prices and is 0.99 for bilateral trade shares. Figure D.2 presents the performance of the baseline model in terms of sectoral shares of consumption, investment, and intermediates used by sector. The correlation between the model and the data is high for all variables, with the lowest value for the sectoral intermediate input shares in agricultural production at 0.92.

Figure D.3 illustrates the unconditional and conditional cross-country variances of the agriculture and services value added shares over time. The dashed lines are for the data and the solid lines are for the baseline model. For the agriculture sector shown in the top panel, the baseline model captures the unconditional variance well, but generates about half of the increases in the conditional variance from 1990 to 2010. For the services sector shown in the bottom panel, the baseline model matches well both variances over time. Figure D.4 plots the implication of industry polarization in the scenario of balanced trade.

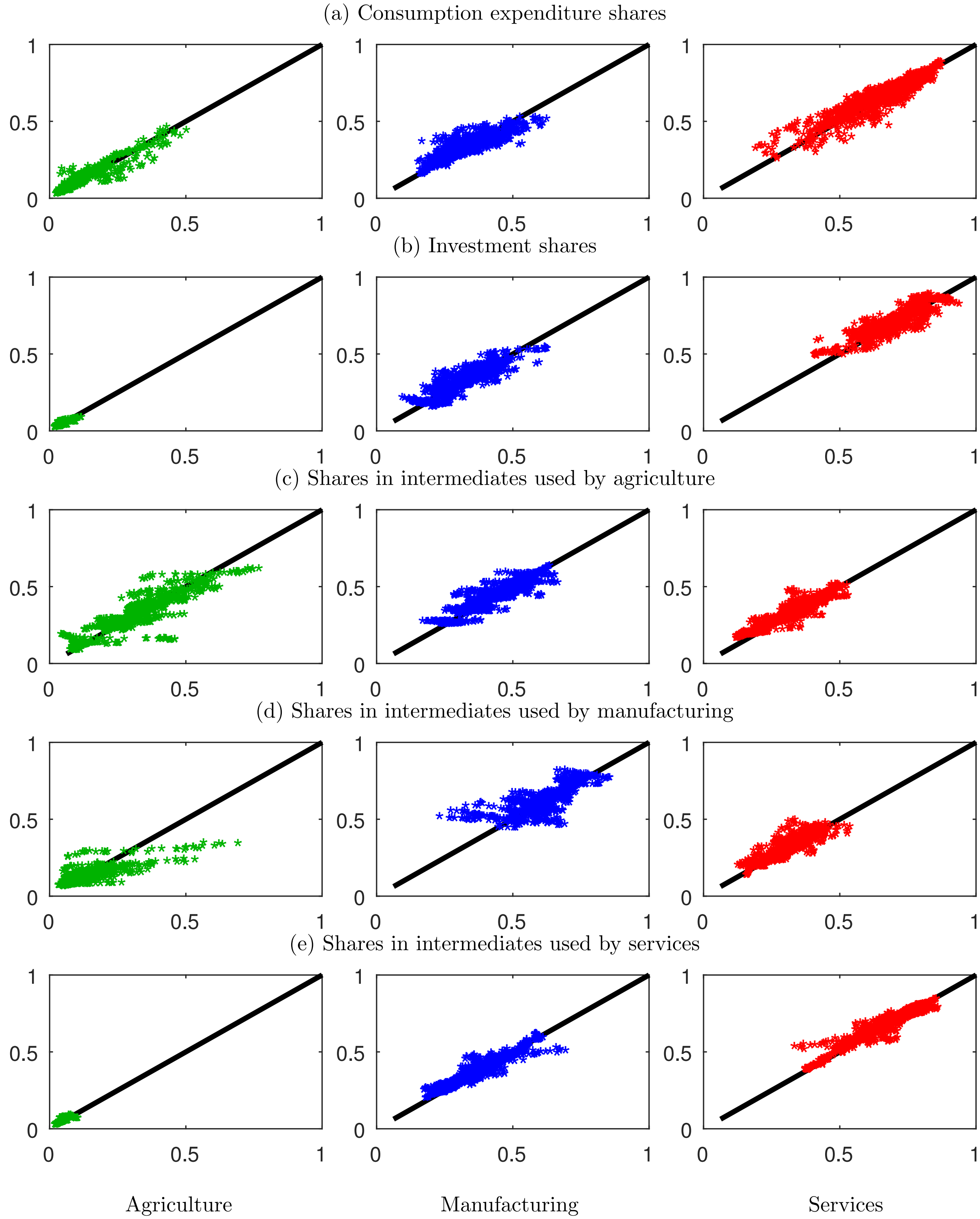
Figure D.1: Model Fit for Prices and Trade Shares

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



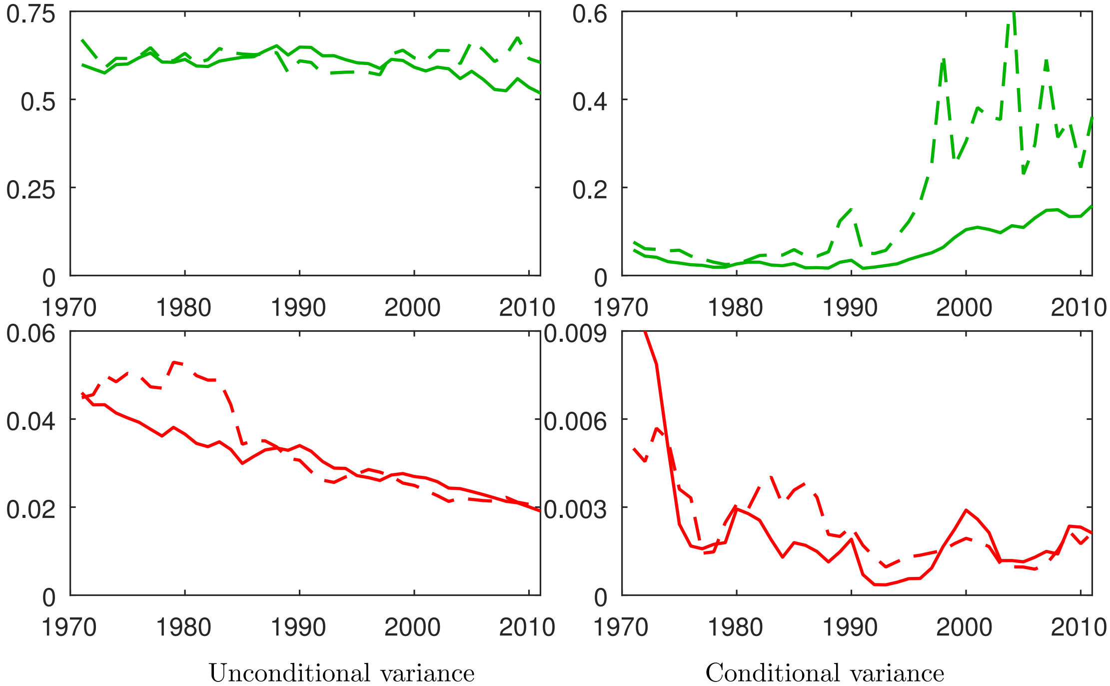
Notes: Model (y-axis) vs Data (x-axis).

Figure D.2: Model Fit for Sectoral Expenditure Shares



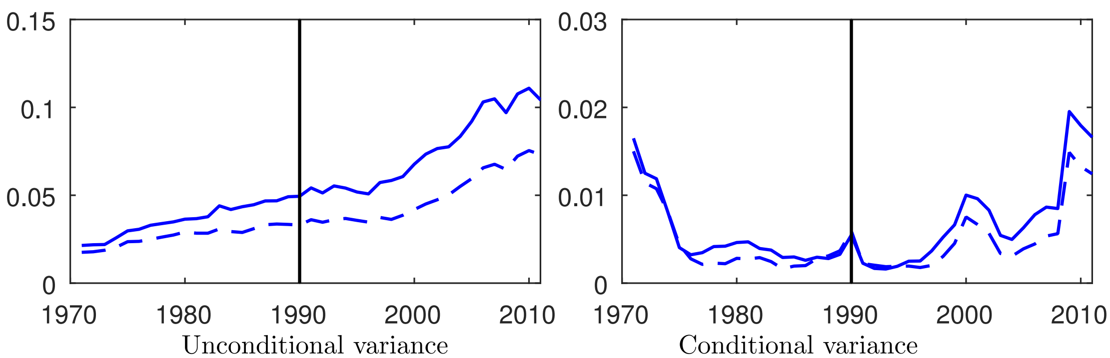
Notes: Model (y-axis) vs Data (x-axis).

Figure D.3: Variance in VA shares of Agriculture and Services: Baseline Model and Data



Notes: Dashed lines - data; Solid lines - model. The upper panel plots variances for the agriculture sector and the bottom panel plots variances for the services sector. Unconditional variance reports the log-variance of the sectoral VA share. Conditional variance reports the mean squared difference between the log VA share and the log predicted VA share using regression (1) across countries in each year.

Figure D.4: Predicted Industry Polarization – Baseline and Balanced Trade



Notes: Unconditional variance reports the log-variance of the manufacturing VA share. Conditional variance reports the mean squared difference between the log simulated VA share and the log predicted share. Solid lines – baseline model; dashed line – balanced trade scenario.