The Evolution of Comparative Advantage: Measurement and Welfare Implications*

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Abstract

Using novel estimates of sectoral total factor productivities for 72 countries across 5 decades we provide evidence of relative productivity convergence: productivity grew systematically faster in initially relatively less productive sectors. These changes have had a significant impact on trade volumes and patterns, and a non-negligible welfare impact. Had productivity in each country's manufacturing sector relative to the US remained the same as in the 1960s, trade volumes would be higher, cross-country export patterns more dissimilar, and intra-industry trade lower than in the data. Relative sectoral productivity convergence – holding average growth fixed – had a modest negative welfare impact.

JEL Classifications: F11, F43, O33, O47

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1 Introduction

How does technology evolve over time? This question is important in many contexts, most notably in economic growth and international trade. Much of the economic growth literature focuses on *absolute* technological differences between countries. In the context of the one-sector model common in this literature, technological progress is unambiguously beneficial. Indeed, one reading of the growth literature is that most of the cross-country income differences are accounted for by technology, broadly construed (Klenow and Rodríguez-Clare, 1997; Hall and Jones, 1999).

By contrast, the Ricardian tradition in international trade emphasizes *relative* technological differences as the reason for international exchange and gains from trade. In the presence of multiple industries and relative sectoral productivity differences between countries, the welfare consequences of technological improvements depend crucially on which sectors experience productivity growth. For instance, it is well known that when productivity growth is biased towards sectors in which a country has a comparative disadvantage, the country and its trading partners may experience a welfare loss, relative to the alternative under which growth is balanced across sectors. Greater relative technological differences lead to larger gains from trade, and thus welfare could be reduced when countries become more similar to each other. This result goes back to at least Hicks (1953), and has been reiterated recently by Samuelson (2004) in the context of productivity growth in developing countries.

To fully account for the impact of technological progress on economic outcomes, it is thus important to understand not only the evolution of average country-level TFP, but also the changes in relative technology across sectors. Until now the literature has focused almost exclusively on estimating differences in technology at the country level. This paper examines the evolution of sector-level TFP over time and its implications. Using a large-scale industry-level dataset on production and bilateral trade, spanning 72 countries, 19 manufacturing sectors, and 5 decades, the analysis begins by estimating productivity in each country, sector, and decade, and documenting the changes in sectoral productivities between the 1960s and today. It then uses these estimates in a multi-sector Ricardian model of production and trade to quantify the implications of changing sectoral productivities on global trade patterns and welfare.

The main results can be summarized as follows. First, there is strong evidence of relative productivity convergence. Controlling for the average productivity growth of all sectors in a country, sectors that were relatively less productive initially grew systematically faster. The speed of convergence in sectoral productivities implied by the estimates is about 18% per decade, and is similar in magnitude in both developed and developing countries. The effect is present in all time periods, although the speed of convergence is somewhat slower in later decades.

Second, changes in sectoral productivity are important for understanding the evolution of trade volumes and trade patterns. The quantitative exercise begins by solving the full model under the observed pattern of sectoral productivities, and computing all the relevant model outcomes under this baseline case. The analysis then compares the baseline to two counterfactual scenarios. In the "No Convergence" counterfactual, productivity in each country and sector remains fixed to its 1960s value relative to the US. Over this period, most countries experienced both relative and absolute catch-up in productivity. To isolate just the relative component, the second, "No Relative Convergence," counterfactual instead assumes that each country's sectoral productivities grow at the same average rate observed between the 1960s and the 2000s, but its relative productivities remain as they were in the 1960s. Because average productivity is allowed to grow, this exercise isolates the role of relative – as opposed to absolute – productivity changes.

In the data, trade patterns became substantially more similar across countries. In the majority of sectors, the standard deviation of (log) world export shares across countries has fallen significantly between the 1960s and the 2000s. In addition, over the same period there has been a substantial increase in intra-industry trade (measured here by the Grubel-Lloyd index). As the baseline model is implemented on observed trade flows, it matches these two patterns well. The baseline also matches the average trade/GDP ratios observed in the data. In both counterfactuals, however, trade volumes as a share of GDP are 15-20% higher in the 2000s, implying that the rise in trade volumes over the past 5 decades would have been even higher had relative productivities not changed. The counterfactuals also produce a much smaller reduction in the dispersion in world export shares, and a much smaller increase in intra-industry trade than observed in the data. The trade outcomes are very similar in the two counterfactuals, which implies that the relative productivity changes are more salient for trade flows than absolute catch-up.

Finally, the productivity changes had an appreciable welfare impact. In the No Convergence counterfactual, welfare in the 2000s would be *lower* than in the baseline, 11.7% in the median OECD country and 16.4% in the median non-OECD country. In the No Relative Convergence counterfactual, however, welfare is *higher* than in the baseline, 1.34% in the OECD and 3% in the non-OECD at the median. Most countries caught up in average productivity between the 1960s and the 2000s, and the No Convergence counterfactual shows that they are better off from this net growth. However, the other counterfactual shows that the relative component in productivity changes has the opposite impact. Had countries grown at their observed average rate, but kept relative productivities unchanged, they would have been even better off.

To estimate productivity, the paper extends the methodology developed by Eaton and Kortum (2002) to a multi-sector framework. It is important to emphasize the advantages of our approach relative to the standard neoclassical methodology of computing measured TFP. The basic difficulty in directly measuring sectoral TFP in a large sample of countries and over time is the lack of comparable data on real sectoral output and inputs. By contrast, the procedure in this paper uses information on bilateral trade, and thus dramatically expands the set of countries, sectors, and time periods for which productivity can be estimated. The approach follows the insight of Eaton and Kortum (2002) that trade flows contain information on productivity.[1] Intuitively, if controlling for the typical gravity determinants of trade, a country spends relatively more on domestically produced goods in a particular sector, it is revealed to have either a high relative productivity or a low relative unit cost in that sector. Using data on factor and intermediate input prices, the procedure nets out the role of factor costs, yielding an estimate of relative productivity.

In addition, the approach in this paper extends the basic multi-sector Eaton-Kortum framework to incorporate many features that are important for reliably estimating underlying technology: multiple factors of production (labor and capital), differences in factor and intermediate input intensities across sectors, a realistic input-output matrix between the sectors, both inter- and intra-sectoral trade, and a non-traded sector. Finally, because our framework allows for international trade driven by both Ricardian and Heckscher-Ohlin forces, it takes explicit account of each country's participation in exports and imports, both of the final output, and of intermediate inputs used in production.

This paper is not the first to use international trade data to estimate technology parameters (see, among others, Eaton and Kortum, 2002; Finicelli et al., 2009; Chor, 2010; Waugh, 2010; Hsieh and Ossa, 2011; Shikher, 2011, 2012; Costinot et al., 2012; Caliendo and Parro, 2015). Relative to existing contributions, the analysis below extends the multi-sector approach to a much greater set of countries, and, most importantly, over time. This makes it possible, for the first time, to examine not only the global cross-section of productivities, but also their evolution over the past 5 decades and the implications of those changes. While existing papers in this literature employ static models, our quantitative framework features endogenous capital accumulation, and thus permits modeling the joint evolution of relative sectoral productivities and the capital stock. Indeed, the quantitative exercise below shows that the response of the capital stock to changes in relative sectoral

[1] Measuring comparative advantage using trade flows has an antecedent in Balassa (1965)'s revealed comparative advantage approach.

productivities had an appreciable welfare impact.

Changes in productivity at the sector level have received comparatively less attention in the literature. Convergence at sector level has been investigated by Bernard and Jones (1996a,b) for TFP, Rodrik (2013) for value adder per worker, and Proudman and Redding (2000) and Hausmann and Klinger (2007) for revealed comparative advantage. Also related is the literature that documents the time evolution of diversification indices, be it of production (e.g. Imbs and Wacziarg, 2003), or trade (e.g. Carrère et al., 2011). Our paper is the first to use a fully specified model of production and trade to estimate changes in underlying TFP. In addition, we greatly expand the sample of countries and years relative to these studies, and use our quantitative framework to compute the impact of the estimated changes in relative sectoral productivities on trade volumes, trade patterns, and welfare.

The rest of the paper is organized as follows. Section 2 lays out the theoretical framework. Section 3 describes the estimation procedure. Section 4 presents the main econometric results on relative convergence. Section 5 examines the quantitative implications of the observed evolution of sectoral productivity. Section 6 concludes. The Online Appendix collects further model, data, estimation, and robustness details.

2 Theoretical Framework

The world is comprised of N countries and $J+1$ sectors. Each sector produces a continuum of goods. The first J sectors are tradeable subject to trade costs, and sector $(J+1)$ is nontradeable. There are two factors of production, labor and capital. Both are mobile across sectors and immobile across countries. Trade is balanced each period, and thus the analysis abstracts from international asset markets. All agents have perfect foresight and all markets are competitive.

In period $t = 0$, the representative household in country n is endowed with capital K_{n0} and labor L_{n0}. Each period, the household saves an exogenous fraction s_{nt} of its current income (as in Solow, 1956; Swan, 1956), investing it into next period's capital, and consumes the remaining fraction $1 - s_{nt}$. The saving rates are country-specific and time-varying.[2]

Period utility of the representative consumer in country n is given by $U(C_{nt})$, where C_{nt} denotes aggregate consumption in country n and period t. The function $U(\cdot)$ satisfies all the usual regularity conditions. The flow budget constraint of the household in period t is given by

$$P_{nt}(C_{nt} + I_{nt}) = P_{nt}Y_{nt} = w_{nt}L_{nt} + r_{nt}K_{nt}, \tag{1}$$

where P_{nt} is the price of aggregate final output, I_{nt} is flow saving/investment, Y_{nt} is aggregate final output, K_{nt} is the capital stock, L_{nt} is the effective labor endowment, and w_{nt} and r_{nt} are the wage rate and the rental return to capital, respectively. Since investment I_{nt} is simply $s_{nt}Y_{nt}$, the law of motion for capital is given by

$$K_{nt+1} = (1 - \delta_{nt})K_{nt} + s_{nt}Y_{nt}, \tag{2}$$

where δ_{nt} is the country-specific and time-varying depreciation rate.

The aggregate final output Y_{nt} is an aggregate of sectoral composite goods:

$$Y_{nt} = \left(\sum_{j=1}^{J} \omega_j^{\frac{1}{\eta}} \left(Y_{nt}^j \right)^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}\xi_{nt}} \left(Y_{nt}^{J+1} \right)^{1-\xi_{nt}}, \tag{3}$$

where Y_{nt}^j is the composite good in tradeable sector j, and Y_{nt}^{J+1} is the nontradeable-sector composite good. The parameter ξ_{nt} is thus the Cobb-Douglas weight on the tradeable

[2] The treatment of capital accumulation is similar to that in Eaton et al. (2013), who calibrate a series of exogenous shocks to the value of capital to perfectly match the evolution of the observed capital series. Here, exogenous savings rates are set to match the evolution of capital stocks in the data. The variation in s_{nt} is meant to capture the influence of demographics, economic growth rates, market frictions, and distortions or subsidies to savings and/or investment due to government policy, or other underlying fundamental differences across countries and over time. It is important to emphasize that the model of capital accumulation has no impact on either the productivity estimation in Section 3 or the relative productivity convergence results in Section 4. The assumptions on capital accumulation do enter the general equilibrium counterfactuals in Section 5. In order to highlight how the endogenous response of capital accumulation affects the results, Section 5 also reports counterfactuals without the response of capital to productivity changes. The same is true for the trade balance assumption: neither the productivity estimation procedure nor the relative convergence results rely on trade balance in any way, but trade balance does enter the model solutions in the baseline and the counterfactuals.

sector composite good, η is the elasticity of substitution between the tradeable sectors, and ω_j is the taste parameter for tradeable sector j. The expenditure share on tradeables ξ_{nt} varies over time as well as across countries, to capture in a reduced-form way the positive relationship between income and the non-tradeable consumption share observed in the data.

Output in each sector j and country n and period t is produced using a CES production function that aggregates a continuum of varieties $q \in [0,1]$ unique to each sector:

$$Q_{nt}^{j} = \left[\int_0^1 Q_{nt}^{j}(q)^{\frac{\varepsilon-1}{\varepsilon}} dq \right]^{\frac{\varepsilon}{\varepsilon-1}},$$

where ε denotes the elasticity of substitution across varieties q, Q_{nt}^{j} is the total sector j output in country n, and $Q_{nt}^{j}(q)$ is the amount of variety q that is used in production. It is well known that the price of sector j's output is given by:

$$p_{nt}^{j} = \left[\int_0^1 p_{nt}^{j}(q)^{1-\varepsilon} dq \right]^{\frac{1}{1-\varepsilon}},$$

where $p_{nt}^{j}(q)$ is the price of variety q in sector j and country n.

Producing one unit of good q in sector j in country n requires $\frac{1}{z_n^j(q)}$ input bundles. The cost of an input bundle is:

$$c_{nt}^{j} = \left(w_{nt}^{\alpha_j} r_{nt}^{1-\alpha_j} \right)^{\beta_j} \left(\prod_{j'=1}^{J+1} \left(p_{nt}^{j'} \right)^{\gamma_{j'j}} \right)^{1-\beta_j}.$$

That is, production in sector j requires labor, capital, and a bundle of intermediate inputs, coming from all sectors $j' = 1, ..., J+1$. The value-added based labor intensity is given by α_j, while the share of value added in total output is given by β_j. Both of these vary by sector. The weights on inputs from other sectors $\gamma_{j'j}$ vary by output industry j as well as input industry j'.

Productivity $z_{nt}^{j}(q)$ for each $q \in [0,1]$ in each sector j and period t is equally available to all agents in country n, and product and factor markets are perfectly competitive. Following Eaton and Kortum (2002, henceforth EK), the productivity draw $z_{nt}^{j}(q)$ is random and comes from the Fréchet distribution with the cumulative distribution function

$$F^j_{nt}(z) = e^{-T^j_{nt} z^{-\theta}}.$$

In this distribution, the absolute advantage term T^j_{nt} varies by country, sector, and time, with higher values of T^j_{nt} implying higher average productivity draws in sector j in country n and period t. The parameter θ captures dispersion, with larger values of θ implying smaller dispersion in draws.

The cost of producing one unit of good q in sector j and country n is $c^j_{nt}/z^j_{nt}(q)$. International trade is subject to iceberg costs: in order for one unit of good q produced in sector j to arrive in country n from country i in period t, $d^j_{nit} > 1$ units of the good must be shipped. Domestic trade costs are normalized to $d^j_{nnt} = 1$ for each country n and period t in each tradeable sector j. Note that the trade costs will vary by destination pair, by sector, and time, and need not be directionally symmetric: d^j_{nit} need not equal d^j_{int}. Under perfect competition, the price at which country i can supply tradeable good q in sector j to country n is equal to $p^j_{nit}(q) = \left(\frac{c^j_{it}}{z^j_{it}(q)}\right) d^j_{nit}$. Buyers of each good q in tradeable sector j in country n and period t will select to buy from the cheapest source country. Thus, the price actually paid for this good in country n will be $p^j_{nt}(q) = \min_{i=1,\ldots,N} \left\{p^j_{nit}(q)\right\}$.

Appendix A.1 lays out the complete set of equilibrium conditions and Appendix A.2 describes the model solution algorithm used in the quantitative assessment.

3 Productivity Estimation

This section describes in detail the estimation procedure for the technology parameters in the tradeable sectors relative to the US using data on sectoral output and bilateral trade. This step also produces estimates of bilateral trade costs at the sector level over time. The end of the section assesses the external validity of the resulting estimates.

Standard steps lead to the familiar result that the probability of importing good q in sector j from country i in period t, π^j_{nit}, is equal to the share of total spending on goods coming from country i, X^j_{nit}/X^j_{nt}, and is given by:

$$\frac{X^j_{nit}}{X^j_{nt}} = \pi^j_{nit} = \frac{T^j_{it}\left(c^j_{it}d^j_{nit}\right)^{-\theta}}{\Phi^j_{nt}},$$

where the "multilateral resistance" term is defined as $\Phi^j_{nt} = \sum_{i=1}^{N} T^j_{it}\left(c^j_{it}d^j_{nit}\right)^{-\theta}$. Following the standard EK approach, first divide trade shares by their domestic counterpart:

$$\frac{\pi^j_{nit}}{\pi^j_{nnt}} = \frac{X^j_{nit}}{X^j_{nnt}} = \frac{T^j_{it}\left(c^j_{it}d^j_{nit}\right)^{-\theta}}{T^j_{nt}\left(c^j_{nt}\right)^{-\theta}},$$

which in logs becomes:

$$\ln\left(\frac{X^j_{nit}}{X^j_{nnt}}\right) = \ln\left(T^j_{it}(c^j_{it})^{-\theta}\right) - \ln\left(T^j_{nt}(c^j_{nt})^{-\theta}\right) - \theta \ln d^j_{nit}.$$

Let the (log) iceberg costs be given by the following expression:

$$\ln d^j_{nit} = d^j_{k,t} + b^j_{nit} + \mathrm{CU}^j_{nit} + \mathrm{RTA}^j_{nit} + ex^j_{it} + \nu^j_{nit},$$

where $d^j_{k,t}$ is the contribution to trade costs of the distance between n and i being in a certain interval (indexed by k). Following EK, the distance intervals are, in miles: [0, 350], [350, 750], [750, 1500], [1500, 3000], [3000, 6000], [6000, maximum). Additional variables include whether the two countries share a common border (which changes the trade costs by b^j_{nit}), belong to a currency union (CU^j_{nit}), or to a regional trade agreement (RTA^j_{nit}). The inclusion of an exporter fixed effect ex^j_{it} follows Waugh (2010), who shows that the exporter fixed effect specification does a better job at matching the patterns in both country incomes and observed price levels. Finally, there is an error term ν^j_{nit}. Appendix A.6 assesses the robustness of the estimates to both the set of geographic controls and the assumption of the exporter fixed effect in d^j_{nit}. Note that all the variables have a time subscript and a sector superscript j: all the trade cost proxy variables affect true iceberg trade costs d^j_{nit} differentially across both time periods and sectors.

This leads to the following final estimating equation:

$$\ln\left(\frac{X_{nit}^j}{X_{nnt}^j}\right) = \underbrace{\ln\left(T_{it}^j(c_{it}^j)^{-\theta}\right) - \theta e x_{it}^j}_{\text{Exporter Fixed Effect}} \underbrace{- \ln\left(T_{nt}^j\left(c_{nt}^j\right)^{-\theta}\right)}_{\text{Importer Fixed Effect}} \quad (4)$$
$$\underbrace{-\theta d_{k,t}^j - \theta b_{nit}^j - \theta \mathrm{CU}_{nit}^j - \theta \mathrm{RTA}_{nit}^j}_{\text{Bilateral Observables}} \underbrace{-\theta \nu_{nit}^j}_{\text{Error Term}} .$$

This specification is estimated for each sector and decade separately, allowing for complete flexibility in how the coefficients vary both across sectors and over time. Estimating this relationship will thus yield, for each country and time period, an estimate of its technology-cum-unit-cost term in each sector j, $T_{nt}^j(c_{nt}^j)^{-\theta}$, which is obtained by exponentiating the importer fixed effect. The available degrees of freedom imply that these estimates are of each country's $T_{nt}^j(c_{nt}^j)^{-\theta}$ relative to a reference country, which in this estimation is the United States. S_{nt}^j denotes this estimated value:

$$S_{nt}^j = \frac{T_{nt}^j}{T_{ust}^j}\left(\frac{c_{nt}^j}{c_{ust}^j}\right)^{-\theta}, \quad (5)$$

where the subscript us denotes the United States. It is immediate from this expression that estimation delivers a convolution of technology parameters T_{nt}^j and cost parameters c_{nt}^j. Both will of course affect trade volumes, but the goal of the exercise is to extract technology T_{nt}^j from these estimates. The cost of the input bundles relative to the US can be written as:

$$\frac{c_{nt}^j}{c_{ust}^j} = \left(\frac{w_{nt}}{w_{ust}}\right)^{\alpha_j\beta_j}\left(\frac{r_{nt}}{r_{ust}}\right)^{(1-\alpha_j)\beta_j}\left(\prod_{j'=1}^{J}\left(\frac{p_{nt}^{j'}}{p_{ust}^{j'}}\right)^{\gamma_{j'j}}\right)^{1-\beta_j}\left(\frac{p_{nt}^{J+1}}{p_{ust}^{J+1}}\right)^{\gamma_{J+1,j}(1-\beta_j)} .$$

Using information on relative wages, returns to capital, estimates of price levels in each tradeable sector, and the nontradeable sector price relative to the US, it is thus possible to impute the costs of the input bundles relative to the US in each country and each sector. Armed with those values of c_{nt}^j/c_{ust}^j, the relative technology parameters T_{nt}^j/T_{ust}^j are computed directly from (5).

This approach bears a close affinity to development accounting (see, e.g. Caselli, 2005). Development accounting starts with an observable variable to be accounted for (real per capita income), and employs other observables – physical capital, human capital, health endowments, etc. – to absorb as much cross-country variation in the variable of interest as possible. The unexplained remainder is called TFP. In our procedure, the outcome variable of interest is not income but S^j_{nt}. Intuitively, if, controlling for the typical gravity determinants of trade, a country spends relatively more on domestically produced goods in a particular sector – S^j_{nt} is high – it is revealed to have either a high relative productivity or a low relative factor and input cost in that sector. Just as in development accounting, the procedure described above then uses measured factor and intermediate input prices to net out the role of factor and input costs, yielding an estimate of relative productivity as a residual.[3] As in development accounting, to reach reliable estimates it is important to net out the impact of as many observables as possible. Thus, the implementation features human and physical capital and sophisticated input linkages, including explicit nontradeable inputs. To accurately reflect sectoral factor and input cost differences, production function parameters are sector-specific.

Appendix A.3 describes the estimation procedures for other parameters (US tradeable sector productivities, non-tradeable productivities, and taste parameters ω_j). The calibration of the remaining parameters is more straightforward. Some parameters – $\alpha_j, \beta_j, \gamma_{j'j}, s_{nt}, \xi_{nt}, L_{nt}$, and K_{nt} – come directly from the data. A small number of parameters – θ, η, and ε – are taken from elsewhere in the literature. Appendix A.4 details data sources and the parameter choices. Appendix A.5 describes the basic summary statistics and patterns in sectoral productivity estimates. Appendix A.6 describes a battery of robustness checks on the productivity estimates. Throughout the analysis, the tradeable sectors are comprised of manufacturing only, and the non-tradeable sector is assumed to

[3] Since this approach uses factor prices rather than factor endowments, it is closer in spirit to the "dual" approach to growth accounting (e.g. Hsieh, 2002).

correspond to services. While international trade in services is increasingly important to the world economy, currently the trade and production data required to add services to the set of tradeable sectors are not available.

3.1 External Validation

This section compares the productivity estimates obtained by our procedure and used throughout the paper with estimates of measured TFP and labor productivity that can be obtained directly. Computing sectoral measured TFP requires data on total output, employment, capital stocks, and intermediate input usage, all in real terms, by sector. This information is only available at sector level and on a consistent basis for many countries through the OECD Structural Analysis (STAN) database. The set of countries and sectors for which this measured TFP can be computed is not large. There are only 9 countries with all the required data in at least some sectors: Austria, Czech Republic, Denmark, Finland, France, Greece, Italy, Norway, and Sweden.[4] The data are in principle available for the period 1970-2008, though in practice earlier years are often not available in individual countries. Appendix A.3 describes the details of TFP estimation in STAN.

<< TABLE 1 ABOUT HERE >>

Panel A of Table 1 reports, for each sector, the Spearman rank correlation between the TFP values estimated based on STAN with the T's from the baseline procedure for the 2000s, as the latest time period has the largest number of observations. These tend to be high: the mean correlation across sectors is 0.71, and the median 0.80. The last column reports the number of countries for which STAN-based TFP is available in each sector. There is information for less than 9 countries per sector. To make more efficient use of the data, the next exercise pools the sectors and examines the correlation between the two

[4] In practice, the main bottleneck appears to be data on investment, and therefore capital stocks.

productivity measures in a regression framework:

$$\log \text{TFP-STAN}_n^j = \beta \log \left(T_n^j\right)^{1/\theta} + \delta_n + \delta_j + \epsilon_{nj},$$

where TFP-STAN$_n^j$ is the TFP as implied by the STAN data, and T_n^j is as defined in the rest of the paper. The specification includes both country and sector effects, and thus the average productivity levels in individual countries and sectors are netted out. Panel B of Table 1 presents the results. The first column reports the simple bivariate regression of the two measures. The coefficient is highly statistically significant. The correlation between the two variables is 0.37. The second column adds sector effects. The coefficient remains statistically significant at the 1% level, and the partial correlation, obtained after netting the sector effects from both measures of productivity, is much higher at 0.583. Finally, column (3) includes both sector and country effects. The coefficient of interest is significant at the 5% level. With country and sector fixed effects, the overall R^2 is about 0.89. Given this, it is remarkable that the partial correlation between the two measures, after controlling for both country and sector effects is 0.29. Thus, even after netting out all the sector and country effects, the association between these two variables is close and statistically significant.

While the data required to compute TFP are not available for many countries, labor productivity – value added per worker – is readily available for most of the countries in the sample. An alternative exercise thus compares labor productivity implied by our estimates of T_n^j to the data. Unlike in the TFP comparison, this exercise requires implementing the full model and solving for equilibrium, since to go from T_n^j to value added per worker requires both prices and factor allocations. The right panel of Table 1 reports the Spearman rank correlations between labor productivity implied by our model and the data in the 2000s. The sample of countries is considerably larger than in the TFP comparison. The mean correlation of 0.835 and median of 0.876. The correlations are similar for other decades and are not reported to conserve space. Similarly to the TFP comparison, the bottom right panel of Table 1 reports the results of regressing log labor productivity in the data against the corresponding value in the model under our estimates. There is a strong positive association between labor productivity in the data and that implied by our model.[5]

These exercises suggest that our estimation procedure which relies on bilateral trade to measure productivity delivers results that are in line with the more conventional approaches.[6]

4 Relative Convergence

To shed light on the patterns in relative sectoral productivity, we estimate a convergence specification in the spirit of Barro (1991) and Barro and Sala-i-Martin (1992):

$$\Delta \log \left(T_n^j\right)^{1/\theta} = \beta \log \left(\text{Initial } T_n^j\right)^{1/\theta} + \delta_n + \delta_j + \epsilon_{nj}. \tag{6}$$

Unlike the classic cross-country convergence regression, this specification pools countries and sectors. On the left-hand side is the log change in the productivity of sector j in country n. The right-hand side regressor of interest is its beginning-of-period value. All of the specifications include country and sector fixed effects, which affects the interpretation of the coefficient. The country effect absorbs the average change in productivity across all sectors in each country. Thus, β picks up the impact of the initial relative productivity on the *relative* growth of a sector within a country. In particular, a negative value of β implies that relative to the country-specific average, the most backward sectors grew the fastest.

<< TABLE 2 ABOUT HERE >>

[5]The table does not report the results with both country and sector effects because country and sector effects turn out to span model-implied labor productivity. This is not surprising given that the model imposes factor market clearing with the same wage and return to capital across sectors in each country, and the Cobb-Douglas production function implies the same capital share in all countries in each sector.

[6]An additional exercise would be to compare labor productivity in the non-tradeable sector implied by our model to the data. Note that the non-tradeable sector productivity is chosen to match perfectly per-capita incomes to the data, and does not use any data on service sector output, employment or productivity. The correlation between service sector labor productivity in the model and the data (collected from the World Bank's World Development Indicators) is 0.97.

Table 2 presents the results. The first column reports the coefficients for the longest differences: the 1960s to the 2000s, while the second column estimates the specification starting in the 1980s. The following 4 columns carry out the estimation decade-by-decade, 1960s to 1970s, 1970s to 1980s, and so on. Since the length of the time period differs across columns, the coefficients are not directly comparable. To help interpret the coefficients, the table also reports the speed of convergence, calculated according to the standard Barro and Sala-i-Martin (1992) formula: $\beta = e^{-\lambda\mathcal{T}} - 1$, where β is the regression coefficient on the initial value of productivity, $\mathcal{T}$ is the number of decades between the initial and final period, and λ is the convergence speed. This number gives how much of the initial difference between productivities is expected to disappear in a decade. All of the standard errors are clustered by country, to account for unspecified heteroscedasticity at the country level. All of the results are robust to clustering instead at the sector level; those standard errors are not reported to conserve space.

Column 1 of the top panel reports the estimates for the long-run convergence in the pooled sample of all countries. The coefficient is negative, implying that there is convergence: within a country, the weakest sectors tend to grow faster. It is highly statistically significant, with the t-statistic of nearly 12. The speed of convergence implied by this coefficient is 18% per decade. As a benchmark, the classic Barro and Sala-i-Martin (1992) rate of convergence is 2% per year, or 22% per decade, close to what was found here in a very different setting. The second column estimates the long-difference specification from the 1980s to the 2000s. Once again, the coefficient is negative and highly significant, but it implies a considerably slower rate of convergence, 11.7% per decade. The rest of the columns report the results decade-by-decade. Though there is statistically significant convergence in each decade, the speed of convergence trends downward, from 26% from the 1960 to the 1970s, to 11.4% in the most recent period.

In order to assess how the results differ across country groups, Panels B and C report the results for the OECD and the non-OECD subsamples separately. Breaking it down produces slightly faster convergence rates than in the full sample. In the decade-to-decade specifications, the non-OECD countries are catching up somewhat faster, which is not surprising.

<< FIGURE 1 ABOUT HERE >>

Figures 1 and 2 present the results graphically. Figure 1 plots the unconditional bivariate relationship between the log change in productivity and the log initial level in each sector. Within most sectors, the negative relationship is evident. In every sector, the estimated coefficient is negative, and in 14 of the 19 sectors, it is significant at the 5% level. Figure 2 plots the partial correlation between the initial level and subsequent growth, after netting out country and sector fixed effects. This is the partial correlation plot underlying the first coefficient reported in Table 2. Once again, the negative relationship is evident in the pooled sample.

<< FIGURE 2 ABOUT HERE >>

Appendix Table A4 reports the results of estimating the convergence equation (6) country by country from the 1960s to today. These results should be treated with more caution, as the sample size is at most 19. The columns report the coefficient, the standard error, the number of observations, the R^2, as well as the implied speed of convergence for each country. There is considerable evidence of convergence in these country-specific estimates. In all countries, the convergence coefficient is negative, and significant at the 10% level or below in 38 out of 50 available countries (76%). Appendix A.7 describes some simple heuristic patterns in the trade data that are consistent with the relative convergence finding.

All in all, these results provide robust evidence of relative convergence: in all time periods and broad sets of countries in the sample, relatively weak sectors grow faster, with sensible rates of convergence.

4.1 Discussion and Mechanisms

A large literature in growth, synthesized by Acemoglu (2008, Ch. 18), studies aggregate country-level technology differences using multi-country models of technology adoption. This literature has pursued two broad directions. The first postulates that aggregate productivity differences persist because there are frictions in technology adoption. In order to ensure a stable world income distribution, a central assumption in this type of framework is that countries farther behind the world productivity frontier find it easier to increase productivity. This hypothesis dates back to Gerschenkron (1962), and is typically introduced as a reduced-form relationship in these models. The second approach postulates that all technologies are freely available to all countries at all times, but due to capital and/or skill endowment or institutional differences, poorer countries cannot make the best use of the available technologies (Atkinson and Stiglitz, 1969; Basu and Weil, 1998; Acemoglu and Zilibotti, 2001; Caselli and Coleman, 2006; Acemoglu et al., 2007).

Since these models are framed in terms of aggregate technology differences, they are challenging to evaluate empirically. This is because at the country level, it is difficult to distinguish between the role of distance to the world frontier and other country-specific factors, especially when these factors themselves condition the speed of productivity convergence. By opening up a sectoral dimension, our results can provide some empirical evidence on these theories. Our convergence regressions include country fixed effects, and thus control for country-specific determinants of productivity growth affecting all the sectors equally. Though our convergence coefficients capture the notion of *within-country* convergence, they nonetheless lend support to the key assumption in models of slow technology diffusion: it is easier to catch up starting from a more backward position.

The second approach rationalizes persistent technology gaps by appealing to the appropriateness of world frontier technologies for local country conditions, such as the capital-labor ratio (Atkinson and Stiglitz, 1969; Basu and Weil, 1998), skill endowment (Acemoglu and Zilibotti, 2001; Caselli and Coleman, 2006), or institutional quality (Acemoglu et al., 2007). The relative convergence specification can be augmented to provide some supporting evidence for these mechanisms. We interact $\log\left(\text{Initial } T_n^j\right)^{1/\theta}$ in equation (6) with these country characteristics to see whether the speed of convergence is faster in countries with better institutions, and higher human and physical capital per worker. Since these vary by country, the main effects of these country characteristics are absorbed by the country effects, but the specification is still informative on whether they have a differential impact on the speed of convergence.

<< TABLE 3 ABOUT HERE >>

The first three columns of Table 3 reports the results. All three country characteristics have negative interacted coefficients, consistent with theory: countries with better institutions and higher human and physical capital experience faster relative convergence, in the sense that initially lower productivity leads to faster subsequent productivity growth in those countries. Institutions and physical capital are statistically significant, whereas human capital is not.

In contrast to the aggregate productivity literature, theories of the dynamics of sectoral technology are quite scarce. Krugman (1987) and Young (1991) develop learning-by-doing models of productivity evolution. A strong implication of these models is that relative productivity differences *increase* over time – comparative advantage strengthens. This is because learning is faster in sectors that produce more, and comparative advantage sectors are the ones that produce more. Our results are clearly inconsistent with the main prediction of the learning-by-doing models, at least not at the level of broad sectors. Similarly, Grossman and Helpman (1991, Ch. 8) develop a model with a traditional and a knowledge-based sector, and show that one country's initial advantage in the stock of R&D leads to an increasingly stronger comparative advantage in the knowledge-based sector. Once again, our findings of pervasive convergence in productivity do not support this type of theoretical prediction.

A theoretical and quantitative framework with endogenous sectoral productivity that can be used for understanding the empirical patterns uncovered here has not yet been developed, and remains a potentially fruitful direction for future research. One promising possibility is the framework of "defensive innovation" in response to import competition recently developed by Bloom et al. (2012) (see also Bloom et al., 2011). Under this theory, greater import penetration will make productivity growth faster. Column 4 of Table 3 evaluates this prediction in our data by interacting $\log\left(\text{Initial } T_n^j\right)^{1/\theta}$ with π_{nn}^j, or one-minus import penetration in sector j, country n. Since π_{nn}^j varies by both country and sector, the specification also includes the main effect. The interaction coefficient is significant at 10% and consistent with this theory: country-sectors with higher import penetration (lower π_{nn}^j) tend to converge faster when starting from lower productivity.

The literature has also called attention to the role of imported intermediate inputs in stimulating productivity growth (e.g. Amiti and Konings, 2007; Kasahara and Rodrigue, 2008). It is not observed directly which country-sectors (much less firms) use imported intermediates. However, it is feasible to construct the following heuristic indicator of availability of imported inputs:

$$\text{Imp.Inputs}_n^j = (1-\beta_j)\sum_{j'}\gamma_{j'j}\left(1-\pi_{nn}^{j'}\right),$$

where, as above, $\left(1-\pi_{nn}^{j'}\right)$ is import penetration (share of imports in total absorption), $\gamma_{j'j}$ is the share of input spending in sector j on inputs from sector j', and $(1-\beta_j)$ is the share of input spending in total output. Thus, Imp.Inputs_n^j will be high if country n imports a lot in sectors used intensively by j as inputs (high combined $(1-\beta_j)\gamma_{j'j}$). Column 5 of Table 3 presents the results. There does appear to be some suggestive evidence that in country-sectors with higher potential availability of imported inputs, convergence from lower initial productivity is faster: the interaction coefficient is negative and significant at the 10% level.[7]

Finally, an interesting question is whether relative convergence is faster or slower in more labor-intensive sectors. Column 6 of Table 3 reports the result of interacting initial productivity with α_j, labor share in value added. Relative convergence appears slower in more labor-intensive sectors (the interaction coefficient is positive), but the difference is not statistically significant.

5 Quantitative Implications

To assess the impact of sectoral productivity growth and reductions in trade costs on aggregate outcomes, this section compares the benchmark model to a pair of counterfactual scenarios. The "No Convergence" (NC) counterfactual implements the model while keeping productivities in each country and sector relative to the US to be the same as in the 1960s:

$$\frac{\widetilde{T}_{nt}^{j,NC}}{T_{ust}^{j}} = \frac{T_{n1960s}^{j}}{T_{us1960s}^{j}} \qquad \forall t, n, j \in 1, ..., J.$$

This counterfactual reveals what would have happened to the world economy if the configuration of sectoral productivities in manufacturing had stayed the same relative to the US throughout the period. Figure 3 illustrates this counterfactual using productivity estimates of South Korea. The hollow triangles display the estimated productivity in South Korea in the 2000s relative to the US in each sector, with the solid triangle depicting the geometric mean in the 2000s. The circles display the estimated productivity in South Korea in the 1960s. The sectors are ordered in descending 1960s productivity relative to the US. The No Convergence counterfactual simply sets South Korean productivity relative to the US to its 1960s values in each sector.

[7] The main effect of Imp.Inputs$_n^j$ appears to be negative, meaning that productivity growth is slower on average in sectors with high potential availability of imported inputs. In the presence of interaction coefficients, the main effect coefficient should be interpreted with caution. Nonetheless, at the mean value of $\log\left(\text{Initial } T_n^j\right)^{1/\theta}$ it is still the case that the total effect of an increase in Imp.Inputs$_n^j$ on TFP growth is negative. While we do not have an economic explanation for the sign of this coefficient, it captures a highly conditional correlation after controlling for both relative convergence and country and sector effects.

<< FIGURE 3 ABOUT HERE >>

Figure 3 and the relative convergence results in Section 4 reveal that sector level convergence has two facets. The first is the catch-up in average productivity, illustrated by the fact that the mean productivity in the 2000s relative to the US is higher than in the 1960s. The second is the relative convergence: different sectors caught up at different speeds, with the initially weakest sectors catching up systematically faster. To separate this second mechanism, the "No Relative Convergence" (NRC) counterfactual exercise assumes that for each decade t after the 1960s, each country's sectoral productivities relative to the US grew at their geometric average rate, but relative sectoral productivities remained the same as in the 1960s. Precisely, the counterfactual T's are calculated as:

$$\frac{\widetilde{T}_{nt}^{j,NRC}}{T_{ust}^{j}} = \frac{T_{n1960s}^{j}}{T_{us1960s}^{j}} \times \frac{\left(\prod_{k=1}^{J} \frac{T_{nt}^{k}}{T_{ust}^{k}}\right)^{\frac{1}{J}}}{\left(\prod_{k=1}^{J} \frac{T_{n1960s}^{k}}{T_{us1960s}^{k}}\right)^{\frac{1}{J}}}.$$

Figure 3 also illustrates this counterfactual in the case of South Korea. The NRC counterfactual productivities preserve the average catch-up of each country, since the mean productivity across sectors in this counterfactual is by construction the same as under the benchmark estimates (labeled "2000s" in the figure). However, it also preserves the configuration of relative productivities observed in the country in the 1960s.

The third and final counterfactual is to keep the trade costs d_{nit}^{j} to their 1960s values throughout the sample period. This counterfactual reveals what would have happened had the trade costs not fallen as they did in the data over this period. In this exercise, the trade costs of the countries not present in the sample in the 1960s are set to infinity – i.e., these countries are in autarky – and the outcomes are reported for countries present in the sample in the 1960s. This is a good approximation: the countries present in our sample in the 1960s account for 90% of world trade in the 1960s.

Countries that join the sample later than the 1960s in the counterfactuals keep their relative productivities fixed to the first decade they are in the data. Those initial productivities are our best guess for their pattern of relative sectoral productivities as of the 1960s.

5.1 Trade Volumes and Trade Patterns

We begin with the discussion of the impact of changing sectoral productivities on observable outcomes, namely international trade volumes and patterns. Table 4 presents the results. The first column reports the value of each moment in the data, the second in the benchmark model, and the third and fourth in the No Convergence and the No Relative Convergence counterfactuals, respectively.[8] The numbers in italics under the averages are the correlations across countries in each moment between the model and the data.

<< TABLE 4 ABOUT HERE >>

The first row assesses the impact of changes in sectoral productivities on trade volumes. It reports the average manufacturing imports/GDP ratio in the 2000s across the countries in the sample. The mean in the benchmark model matches that in the data almost perfectly, and the correlation between the two is also high at nearly 0.6. The next column reports the manufacturing import/GDP ratio for the NC counterfactual. It is clear that in the absence of convergence, world trade volumes would actually be *higher* than they are today. The difference is sizable: imports to GDP would be 4.7 percentage points higher if all countries kept their initial relative productivities, a 20% difference. The next column reports trade volumes in the NRC counterfactual. It is clear that most of the counterfactual increase in trade volumes is actually due to relative rather than absolute productivity changes.

Next, we look at trade patterns rather than trade volumes, and examine whether the model can match the long-run changes observed in the data. One sharp pattern in the data is that within a sector, export volumes are becoming more similar across countries over time. This is captured in the table by the change in the standard deviation of log

[8] Appendix A.8 discusses the fit of the benchmark model implementation to other data moments, such as factor prices and bilateral trade flows.

shares of world exports within a particular sector across countries. The first column shows that in the data it has decreased systematically between the 1960s and today. While the table reports the cross-sectoral average, this pattern is also pervasive: in 17 out of 19 sectors, the dispersion of log country shares of world exports has fallen. The next column reports the same statistic in the benchmark model, as well as the correlation across sectors between the model and the data. The model matches quite well both the overall decrease, and the cross-sectoral pattern in changes in dispersion. This is not surprising, since the benchmark model parameters are estimated on observed trade flows in each decade, but nonetheless reassuring. The next two columns report the same statistic in the NC and NRC counterfactuals. Without productivity changes, the cross-country dispersion in world export shares is predicted to fall by about half of the observed decrease, and the correlations between the counterfactuals and the data are much lower than for the baseline.

Finally, to examine the patterns of intra-industry trade, we construct the change in the Grubel-Lloyd (GL) index for each country and sector, and report the simple average change in the GL index across countries and sectors. There has been a considerable increase in the extent of intra-industry trade over time, with an average increase in the data of 0.16 (the GL index has a range of 0 to 1). The baseline model matches roughly two-thirds of this magnitude. By contrast, there would be virtually no increase in the GL index had sectoral productivities not changed, and the correlations between the counterfactual and the data are much lower than for the baseline. The numbers are once again quite similar between the NC and the NRC counterfactuals.

To summarize, observed changes in relative sectoral productivities had an appreciable impact on world trade. Had relative sectoral productivities not changed as they did in the data, trade volumes would be even higher than they are today. In addition, the convergence in relative productivity across sectors within countries accounts well for the increased similarity in export flows between 1960s and today, and for the observed increase in intra-industry trade.

To compare these results to the impact of changes in trade costs, the last column of Table 4 reports the outcomes of the counterfactual under benchmark productivities but 1960s trade costs throughout. Not surprisingly, trade volumes are considerably lower than in the baseline. Less trivially, the dispersion in world export shares would fall much less than in the data, and there would be no increase in intra-industry trade had the d_{nit}^j not fallen. Thus, while changes in relative productivities and changes in trade costs have opposite effects on the overall trade volumes, they have a complementary impact on the evolution of trade patterns. Without both productivity changes and falls in trade costs, trade patterns would not have changed as they did in the data.

5.2 Welfare

Finally, we evaluate the welfare impact of productivity and trade cost changes. The measure of welfare is real per capita income:

$$\frac{w_{nt} + r_{nt}k_{nt}}{P_{nt}}, \tag{7}$$

where $k_{nt} = K_{nt}/L_{nt}$ is capital per effective unit of labor. This measure of welfare in the baseline for the 2000s is compared to welfare for the same decade in the counterfactuals. The model solution assumes that the world is in steady state from the 2000s onwards, and thus analyzing the present discounted value of utility in the 2000s is equivalent to focusing on the period utility in the 2000s.

<< TABLE 5 ABOUT HERE >>

Table 5 summarizes the results, separating the OECD and the non-OECD countries. The top panel reports the results of the No Convergence counterfactual, expressed as the percentage changes in welfare for the counterfactual relative to the benchmark. Thus, the negative median values in the first column indicate that on average, welfare would have been considerably lower had sectoral productivities not converged since the 1960s. At the median, welfare would have been 11.66% lower in the OECD and 16.40% lower in the non-OECD countries. This is not surprising, as many countries caught up in productivity relative to the US over this period.

The second panel presents the welfare comparison between the No Relative Convergence counterfactual and the baseline. Here the result is the opposite: welfare would have been higher had the countries caught up on average but kept their relative productivities constant at the 1960s values. For the median OECD country, welfare would have been 1.34% higher had its relative sectoral productivities not changed. For the non-OECD countries, the welfare difference is 3.00% at the median. This accords well with what is predicted by theory, given the pronounced convergence in relative sectoral productivities found in the data in Section 4.

The second notable aspect of the results is the large dispersion. Among the OECD countries, the standard deviation of welfare changes in the No Convergence counterfactual is 7.15%, while for the non-OECD, it twice as high, 14.40%. In the No Relative Convergence case, the standard deviation is somewhat smaller, at 1.4% and 8.68% in the OECD and non-OECD, respectively. Importantly, among the non-OECD countries, welfare changes range from substantially negative to substantially positive, indicating that heterogeneity across countries is first-order.

The panel labeled "1960s d_{nit}^j" reports the welfare impact of keeping the trade costs to their 1960s values. Welfare in the 2000s would have been about 2.5% lower had trade costs not decreased since the 1960s. These magnitudes are comparable to the NRC counterfactual, and much smaller than in the NC counterfactual. Thus, relative productivity changes are at least as important for welfare as reductions in trade costs.[9]

To cross-check these results and compare magnitudes, the bottom panel of Table 5 reports the same summary statistics for the overall gains from trade compared to autarky

[9]The impact of reductions in trade costs ranges from positive to negative. It is well known that even in this neoclassical model, a country's welfare may fall due to a worldwide reduction in trade costs if that improves market access of countries, such as China, that compete with its exports in world markets.

for the 2000s in the baseline model. The gains from trade are 5.62% for the median OECD country, and 7.44% for the median non-OECD country. It is also possible to compare the extent of variation in the welfare impact of technological changes to that in the welfare gains from trade. In the OECD, the gains from trade have a standard deviation of about 3.17% and a range of about 12%: from a minimum of 1.5 to a maximum of 13.09%. Thus, for the OECD countries the variation in welfare changes due to technology is higher, with a range of 27 percentage points in the NC counterfactual. For the non-OECD countries, technology changes have similarly greater dispersion of welfare impact than gains from trade. In addition, while gains from trade are – of course – always positive, the welfare impact of technological changes takes on both positive and negative values.

From the perspective of the trade literature, the preceding welfare assessment is non-standard in one respect. The standard practice in international trade is to keep the factor supply inelastic and fixed. Our model, however, features endogenous capital accumulation. Thus, as relative sectoral productivities remain fixed from the 1960s to today, each country has different income in each decade in the counterfactual compared to the baseline. While the baseline analysis – by construction – matches perfectly the evolution of the capital stock in each country and decade, the counterfactual capital stocks will differ from their observed values. If a country that keeps its relative sectoral productivities fixed has higher income in each decade and accumulates more capital, that will have an independent effect on welfare in addition to the static impact of relative productivity. Similarly, to compute the gains from trade relative to autarky, the analysis above assumes that each country is in autarky in each decade starting in the 1960s. Lower income in each decade implies lower capital stock in the future decades, and that will impact the welfare at the end of the period.

To check the importance of this mechanism, the bottom panel of Table 5 reports the results of re-implementing the welfare counterfactuals under the assumption that capital is the same as in the baseline. This corresponds to the traditional thought experiment in the trade literature. Without endogenous adjustment of capital, the welfare impact of changes in sectoral productivities is smaller throughout. Now, in the NC counterfactual, the OECD welfare is only 8.07% lower compared to the baseline, and the non-OECD welfare is 10.53% lower. The welfare impact is similarly closer to zero in the NRC counterfactual.

As a side note, it is interesting to compare the gains from trade figures. The gains from trade to the OECD are now 3.74% at the median, or 30% lower than with capital adjustment. The non-OECD median gains are 25% lower. Thus, as frequently suggested, trade opening can have a dynamic impact on factor accumulation that will add to the gains from trade. In our case, the dynamic impact is on the accumulation of capital. This result is consistent with Crucini and Kahn (1996), who were the first to quantify the impact of tariffs with endogenous capital, and demonstrate that changes in trade costs could have amplification effects through capital accumulation. Note that the amplification effects could be even larger in a model with endogenous saving and investment rates and non-Cobb-Douglas production functions.

The mechanism through which productivity changes can reduce welfare in our model is distinct from immiserising growth (Johnson, 1955; Bhagwati, 1958). In that model, productivity growth reduces welfare if the terms of trade deteriorate by more than the improvement in productivity. In our analysis, welfare falls in the NRC counterfactual because countries become more similar and thus gains from trade are lower. It is possible to introduce sectoral heterogeneity in demand elasticity, and thus an interaction between productivity changes and demand elasticity of sectors. In that case, countries that experience productivity improvements in sectors with especially low demand elasticity will experience relatively smaller welfare increases.

6 Conclusion

This paper starts by estimating sectoral productivity in a sample of 72 countries, 19 sectors, and 5 decades, from the 1960s to the 2000s. We document a striking pattern in the data:

relative productivity across sectors within countries has converged. This effect is present in all time periods and major country groups: within a country, sectors with the lowest initial relative productivity experience systematically faster productivity growth than sectors with highest initial productivity. Using counterfactual experiments, we show that had relative sectoral productivities not changed in this way, global trade volumes would be higher, trade shares more dissimilar across countries, and intra-industry trade would be lower. While overall catch-up in productivity since the 1960s improved welfare, it turns out that relative productivity changes – holding average growth fixed – had a modest negative welfare impact.

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ONLINE APPENDIX

The Evolution of Comparative Advantage: Measurement and Welfare Implications

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January 13, 2016

Appendix A Implementation

A.1 Equilibrium

The **competitive equilibrium** of this model world economy consists of sequences of prices, allocation rules, and trade shares such that (i) given the prices, all firms' inputs satisfy the first-order conditions, and their output is given by the production function; (ii) the households' aggregate consumption and investment decisions are consistent with the exogenous saving rates, and their sectoral demands satisfy the first order conditions given the prices; (iii) the prices ensure the market clearing conditions for labor, capital, tradeable goods and nontradeable goods; (iv) trade shares ensure balanced trade for each country.

The set of prices includes the wage rate w_{nt}, the rental rate r_{nt}, the sectoral prices $\{p_{nt}^j\}_{j=1}^{J+1}$, and the aggregate price P_{nt} in each country n and period t. The allocation rules include aggregate consumption C_{nt}, investment I_{nt}, capital K_{nt}, the capital and labor allocation across sectors $\{K_{nt}^j, L_{nt}^j\}_{j=1}^{J+1}$, final demand $\{Y_{nt}^j\}_{j=1}^{J+1}$, and total demand $\{Q_{nt}^j\}_{j=1}^{J+1}$ (both final and intermediate goods) for each sector. The trade shares include the expenditure shares π_{nit}^j in country n on goods coming from country i in sector j.

Characterization of Equilibrium

The aggregate (consumption) price index in country n and period t is:

$$P_{nt} = B_n \left(\sum_{j=1}^{J} \omega_j (p_{nt}^j)^{1-\eta} \right)^{\frac{1}{1-\eta}\xi_{nt}} (p_{nt}^{J+1})^{1-\xi_{nt}},$$

where $B_n = \xi_{nt}^{-\xi_{nt}}(1-\xi_{nt})^{-(1-\xi_{nt})}$ and p_{nt}^j is the price of the sector j composite. In addition, the price of good j in country n and period t is simply

$$p_{nt}^j = \Gamma \left(\Phi_{nt}^j\right)^{-\frac{1}{\theta}}, \tag{A.1}$$

where $\Gamma = \left[\mathbf{\Gamma}\left(\frac{\theta+1-\varepsilon}{\theta}\right)\right]^{\frac{1}{1-\varepsilon}}$, and $\mathbf{\Gamma}$ is the Gamma function.

Given the set of prices $\{w_{nt}, r_{nt}, P_{nt}, \{p_{nt}^j\}_{j=1}^{J+1}\}_{n=1}^{N}$, the optimal sectoral allocations are first characterized from final demand. Consumers maximize utility subject to the budget constraint (1), (2), and (3). The first order conditions associated with this optimization problem imply the following final demand across sectors:

$$p_{nt}^j Y_{nt}^j = \xi_{nt}(w_{nt}L_{nt} + r_{nt}K_{nt}) \frac{\omega_j (p_{nt}^j)^{1-\eta}}{\sum_{k=1}^{J} \omega_k (p_{nt}^k)^{1-\eta}}, \text{ for all } j = \{1, .., J\} \tag{A.2}$$

and

$$p_{nt}^{J+1}Y_{nt}^{J+1} = (1-\xi_{nt})(w_{nt}L_{nt} + r_{nt}K_{nt}).$$

To characterize the production and factor allocations across the world, let Q_{nt}^j denote the total sectoral demand in country n and sector j in period t. Q_{nt}^j is used for both final demand and intermediate inputs in domestic production of all sectors. That is,

$$p_{nt}^j Q_{nt}^j = p_{nt}^j Y_{nt}^j + \sum_{j'=1}^{J}(1-\beta_{j'})\gamma_{jj'}\left(\sum_{i=1}^{N}\pi_{int}^{j'}p_{it}^{j'}Q_{it}^{j'}\right) + (1-\beta_{J+1})\gamma_{j,J+1}p_{nt}^{J+1}Q_{nt}^{J+1}.$$

Total expenditure in sector $j = 1, ..., J+1$ of country n, $p_{nt}^j Q_{nt}^j$, is the sum of (i) domestic final consumption expenditure $p_{nt}^j Y_{nt}^j$; (ii) expenditure on sector j goods as intermediate inputs in all the traded sectors $\sum_{j'=1}^{J}(1-\beta_{j'})\gamma_{jj'}\left(\sum_{i=1}^{N}\pi_{int}^{j'}p_{it}^{j'}Q_{it}^{j'}\right)$, and (iii) expenditure on intermediate inputs from sector j in the domestic non-traded sector $(1-\beta_{J+1})\gamma_{j,J+1}p_{nt}^{J+1}Q_{nt}^{J+1}$. These market clearing conditions summarize the two important features of the world economy captured by our model: complex international production linkages, as much of world trade is in intermediate inputs, and a good crosses borders multiple times before being consumed (Hummels et al., 2001); and two-way input linkages between the tradeable and the nontradeable sectors.

In each tradeable sector j, some goods q are imported from abroad and some goods q are exported to the rest of the world. Country n's exports in sector j and period t are given by $EX_{nt}^j = \sum_{i=1}^{N}\mathbb{1}_{i\neq n}\pi_{int}^j p_{it}^j Q_{it}^j$, and its imports in sector j are given by $IM_{nt}^j = \sum_{i=1}^{N}\mathbb{1}_{i\neq n}\pi_{nit}^j p_{nt}^j Q_{nt}^j$, where $\mathbb{1}_{i\neq n}$ is the indicator function. The total exports of country n are then $EX_{nt} = \sum_{j=1}^{J}EX_{nt}^j$, and total imports are $IM_{nt} = \sum_{j=1}^{J}IM_{nt}^j$. Trade balance requires that for every country n and time t, $EX_{nt} - IM_{nt} = 0$.

Factor allocations across sectors: the total production revenue in tradeable sector j in country n and period t is given by $\sum_{i=1}^{N}\pi_{int}^j p_{it}^j Q_{it}^j$. The optimal sectoral factor allocations in country n and tradeable sector j in period t must thus satisfy

$$\sum_{i=1}^{N}\pi_{int}^j p_{it}^j Q_{it}^j = \frac{w_{nt}L_{nt}^j}{\alpha_j\beta_j} = \frac{r_{nt}K_{nt}^j}{(1-\alpha_j)\beta_j}.$$

For the nontradeable sector $J+1$, the optimal factor allocations in country n are simply given by

$$p_{nt}^{J+1}Q_{nt}^{J+1} = \frac{w_{nt}L_{nt}^{J+1}}{\alpha_{J+1}\beta_{J+1}} = \frac{r_{nt}K_{nt}^{J+1}}{(1-\alpha_{J+1})\beta_{J+1}}.$$

Finally, the feasibility conditions for factors are given by, for any n,

$$\sum_{j=1}^{J+1} L_{nt}^j = L_{nt} \text{ and } \sum_{j=1}^{J+1} K_{nt}^j = K_{nt}.$$

Given all of the model parameters, factor endowments, trade costs, and productivities, the model is solved using the algorithm described in Appendix A.2.

A.2 Solution Algorithm

A model period is one decade. The calibration and estimation yields the following series: (i) country-specific and time-varying series $\{L_{nt}, T_{nt}^j, \xi_{nt}, \delta_{nt}, s_{nt}, d_{nit}^j\}$ for 5 decades; and (ii) time-invariant parameters common across countries and decades $\{\varepsilon, \eta, \theta, \omega_j, \alpha_j, \beta_j, \gamma_{j'j}\}$. The capital stocks in the initial decade are K_{n0}. The model economy is assumed to be in steady state from fifth period (the last period of the data) onward by setting the time-varying series at their fifth decade values for all $t > 5$ in each country n. The competitive equilibrium of the model is computed for each period as follows:

1. Guess $\{w_{nt}, r_{nt}\}_{n=1}^N$.

   - Compute prices from the following equations:

$$c_{nt}^j = \left(w_{nt}^{\alpha_j} r_{nt}^{1-\alpha_j}\right)^{\beta_j} \left(\prod_{j'=1}^{J+1} \left(p_{nt}^{j'}\right)^{\gamma_{j'j}}\right)^{1-\beta_j} \quad \text{for all } n \text{ and } j,$$

$$\Phi_{nt}^j = \sum_{i=1}^N T_{it}^j \left(c_{it}^j d_{nit}^j\right)^{-\theta} \quad \text{for all } n \text{ and } j \in \{1, ..., J\},$$

$$\Phi_{nt}^{J+1} = T_{nt}^{J+1} \left(c_{nt}^{J+1}\right)^{-\theta} \quad \text{for all } n,$$

$$p_{nt}^j = \Gamma \left(\Phi_{nt}^j\right)^{-\frac{1}{\theta}} \quad \text{for all } n \text{ and } j,$$

$$P_{nt} = B_n \left(\sum_{j=1}^J \omega_j (p_{nt}^j)^{1-\eta}\right)^{\frac{1}{1-\eta}\xi_{nt}} (p_{nt}^{J+1})^{1-\xi_{nt}} \quad \text{for all } n.$$

   - Compute final demand as follows: for any country n,

$$Y_{nt}^j = \xi_{nt} \frac{w_{nt} L_{nt} + r_{nt} K_{nt}}{p_{nt}^j} \frac{\omega_j (p_{nt}^j)^{1-\eta}}{\sum_{k=1}^J \omega_k (p_{nt}^k)^{1-\eta}}, \quad \text{for } j = \{1, .., J\},$$

$$Y_{nt}^{J+1} = (1-\xi_{nt})\frac{w_{nt}L_{nt} + r_{nt}K_{nt}}{p_{nt}^{J+1}}.$$

- Compute consumption, investment and next-period capital: for any country n,

$$C_{nt} = (1-s_{nt})Y_{nt}; \quad I_{nt} = s_{nt}Y_{nt}; \quad K_{nt+1} = (1-\delta_{nt})K_{nt} + I_{nt}.$$

- Compute the trade shares as follows: for any country pair (n,i) and $j \in \{1,...,J\}$

$$\pi_{nit}^{j} = \frac{T_{it}^{j}\left(c_{it}^{j}d_{nit}^{j}\right)^{-\theta}}{\Phi_{nt}^{j}}.$$

- Compute total demand as follows: for any country n and any sector j

$$p_{nt}^{j}Y_{nt}^{j} + \sum_{j'=1}^{J}(\sum_{i=1}^{N} Q_{it}^{j'}p_{it}^{j'}\pi_{int}^{j'})(1-\beta_{j'})\gamma_{jj'} + Q_{nt}^{J+1}p_{nt}^{J+1}(1-\beta_{J+1})\gamma_{j,J+1} = p_{nt}^{j}Q_{nt}^{j}.$$

- Compute the factor allocations across sectors as follows: for any country n,

$$\sum_{i=1}^{N} p_{it}^{j}Q_{it}^{j}\pi_{int}^{j} = \frac{w_{nt}L_{nt}^{j}}{\alpha_j\beta_j} = \frac{r_{nt}K_{nt}^{j}}{(1-\alpha_j)\beta_j}, \text{ for all } j = \{1,..,J\},$$

$$p_{nt}^{J+1}Q_{nt}^{J+1} = \frac{w_{nt}L_{nt}^{J+1}}{\alpha_{J+1}\beta_{J+1}} = \frac{r_{nt}K_{nt}^{J+1}}{(1-\alpha_{J+1})\beta_{J+1}}.$$

2. Update $\{w'_{nt}, r'_{nt}\}_{n=1}^{N}$ with the feasibility conditions for factors: for any n,

$$\sum_{j=1}^{J+1} L_{nt}^{j} = L_{nt}, \quad \sum_{j=1}^{J+1} K_{nt}^{j} = K_{nt}.$$

3. Repeat the above procedures until $\{w'_{nt}, r'_{nt}\}_{n=1}^{N}$ is close enough to $\{w_{nt}, r_{nt}\}_{n=1}^{N}$.

A.3 Complete Estimation

The main text describes the estimation of the levels of technology of the tradeable sectors relative to the United States. To complete the estimation, it is still required to find (i) the levels of T for the tradeable sectors in the United States; (ii) the taste parameters ω_j, and (iii) the nontradeable technology levels for all countries.

To obtain (i), we use the NBER-CES Manufacturing Industry Database for the US

(Bartelsman and Gray, 1996). The procedure starts by measuring the observed TFP levels for the tradeable sectors in the US. The form of the production function gives

$$\ln Z_{ust}^{j} = \ln \Lambda_{ust}^{j} + \beta_j \alpha_j \ln L_{ust}^{j} + \beta_j (1-\alpha_j) \ln K_{ust}^{j} + (1-\beta_j) \sum_{j'=1}^{J+1} \gamma_{j'j} \ln M_{ust}^{j'j}, \qquad \text{(A.3)}$$

where Λ^j denotes the measured TFP in sector j, Z^j denotes the output, L^j denotes the labor input, K^j denotes the capital input, and $M^{j'j}$ denotes the intermediate input from sector j'. The NBER-CES Manufacturing Industry Database offers information on output, and inputs of labor, capital, and intermediates, along with deflators for each. Thus, the observed TFP level for each manufacturing tradeable sector can be estimated using the above equation.

If the United States were a closed economy, the observed TFP level for sector j would be given by $\Lambda_{ust}^{j} = (T_{ust}^{j})^{\frac{1}{\theta}}$. In the open economies, the goods with inefficient domestic productivity draws will not be produced and will be imported instead. Thus, international trade and competition introduce selection in the observed TFP level, as demonstrated by Finicelli et al. (2013). Thus, the true level of T_{ust}^{j} of each tradeable sector in the United States can be backed out using the following relationship (Finicelli et al., 2013):

$$(\Lambda_{ust}^{j})^{\theta} = T_{ust}^{j} + \sum_{i \neq us} T_{it}^{j} \left(\frac{c_{it}^{j} d_{usit}^{j}}{c_{ust}^{j}} \right)^{-\theta}.$$

Thus:

$$(\Lambda_{ust}^{j})^{\theta} = T_{ust}^{j} \left[1 + \sum_{i \neq us} \frac{T_{it}^{j}}{T_{ust}^{j}} \left(\frac{c_{it}^{j} d_{usit}^{j}}{c_{ust}^{j}} \right)^{-\theta} \right] = T_{ust}^{j} \left[1 + \sum_{i \neq us} S_{it}^{j} \left(d_{usit}^{j} \right)^{-\theta} \right]. \qquad \text{(A.4)}$$

This equation can be solved for underlying technology parameters T_{ust}^{j} in the US, given estimated observed TFP Λ_{ust}^{j}, and all the S_{it}^{j}'s and d_{usit}^{j}'s estimated in the previous subsection.

The taste parameters $\{\omega_j\}_{j=1}^{J}$ are estimated using information on final consumption shares in the tradeable sectors in the US. Starting with a guess of $\{\omega_j\}_{j=1}^{J}$, we find sectoral prices $p_{nt}^{j\prime}$ as follows. For an initial guess of sectoral prices, compute the tradeable sector aggregate price and the nontradeable sector price using the data on the relative prices of nontradeables to tradeables. Using these prices, calculate sectoral unit costs and Φ_{nt}^{j}'s, and update prices according to equation (A.1), iterating until the prices converge. Then update the taste parameters according to equation (A.2), using the data on final sectoral expenditure shares in the US. Normalize the vector of ω_j's to have a sum of one, and repeat the above procedure until the values for the taste parameters converge. This procedure is carried out on the 2000s, and the resulting values applied to the entire period.

Finally, the nontradeable sector TFP in each country are calibrated to match the observed PPP-adjusted income per capita. This step involves solving the model with an initial guess of $\{T_{nt}^{J+1}\}_{n=1}^{N}$ and iteratively updating it until the model-implied income per capita adjusted for the aggregate price converges to that in the data for each country and each decade. This calibration approach guarantees that the model produces a cross-country income distribution identical to the data for each decade.

A.3.1 Direct Productivity Estimation in OECD STAN

The first step computes sectoral capital stocks using data on real investment and the perpetual inventory method.[10] The second step is to compute sector-level measured TFP from data on total output, employment, capital, and inputs following equation (A.3), for all the countries for which the required data are available. It is now well understood that differences in trade openness across sectors will affect measured TFP systematically (see Finicelli et al., 2013, and Appendix A.3). To go from measured TFP to true underlying TFP, the Finicelli et al. (2013) correction specified for the US in equation (A.4) is applied to all countries and sectors.

A.4 Data Description and Implementation

The data on production and trade are for a sample of up to 72 countries, 19 manufacturing sectors, and spanning 5 decades, from the 1960s to the 2000s. Production data come from the 2009 UNIDO Industrial Statistics Database, which reports output, value added, employment, and wage bills at roughly 2-digit ISIC Revision 3 level of disaggregation for the period 1962-2007 in the best of cases. The corresponding trade data come from the COMTRADE database compiled by the United Nations. The trade data are collected at the 4-digit SITC level, and aggregated up to the 2-digit ISIC level using a concordance developed by the authors. Production and trade data were extensively checked for quality, and a number of countries were discarded due to poor data quality. In addition, in less than 5% of country-year-sector observations, the reported total output was below total exports, and thus had to be imputed based on earlier values and the evolution of exports.

[10] Though the STAN database contains a variable for sectoral capital stock, it is only available for 6 countries.

The distance and common border variables are obtained from the comprehensive geography database compiled by CEPII. Information on regional trade agreements comes from the RTA database maintained by the WTO. The currency union indicator comes from Rose (2004), and was updated for the post-2000 period using publicly available information (such as the membership in the Euro area, and the dollarization of Ecuador and El Salvador).

In addition to providing data on output for gravity estimation, the UNIDO data are used to estimate production function parameters α_j and β_j. The parameter α_j for each sector is computed as the simple mean across countries of the share of the total wage bill in value added (taking the mean yields essentially the same results). The parameter β_j is the mean of value added divided by total output.

The intermediate input coefficients $\gamma_{j'j}$ are obtained from the Direct Requirements Table for the United States. We use the 1997 Benchmark Detailed Make and Use Tables (covering approximately 500 distinct sectors), as well as a concordance to the ISIC Revision 3 classification to build a Direct Requirements Table at the 2-digit ISIC level. The Direct Requirements Table gives the value of the intermediate input in row $j\prime$ required to produce one dollar of final output in column j. Thus, it is the direct counterpart of the input coefficients $\gamma_{j'j}$. In addition, the following values also come from the US I-O matrix: (i) the shares of total final consumption expenditure going to each sector, used to pin down taste parameters ω_j in traded sectors $1, ..., J$; (ii) α_{J+1} and β_{J+1} in the nontradeable sector, which cannot be obtained from UNIDO.[11] The baseline analysis assumes α_j, β_j, and $\gamma_{j'j}$ to be the same in all countries. Section A.6 assesses the robustness of the productivity estimates to allowing these parameters to vary by country.

The total labor force in each country, L_{nt}, and the total capital stock, K_{nt}, are obtained from the Penn World Tables 8.0 (PWT8.0). The labor endowment L_{nt} is corrected for human capital (schooling) differences using the human capital variable available in PWT8.0. Thus, the wage w_{nt} captures the relative price of an efficiency unit of labor. The capital series K_{nt} is available directly in PWT8.0. The saving/investment rate s_{nt} is calculated based on the Penn World Tables as the implied decadal s_{nt} that matches the evolution of capital from t to $t+1$, given real income and the country-time specific depreciation rate. This approach, together with the fact that our calibration procedure matched perfectly the relative real per capita incomes for each country, ensures that the model matches the observed capital stock from period to period.

[11] The US I-O matrix provides an alternative way of computing α_j and β_j. These parameters calculated based on the US I-O table are very similar to those obtained from UNIDO, with the correlation coefficients between them above 0.85 in each case. The US I-O table implies greater variability in α_j's and β_j's across sectors than does UNIDO.

The computation of relative costs of the input bundle requires information on wages and the returns to capital. To compute w_{nt}, the gross non-PPP adjusted labor income in PWT8.0 is divided by the effective endowment of labor, namely the product of the total employment and the per capita human capital. This yields the payment to one efficiency unit of labor in each country and decade.

Obtaining information on the return to capital, r_{nt}, is less straightforward, since it is not observable directly. The baseline analysis imputes r_{nt} from the information on the total income, endowment of capital, and the labor share: $r_{nt} = (1-\alpha_{nt})Y_{nt}/K_{nt}$, where the labor share α_{nt}, total income Y_{nt}, and total capital K_{nt} come directly from the PWT8.0. Since the return to capital is notoriously difficult to measure, Section A.6 evaluates the robustness of the estimates to four alternative ways of inferring r_{nt}.

The price of nontradeables relative to the US, $p_{nt}^{J+1}/p_{ust}^{J+1}$, are computed using the detailed price data collected by the International Comparison of Prices Program (ICP). For a few countries and decades, these relative prices are extrapolated using a simple linear fit to log PPP-adjusted per capita GDP from the Penn World Tables. The the sectoral price indices in the tradeable sectors p_{nt}^j/p_{ust}^j for $j = 1, ..., J$ are computed following the approach of Shikher (2012). In particular, for each country n, the share of total spending going to home-produced goods is given by

$$\frac{X_{nnt}^j}{X_{nt}^j} = T_{nt}^j \left(\frac{\Gamma c_{nt}^j}{p_{nt}^j} \right)^{-\theta}.$$

Dividing by its US counterpart yields:

$$\frac{X_{nnt}^j/X_{nt}^j}{X_{us,us,t}^j/X_{ust}^j} = \frac{T_{nt}^j}{T_{ust}^j} \left(\frac{c_{nt}^j}{c_{ust}^j} \frac{p_{ust}^j}{p_{nt}^j} \right)^{-\theta} = S_{nt}^j \left(\frac{p_{ust}^j}{p_{nt}^j} \right)^{-\theta},$$

and thus the ratio of price levels in sector j relative to the US becomes:

$$\frac{p_{nt}^j}{p_{ust}^j} = \left(\frac{X_{nnt}^j/X_{nt}^j}{X_{us,us,t}^j/X_{ust}^j} \frac{1}{S_{nt}^j} \right)^{\frac{1}{\theta}}. \tag{A.5}$$

The entire right-hand side of this expression is either observable or estimated. Thus, the price levels relative to the US in each country and each tradeable sector can be imputed from this expression.

The relative TFP's in the tradeable sectors in the US are estimated using the 2009 version of the NBER-CES Manufacturing Industry Database, which reports the total output, total input usage, employment, and capital stock, along with deflators for each of these in each sector. The data are available in the 6-digit NAICS classification for the period 1958 to 2005, and are converted into ISIC 2-digit sectors using a concordance developed by the authors. The procedure yields sectoral measured TFP's for the US in each tradeable sector $j = 1, ..., J$ and each decade.

The share of expenditure on traded goods, ξ_{nt} in each country and decade is sourced from Uy et al. (2013), who compile this information for 30 developed and developing countries. For countries unavailable in the Uy, Yi and Zhang data, values of ξ_{nt} are imputed based on fitting a simple linear relationship to log PPP-adjusted per capita GDP from the Penn World Tables. In each decade, the fit of this simple bivariate regression is typically quite good, with R^2's of 0.30 to 0.80 across decades.

The baseline analysis assumes that the dispersion parameter θ does not vary across sectors and sets $\theta = 8.28$, which is the preferred estimate of EK. Section A.6 shows that the productivity estimates are quite similar under two alternative sets of assumptions on θ: (i) a lower value of $\theta = 4$, and (ii) sector-specific values of θ_j.

The elasticity of substitution between broad sectors within the tradeable bundle, η, is set to 2. Since these are very large product categories, it is sensible that this elasticity would be relatively low. It is higher, however, than the elasticity of substitution between tradeable and nontradeable goods, which is set to 1 by the Cobb-Douglas assumption. The elasticity of substitution between varieties within each tradeable sector, ε, is set to 4 (as is well known, in the EK model this elasticity plays no role, entering only the constant Γ).

Appendix Table A1 lists the countries used in the analysis along with the time periods for which data are available for each country, and Appendix Table A2 lists the sectors along with the key parameter values for each sector: α_j, β_j, the share of nontradeable inputs in total inputs $\gamma_{J+1,j}$, and the taste parameter ω_j. All of the variables that vary over time are averaged for each decade, from the 1960s to the 2000s, and these decennial averages are used in the analysis throughout. Thus, our unit of time is a decade.

A.5 Basic Patterns

This section describes the basic patterns in how estimated sector-level technology varies across countries and over time. Going through the steps described in Section 3 yields, for each country n, tradeable sector j, and decade t, the state of technology relative to the US, T^j_{nt}/T^j_{ust}. Since mean productivity in each sector is equal to $(T^j_{nt})^{1/\theta}$, the analysis is carried out on this exponentiated value, rather than T^j_{nt}.

Table A3 presents summary statistics for the OECD and non-OECD countries in each decade. The first column reports the mean productivity relative to the US across all sectors in a country. The OECD countries as a group catch up to the US between the 1960s and the 2000s, with productivities going up from 0.91 to in excess of 1 over the period. The non-OECD countries' productivity is lower throughout, but the catch-up is also evident. The second column in each panel summarizes the magnitude of within-country differences in productivity across sectors, i.e., the coefficient of variation of sectoral productivities within a country, averaged by country group and decade. The average coefficient of variation is about 50% lower in the OECD countries compared to the non-OECD, reflecting higher dispersion of sectoral productivities in poorer countries. In both country groups, there is a clear downward trend in the coefficient of variation, which is first evidence that sectoral relative productivity dispersion within a country is falling.

The bottom panel presents the same statistics but balancing the country sample across decades. There are virtually no changes for the OECD, since the OECD sample is more or less balanced to begin with. For the non-OECD, balancing the sample implies dropping 19 countries in later decades, but the basic patterns are unchanged.

The evolution of these averages over time masks a great deal of heterogeneity among countries. To visualize this heterogeneity, Figures A1(a) and A1(b) plot the changes in the average $T^{1/\theta}$ against their initial average values. The left panel does this from the 1960s to the 2000s, the right panel from the 1990s. These plots can be thought of as capturing the traditional (cross-country) notion of absolute convergence. There is quite a bit of dispersion in the extent to which countries caught up on average to US productivity, including a few countries that fell behind on average relative to the US. There is an apparent negative relationship between the extent of catch-up and the initial average level, stronger from the 1990s.

Figures A1(c) and A1(d) plot the within-country dispersions of productivities (the coefficients of variation) in the 2000s against their values in the 1960s and the 1990s, respectively. For convenience, 45-degree lines are added to these plots. There is a fair amount of cross-country variation in productivity dispersion, and this variation appears to be persistent over time. Since the 1960s, sectoral productivity dispersion fell in the majority of countries (in all but 13). Between the 1990s and the 2000s, there is no systematic fall in dispersion: Table A3 shows that the coefficient of variation actually rises on average between those two decades in both groups of countries.

A.6 Robustness of T Estimates

This section presents a battery of robustness checks on our productivity estimation procedure. The outcomes are summarized in Appendix Table A5. The table reports the mean productivity $T^{1/\theta}$ relative to the US, its standard deviation across countries and sectors, the correlation with the baseline productivity estimates across countries and sectors, and the convergence coefficient and standard error from the main regression specification (6), estimated on the alternative sets of productivity estimates. To ease comparison, the top row reports the values for the baseline $T^{1/\theta}$ estimates.

A.6.1 Gravity Equation Specification and Estimation

The first set of checks concerns the specification of the gravity equation (4). To assess whether the estimates are sensitive to the set of distance and gravity variables included in estimation, we repeat the analysis while doubling the set of distance intervals (from 6 to 12), and including standard additional controls for common language and colonial ties, which are absent from the baseline specification. As the row labeled "Additional gravity" reveals, the resulting productivity estimates and convergence results are virtually indistinguishable from the baseline.

Next, the gravity equation is estimated in levels using the Poisson Pseudo Maximum Likelihood approach suggested by Santos Silva and Tenreyro (2006). This has the convenient property of not dropping zero trade observations from the estimation sample. The results are once again very similar to the baseline across the board.[12]

The next robustness check concerns whether the trade cost specification includes an

[12]A standard feature of the baseline procedure is that the trade shares are logged, so that the zero bilateral import flows are dropped from the estimation sample. Unfortunately, our large-scale model cannot be tractably enriched to explicitly account for zeros in trade while at the same time retaining the structural interpretation linking the fixed effects to underlying productivity. However, it is possible to check the ex-post performance of the estimated model with respect to zeros by solving the full model, and computing within the model the sum of the π^j_{nit}'s in the importer-exporter-sector observations that are zeros in the actual data. We can then examine whether these observations account for large shares of absorption inside the model. If the resulting numbers are large, then the quantitative model predicts substantial trade flows where in reality they are zero. However, if these numbers are small, the model predicts very small flows where the actual flows are zero, providing a good approximation to the data even though baseline productivities are estimated dropping zero trade. The results of this exercise are reported in Appendix Table A6. The exercise takes the most expansive view of the zeros, by assuming that all trade flows missing in the data are actually zeros as well. Observations for which the data exhibit zero/missing trade flows account for a tiny share of overall absorption in our quantitative model: in each decade, these observations add up to on average less than 0.9% of the total absorption. Breaking down across sectors and decades, it is clear that for nearly all individual sectors or decades, these shares are small. Thus, in spite of ignoring the zero trade observations in estimation, our quantitative model is quite close to the data when it comes to small/zero trade flows.

exporter or an importer effect. Waugh (2010) appeals to tradeable prices to argue that the specification with an exporter fixed effect fits the data better. In particular, he documents that in the data, tradeable prices are weakly increasing in income. The model with the exporter fixed effect in d^j_{nit} can match this pattern. However, the model with the importer fixed cost in d^j_{nit} delivers the sharply counterfactual prediction that tradeable prices fall in income. In addition, Waugh (2010) shows that the importer fixed effect specification does less well in other dimensions, such as matching observed income differences between countries.

Though out model is very different from Waugh (2010) – most importantly, we have multiple tradeable sectors, an explicit non-tradeable sector, and input linkages between those – his argument applies in our setting as well, albeit in a milder form. Just as in Waugh (2010), our baseline model with exporter effects in d^j_{nit} delivers a flat tradeable prices-income relationship, matching the data. By contrast, the model re-estimated with importer effects in d^j_{nit} implies a negative relationship between tradeable prices and income.

Nonetheless, row "im^j_{nt} in d^j_{nit}" presents the results of re-estimating sectoral productivities based on the importer effects in d^j_{nit} assumption. The results reveal that the average productivities implied by this alternative approach are lower (0.53 at the mean compared to 0.74 for the baseline). However, the dispersion in those productivities is very similar to the baseline, and the two sets of estimates have a correlation of 0.89. Most importantly, the relative convergence result is clearly evident in these estimates, though the speed of convergence is somewhat slower than in the baseline.

A.6.2 Return to Capital

The second set of robustness checks concerns the measurement of the return to capital r_{nt}, that enters the unit cost terms c^j_{nt}, and thus the productivity estimates. The baseline computes r_{nt} using data on K_{nt}, the total income Y_{nt}, and the (country- and time-specific) labor share. However, the return to capital is notoriously difficult to measure, and thus this section performs a battery of robustness checks on r_{nt}. The first check uses Caselli and Feyrer (2007) correction for natural wealth. The data for natural wealth are for 1995-2005, and come from the World Bank. Even for this later period, not all countries in our baseline sample are covered. In addition, these data are not available before 1995, which forces us to apply the 1995 values to all preceding decades.

The second check uses a measure of the return to capital computed instead from consumption growth. Namely, it exploits the Euler equation in consumption to back out the rate of return on capital: $1 + r_{nt+1} - \delta_{nt} = \frac{U'(C_{nt+1})}{\rho U'(C_{nt})}$, with ρ the discount factor. The data on consumption and the country-specific depreciation rate δ_{nt} come from the Penn World Tables, and the computation uses the standard functional form/parameter assumptions, namely CRRA utility $U(C) = \frac{C^{1-\sigma}}{1-\sigma}$, with $\sigma = 2$ and annual $\rho = 0.96$. The results are reported in row labeled "Euler."

The third check uses data on lending interest rates from the World Development Indicators. This approach yields a 20% smaller sample of countries and decades. The results are in the row labeled "Direct." And finally, the last check adopts the simple assumption that r_{nt} is the same everywhere in the world at a point in time ($r_{nt} = r_{ust}\ \forall n, t$). This assumption can correspond to financial integration, for instance. Caselli and Feyrer (2007) show that at least as of the 1990s, this is not a bad assumption. The results are in the row "Fin. Integration."

The means and standard deviations of estimated productivities under these four alternative approaches do not differ much from the baseline. The correlations to the baseline are also quite high, from 0.91 under the direct measurement to 0.99 under the Caselli-Feyrer correction. The convergence results are also equally strong under these alternative approaches of measuring r_{nt}.

A.6.3 Production Function Parameters

Next, we check the sensitivity of the results to the assumption that the production functions (IO matrices and factor shares) are the same across countries. The row "Country-Specific IO" presents the results of estimating productivities using country-specific IO matrices sourced from GTAP. GTAP's coverage of sectors and countries is not the same as in our analysis, requiring some imputation, and thus these data are not used in the baseline analysis. The row "Country-Specific IO, α, β" in addition assumes that the labor share in value added (α) and the share of value added in output (β) are vary by country and decade (and of course, as always, by sector). These are computed directly for each sector, country, and decade using UNIDO data on the wage bill, value added, and output. These values are not used in the baseline analysis, because the UNIDO data do not have complete coverage, requiring some imputation. In addition, it can be noisy, and thus variation in these empirical factor shares across countries and over time may not provide a reliable indication of true differences in factor intensity. These two alternative approaches yield slightly higher average productivities, but the variation is similar to the baseline and the correlations are very high. The convergence results are also equally strong.

A.6.4 Dispersion Parameter

The final set of checks is on the θ parameters. First, one may be concerned about how the results change under lower values of θ. Lower θ implies greater within-sector heterogeneity in the random productivity draws. Thus, trade flows become less sensitive to the costs of the input bundles (c^j_{nt}), and the gains from intra-sectoral trade become larger relative to the gains from inter-sectoral trade. We repeated the estimation assuming instead a value of $\theta = 4$, which has been advocated by Simonovska and Waugh (2014) and is at or near the bottom of the range that has been used in the literature. Overall, the results are remarkably similar. The mean productivities are virtually the same, and there is actually somewhat greater variability in T^j_{nt}'s under $\theta = 4$. The correlation between estimated T^j_{nt}'s under $\theta = 4$ and the baseline is above 0.94. The convergence results are equally strong.

Second, a number of studies have suggested that θ varies across sectors (see, e.g., Chen and Novy, 2011; Caliendo and Parro, 2015; Imbs and Méjean, 2015). We repeat the estimation allowing θ_j to be sector-specific, with sectoral values of θ_j sourced from Caliendo and Parro (2015). The average productivities are once again quite similar, and have an 0.87 correlation with the baseline. The convergence results are if anything stronger than in the baseline.

A.7 Simple Heuristics: What is Driving the Convergence Finding?

What kinds of basic patterns in the data are driving these results? Though our estimation procedure is based on a theoretically-founded gravity equation and a variety of data sources, and thus is fully internally consistent with the underlying conceptual framework, it would be reassuring if there were some simple heuristic relationships in the data that are consistent with the main finding. We can build intuition as follows: in a simpler model with 2 tradeable and 1 nontradeable sectors, Uy et al. (2013) show analytically that all else equal, a comparative advantage sector has a smaller share of imports in total domestic absorption $1 - \pi^j_{nn}$ than a comparative disadvantage sector. As a country's comparative advantage in sector j weakens, the import share rises in that sector. This is intuitive: when a country becomes *relatively* less productive in a sector, it starts importing more.

Thus, increased relative productivity in the initially least productive sectors should manifest itself in a negative relationship between the initial period import share and the subsequent change in the import share. Sectors within a country with the lowest initial import share $(1 - \pi^j_{nn})$ should see that import share rise. These are the sectors with the highest relative productivity at the beginning of the period. Correspondingly, sectors with the highest initial import share should see their import share drop as they catch up in productivity faster.

Figure A2(a) presents this scatterplot, pooling sectors and countries. The negative relationship is remarkably pronounced: the slope coefficient in the simple bivariate regression is -0.397 with a t-statistic of 16.5 and an R^2 of 18.4%. Note that a significant share of the observations – those below zero on the y-axis – have seen their import share actually fall between the 1960s and today. These declines in import shares would be highly puzzling over the period during which trade costs fell and global trade volumes rose dramatically. Faster relative productivity growth in those sectors provides a plausible explanation: countries are getting relatively better in those industries, and thus they need to import less.

This negative relationship would not necessarily be evidence of relative convergence in the T's if, for instance, trade costs d^j_{nit} fell disproportionately more in sectors in which countries had higher initial import shares. To check for this possibility, Figure A2(b) plots the change in the average trade costs in sector j and country n against the initial import share – the same x-axis variable as in the previous figure. There is virtually no relationship between initial import share and subsequent changes in import costs: the slope coefficient is essentially zero, and the R^2 is correspondingly 0.00. Thus, it does not appear that systematically larger reductions in d^j_{nit} in the initially lowest-productivity sectors were primarily responsible for the pattern in Figure A2(a). Note that our estimation procedure is designed precisely to take into account any changes in d^j_{nit} (as well as unit factor costs) by importer-exporter pair and sector that may have occurred over this period, isolating the underlying productivity changes.

A.8 Model Fit

The baseline corresponds to the actual values of T^j_{nt} estimated for the past five decades. We assess the fit of the baseline model in a number of dimensions. By construction, the model matches perfectly the real PPP-adjusted per capita income in each country. Table A7 compares w's and r's in the model and in the data for 2000s. (The results for the previous decades are similar.) The baseline model performs well: the means and the medians match up fairly well, and the correlation between model and data wages is 0.95. The correlation in r's is somewhat lower at 0.59.

The next panel assesses the model's ability to match the sectoral trade flows. It reports the means and medians, across countries and sectors, of π^j_{nnt}. The model reproduces the overall magnitudes well, and the correlation between the model and the data is 0.92. The same can be said for the cross-border flows π^j_{nit}, $i \neq n$, reported in the bottom panel.

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TABLES AND FIGURES FOR PAPER

Table 1. Comparison of Our Estimates to Measured TFP and Labor Productivity

Panel A: Sector-by-Sector Rank Correlations

	TFP		Labor Productivity	
ISIC code	Correlation	No. of Countries	Correlation	No. of Countries
15	0.800	4	0.843	65
16	1.000	4	0.651	54
17	0.900	5	0.899	63
18	0.100	5	0.888	62
19	-0.200	5	0.876	60
20	0.452	8	0.869	61
21	0.943	6	0.853	64
22	1.000	6	0.888	61
23	0.600	6	0.372	57
24	0.750	7	0.875	64
25	0.810	8	0.899	63
26	0.683	9	0.830	65
27	0.657	6	0.797	62
28	0.943	6	0.899	61
29C	0.810	8	0.909	62
31A	1.000	5	0.884	63
33	0.771	6	0.902	53
34A	0.486	6	0.832	62
36	0.900	5	0.903	63

Panel B: Fixed Effects Regression

	(1)	(2)	(3)	(4)	(5)
		TFP		Labor Productivity	
Dep. Var.: Data Value					
Model Value	0.656***	1.030***	0.532**	0.697***	0.698***
	(0.126)	(0.126)	(0.228)	(0.019)	(0.017)
Observations	115	115	115	1,165	1,165
R^2	0.137	0.556	0.885	0.586	0.665
Partial ρ	0.370	0.591	0.290	0.765	0.798
Sector FE	no	yes	yes	no	yes
Country FE	no	no	yes	no	no

Notes: This table reports the results of comparing our total factor and labor productivity estimates with TFP estimated based on the OECD STAN database (left) and labor productivity (right). Panel A reports the Spearman rank correlations of the two alternative productivity measures by sector. Panel B reports the results of a fixed effects regression of directly computed values on our model-implied values. In Panel B, robust standard errors in parentheses; **: significant at 5%; ***: significant at 1%. "Partial ρ" is the partial correlation between the right-hand side and the left-hand side variables, after netting out the fixed effects included in the column. The legend for ISIC codes is in Online Appendix Table A2.

Table 2. Pooled Regression Results

	(1) 1960s to 2000s	(2) 1980s to 2000s	(3) 1960s to 1970s	(4) 1970s to 1980s	(5) 1980s to 1990s	(6) 1990s to 2000s
Dep. Var: Log Change in $T^{1/\theta}$						
			Panel A: All Countries			
$\text{Log}\big(\text{Initial } T^{1/\theta}\big)$	-0.517***	-0.208***	-0.228***	-0.142***	-0.173***	-0.108***
	(0.044)	(0.034)	(0.027)	(0.023)	(0.029)	(0.032)
NB:						
Speed of convergence, per decade	*0.182*	*0.117*	*0.259*	*0.153*	*0.190*	*0.114*
Observations	893	1,068	955	1,038	1,129	1,282
R^2	0.677	0.636	0.722	0.659	0.667	0.684
			Panel B: OECD			
$\text{Log}\big(\text{Initial } T^{1/\theta}\big)$	-0.676***	-0.369***	-0.250***	-0.176***	-0.220***	-0.146*
	(0.072)	(0.087)	(0.035)	(0.037)	(0.046)	(0.082)
NB:						
Speed of convergence, per decade	*0.282*	*0.230*	*0.288*	*0.194*	*0.248*	*0.158*
Observations	393	405	396	394	407	410
R^2	0.757	0.637	0.742	0.734	0.654	0.548
			Panel C: non-OECD			
$\text{Log}\big(\text{Initial } T^{1/\theta}\big)$	-0.659***	-0.302***	-0.344***	-0.191***	-0.256***	-0.148***
	(0.067)	(0.059)	(0.046)	(0.035)	(0.048)	(0.047)
NB:						
Speed of convergence, per decade	*0.269*	*0.180*	*0.422*	*0.212*	*0.296*	*0.160*
Observations	500	663	559	644	722	872
R^2	0.737	0.635	0.759	0.662	0.621	0.707
Country FE	yes	yes	yes	yes	yes	yes
Sector FE	yes	yes	yes	yes	yes	yes

Notes: Standard errors clustered at the country level in parentheses; ***: significant at 1%; *: significant at 10%. This table reports the results of regressing the growth of estimated technology parameter $\left(T_n^j\right)^{1/\theta}$ on its initial value over different time periods and subsamples. The speed of convergence, per decade, is reported (in italics) underneath each coefficient estimate.

Table 3. Pooled Regression Results: Interactions, 1960s to 2000s

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var: Log Change in $T^{1/\theta}$						
$\text{Log}\big(\text{Initial } T^{1/\theta}\big)$	-0.502***	-0.226	-0.400***	-0.866***	-0.606***	-0.564***
	(0.050)	(0.183)	(0.066)	(0.069)	(0.040)	(0.089)
$\text{Log}\big(\text{Initial } T^{1/\theta}\big) \times \text{INST}_n$	-0.112***					
	(0.034)					
$\text{Log}\big(\text{Initial } T^{1/\theta}\big) \times h_n$		-0.138				
		(0.085)				
$\text{Log}\big(\text{Initial } T^{1/\theta}\big) \times k_n$			-0.071***			
			(0.019)			
$\text{Log}\big(\text{Initial } T^{1/\theta}\big) \times \pi^j_{nn}$				0.088*		
				(0.051)		
π^j_{nn}				0.655***		
				(0.065)		
$\text{Log}\big(\text{Initial } T^{1/\theta}\big) \times \text{Imp.Inputs}$					-0.409*	
					(0.232)	
Imp.Inputs					-1.712***	
					(0.220)	
$\text{Log}\big(\text{Initial } T^{1/\theta}\big) \times \alpha_j$						0.107
						(0.213)
Observations	874	893	893	893	893	893
R^2	0.688	0.680	0.685	0.769	0.73	0.677
Country FE	yes	yes	yes	yes	yes	yes
Sector FE	yes	yes	yes	yes	yes	yes

Notes: Standard errors clustered at the country level in parentheses; ***: significant at 1%; *: significant at 10%. This table reports the results of regressing the growth of estimated technology parameter $\left(T^j_n\right)^{1/\theta}$ on its initial value and the interactions between the initial value and country, sector, and country-sector characteristics. INST_n is the "Rule of Law" institutional quality index sourced from the World Bank's Governance Matters Database. h_n is human capital per worker, and k_n is the physical capital per worker, both sourced from Penn World Tables 8.0.

Table 4. Trade Volumes and Trade Patterns in the Data and in the Model

	Data	Model			
		Benchmark	CF: No Convergence	CF: No Relative Convergence	CF: 1960s d_{nit}^{j}
Imports/GDP	0.230	0.233	0.280	0.273	0.150
$\rho(Model, Data)$		*0.559*	*0.546*	*0.558*	*0.357*
$\Delta\sigma$(ln World Export Shares)	-0.322	-0.283	-0.142	-0.138	-0.064
$\rho(Model, Data)$		*0.608*	*0.341*	*0.397*	*0.554*
Δ GL Index	0.162	0.111	0.026	0.018	-0.029
$\rho(Model, Data)$		*0.423*	*0.183*	*0.171*	*0.265*

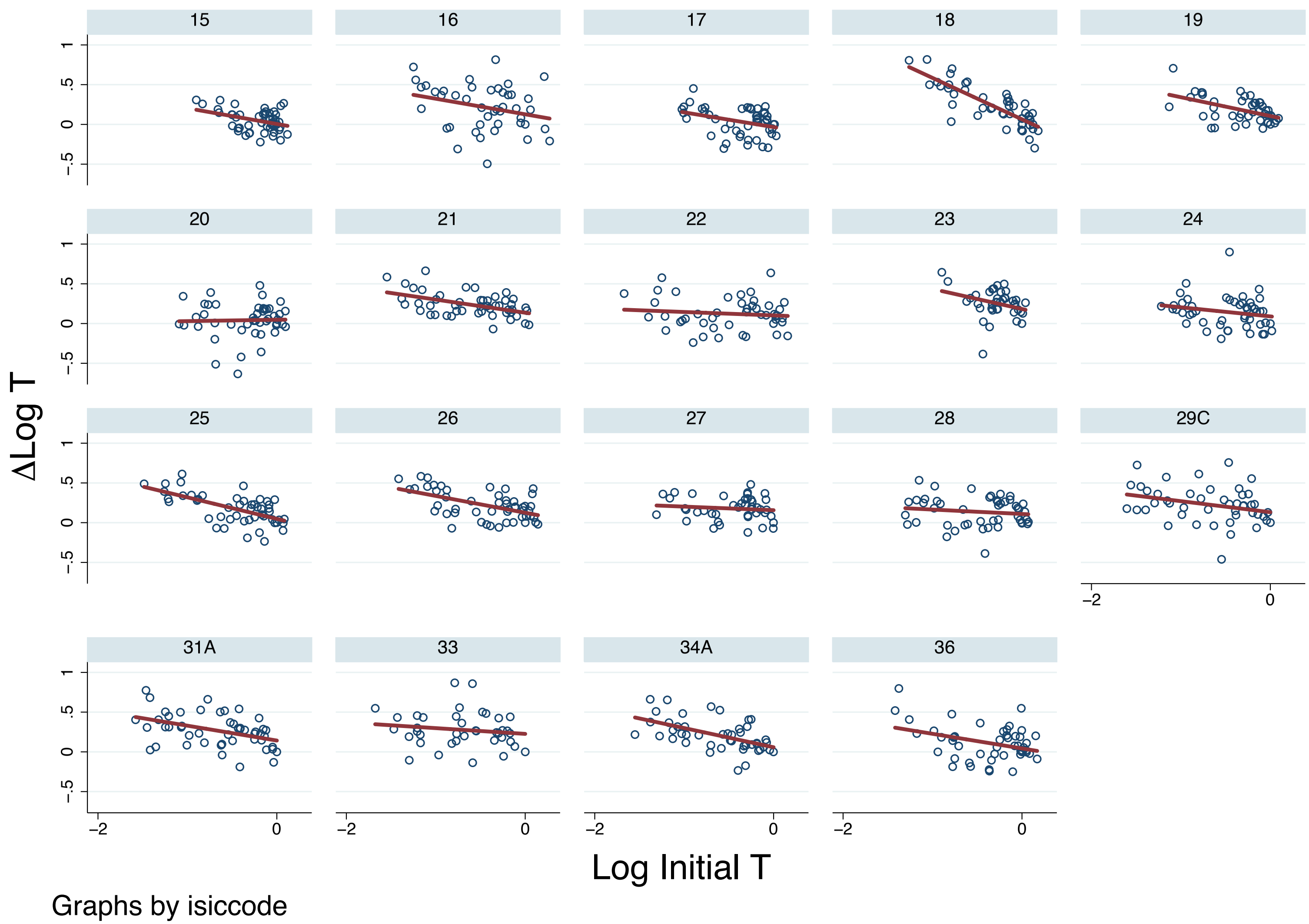
Notes: This table compares the 2000s trade volumes and trade patterns in the data, the benchmark model, and the counterfactuals. The columns labeled "CF" refer to the counterfactuals. The row "$\Delta\sigma$(ln World Export Shares)" presents the change in the standard deviation of log world export shares between the 1960s and the 2000s, averaged across sectors. The row "Δ GL Index" reports the change in the Grubel-Lloyd index, averaged across countries and sectors.

Table 5. Welfare Gains in the Counterfactuals Relative to Baseline

	Median	St. Dev.	Min	Max	Countries
Main Results					
No Convergence					
OECD	-11.66	7.15	-26.50	0.15	21
Non-OECD	-16.40	14.40	-43.48	9.33	31
No Relative Convergence					
OECD	1.34	1.40	-0.16	4.84	21
Non-OECD	3.00	8.68	-4.06	46.08	31
1960s d_{nit}^{j}					
OECD	-2.34	1.09	-5.24	-0.90	21
Non-OECD	-2.95	3.15	-7.07	5.21	31
NB: Overall gains from trade					
OECD	5.62	3.17	1.50	13.09	
Non-OECD	7.44	7.66	1.52	34.46	
Fixed Capital					
No Convergence					
OECD	-8.07	5.71	-21.19	0.83	21
Non-OECD	-10.53	11.66	-29.95	9.25	31
No Relative Convergence					
OECD	1.08	0.95	-0.02	3.24	21
Non-OECD	1.06	6.04	-4.71	29.86	31
1960s d_{ni}^{j}					
OECD	-1.85	0.82	-3.71	-0.78	21
Non-OECD	-2.39	2.70	-5.56	4.04	31
NB: Overall gains from trade					
OECD	3.74	2.10	1.16	8.48	
Non-OECD	5.55	5.16	1.00	23.98	

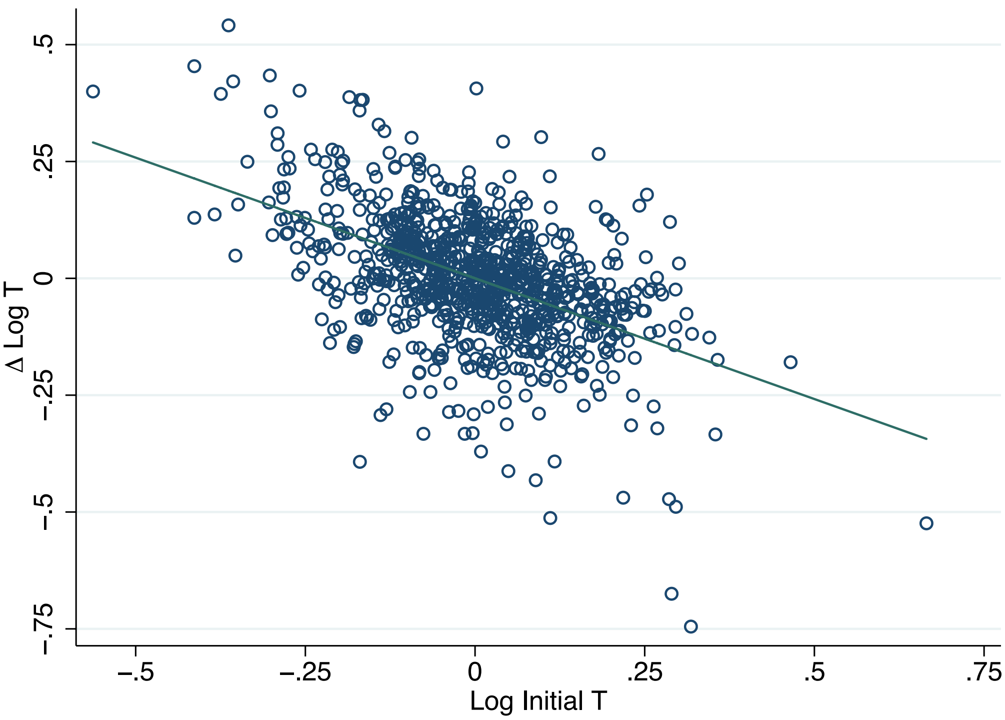
Notes: Units are in percentage points. This table reports the percent change in welfare under the counterfactual scenarios with respect to the baseline. The top panel reports the main results, in which capital accumulation responds endogenously to changes in relative sectoral productivities. The bottom panel reports the results when capital is fixed at its observed values. The table also reports the total gains from trade relative to autarky in the baseline for the 2000s.

Figure 1. Convergence by Sector, 1960s to 2000s



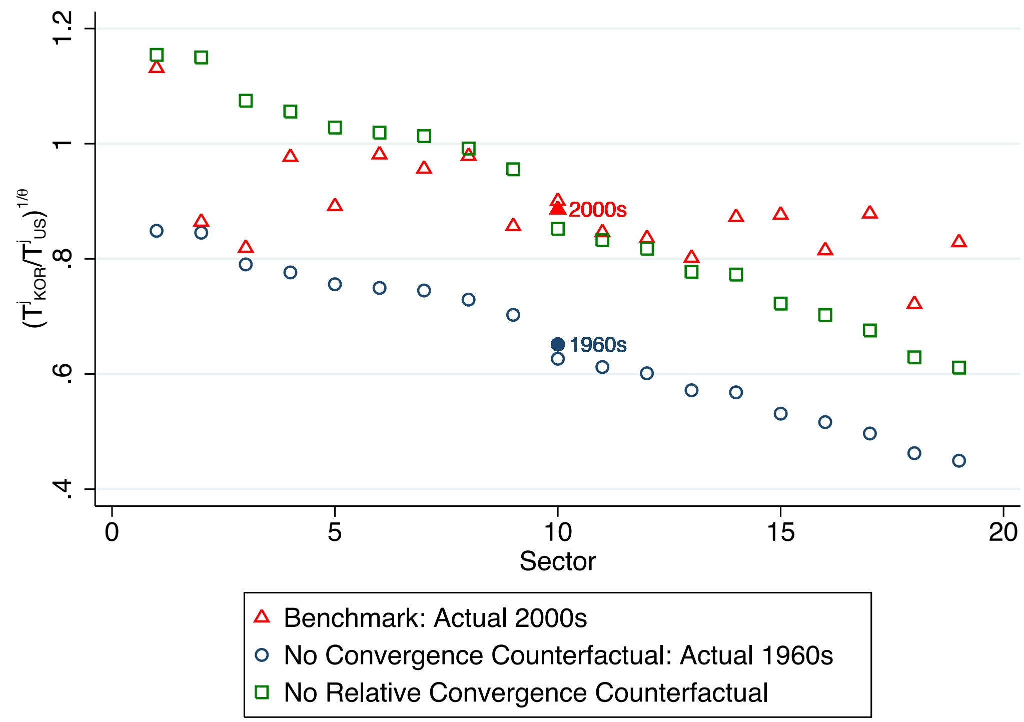
Notes: This figure displays the log change in $\left(T_n^j\right)^{1/\theta}$ against the initial log level, and the OLS fit through the data, for each sector.

Figure 2. Convergence in the Pooled Sample, 1960s to 2000s



Notes: This figure displays partial correlation the log change in $\left(T_n^j\right)^{1/\theta}$ against the initial log level, after netting out country and sector effects, pooling across sectors and countries.

Figure 3. Example: Benchmark and Counterfactual Productivities, South Korea



Notes: This figure displays sectoral T_i^j's for South Korea. It displays the benchmark estimates for 2000s, the No Convergence counterfactual productivities, that are the same as the estimated productivities in the 1960s, and the No Relative Convergence counterfactual productivities, that preserve the average actual productivity in the 2000s, but set relative productivities to be the same as in the 1960s.

TABLES AND FIGURES FOR ONLINE APPENDIX

Table A1. Country Coverage

Country	Period	Country	Period
OECD		Non-OECD	
Australia	1960s−2000s	Argentina	1980s−2000s
Austria	1960s−2000s	Bangladesh	1970s−2000s
Belgium-Luxembourg	1960s−2000s	Bolivia	1960s−2000s
Canada	1960s−2000s	Brazil	1980s−2000s
Denmark	1960s−2000s	Bulgaria	1990s−2000s
Finland	1960s−2000s	Chile	1960s−2000s
France	1960s−2000s	China	1970s−2000s
Germany	1960s−2000s	Colombia	1960s−2000s
Greece	1960s−2000s	Costa Rica	1960s−2000s
Iceland	1960s−2000s	Czech Republic	1990s−2000s
Ireland	1960s−2000s	Ecuador	1960s−2000s
Italy	1960s−2000s	Egypt, Arab Rep.	1960s−2000s
Japan	1960s−2000s	El Salvador	1960s−2000s
Netherlands	1960s−2000s	Ethiopia	1980s−2000s
New Zealand	1960s−2000s	Fiji	1960s−2000s
Norway	1960s−2000s	Ghana	1960s−2000s
Portugal	1960s−2000s	Guatemala	1960s−2000s
Spain	1960s−2000s	Honduras	1960s−2000s
Sweden	1960s−2000s	Hungary	1990s−2000s
Switzerland	1980s−2000s	India	1960s−2000s
United Kingdom	1960s−2000s	Indonesia	1960s−2000s
United States	1960s−2000s	Israel	1960s−2000s
		Jordan	1960s−2000s
		Kazakhstan	1990s−2000s
		Kenya	1960s−2000s
		Korea, Rep.	1960s−2000s
		Malaysia	1960s−2000s
		Mauritius	1960s−2000s
		Mexico	1960s−2000s
		Nigeria	1960s−2000s
		Pakistan	1960s−2000s
		Peru	1980s−2000s
		Philippines	1960s−2000s
		Poland	1990s−2000s
		Romania	1990s−2000s
		Russian Federation	1990s−2000s
		Senegal	1970s−2000s
		Slovak Republic	1990s−2000s
		Slovenia	1990s−2000s
		South Africa	1960s−2000s
		Sri Lanka	1960s−2000s
		Taiwan Province of China	1970s−2000s
		Tanzania	1960s−2000s
		Thailand	1960s−2000s
		Trinidad and Tobago	1960s−2000s
		Turkey	1960s−2000s
		Ukraine	1990s−2000s
		Uruguay	1960s−2000s
		Venezuela, RB	1960s−2000s
		Vietnam	1990s−2000s

Notes: This table reports the countries in the sample and the decades for which data are available for each country.

Table A2. Sectors

ISIC code	Sector Name	α_j	β_j	$\gamma_{J+1,j}$	ω_j
15	Food and Beverages	0.315	0.281	0.300	0.155
16	Tobacco Products	0.264	0.520	0.527	0.026
17	Textiles	0.467	0.371	0.295	0.016
18	Wearing Apparel, Fur	0.493	0.377	0.319	0.124
19	Leather, Leather Products, Footwear	0.485	0.359	0.329	0.025
20	Wood Products (Excl. Furniture)	0.452	0.372	0.288	0.007
21	Paper and Paper Products	0.366	0.344	0.386	0.010
22	Printing and Publishing	0.484	0.469	0.407	0.005
23	Coke, Refined Petroleum Products, Nuclear Fuel	0.244	0.243	0.245	0.087
24	Chemical and Chemical Products	0.308	0.373	0.459	0.006
25	Rubber and Plastics Products	0.385	0.387	0.345	0.011
26	Non-Metallic Mineral Products	0.365	0.459	0.479	0.076
27	Basic Metals	0.381	0.299	0.443	0.002
28	Fabricated Metal Products	0.448	0.398	0.363	0.014
29C	Office, Accounting, Computing, and Other Mach.	0.473	0.390	0.388	0.070
31A	Electrical Machinery, Communication Equipment	0.405	0.380	0.416	0.041
33	Medical, Precision, and Optical Instruments	0.456	0.428	0.441	0.059
34A	Transport Equipment	0.464	0.343	0.286	0.188
36	Furniture and Other Manufacturing	0.460	0.407	0.395	0.080
4A	Nontradeables	0.561	0.651	0.772	
	Mean	0.414	0.393	0.394	0.053
	Min	0.244	0.243	0.245	0.002
	Max	0.561	0.651	0.772	0.188

Notes: This table reports the sectors used in the analysis. The classification corresponds to the ISIC Revision 3 2-digit, aggregated further due to data availability. α_j is the value-added based labor intensity; β_j is the share of value added in total output; $\gamma_{J+1,j}$ is the share of nontradeable inputs in total intermediate inputs; ω_j is the taste parameter for tradeable sector j, estimated using the procedure described in Section A.3. Variable definitions and sources are described in detail in the text.

Table A3. Summary Statistics

	OECD			Non-OECD		
	Mean $T^{1/\theta}$	CV $T^{1/\theta}$	Countries	Mean $T^{1/\theta}$	CV $T^{1/\theta}$	Countries
1960s	0.911	0.128	21	0.474	0.241	31
1970s	1.048	0.110	21	0.571	0.216	35
1980s	0.986	0.110	22	0.586	0.222	39
1990s	1.041	0.103	22	0.553	0.209	50
2000s	1.028	0.108	22	0.585	0.212	50
Balanced Panel of Countries						
1960s	0.911	0.128	21	0.474	0.241	31
1970s	1.048	0.110	21	0.591	0.214	31
1980s	0.973	0.110	21	0.586	0.219	31
1990s	1.031	0.102	21	0.560	0.215	31
2000s	1.026	0.109	21	0.553	0.224	31

Notes: This table reports the summary statistics for the average productivity relative to the US (mean $T^{1/\theta}$), the coefficient of variation among tradeable sector productivities (CV $T^{1/\theta}$), as well as the number of countries for which data are available. The samples are split by decade and into OECD and non-OECD groups.

Table A4. Country-by-Country Estimates of Relative Convergence, 1960s to 2000s

Country	β	s.e.	Obs.	R^2	Speed of Convergence, by decade
United Kingdom	-0.412**	0.186	19	0.258	0.133
Austria	-0.551	0.381	19	0.144	0.200
Belgium-Luxembourg	-0.760***	0.136	19	0.608	0.356
Denmark	-0.695***	0.194	19	0.443	0.297
France	-0.817***	0.198	19	0.603	0.424
Germany	-0.644***	0.116	19	0.558	0.258
Italy	-0.532***	0.145	19	0.442	0.190
Netherlands	-0.583**	0.219	19	0.295	0.219
Norway	-0.985***	0.137	19	0.725	1.047
Sweden	-0.668***	0.165	18	0.482	0.276
Canada	-0.147	0.230	19	0.016	0.040
Japan	-0.885***	0.164	18	0.698	0.540
Finland	-0.720***	0.166	19	0.641	0.318
Greece	-0.299***	0.086	19	0.318	0.089
Iceland	-0.425*	0.229	15	0.295	0.138
Ireland	-0.706*	0.335	19	0.274	0.306
Portugal	-0.490***	0.146	19	0.352	0.168
Spain	-0.493***	0.102	19	0.558	0.170
Turkey	-0.445***	0.104	18	0.591	0.147
Australia	-0.567***	0.150	19	0.499	0.209
New Zealand	-0.247**	0.106	19	0.301	0.071
South Africa	-0.014	0.229	18	0.000	0.004
Bolivia	-0.266**	0.102	17	0.260	0.077
Chile	-0.143	0.104	19	0.065	0.039
Colombia	-0.237	0.139	19	0.180	0.067
Costa Rica	-0.511***	0.165	17	0.394	0.179
Ecuador	-0.245***	0.072	19	0.323	0.070
El Salvador	-0.247	0.145	18	0.103	0.071
Honduras	-0.415**	0.167	17	0.288	0.134
Mexico	-0.462**	0.161	13	0.331	0.155
Uruguay	-0.319**	0.116	19	0.252	0.096
Venezuela, RB	-0.401***	0.133	19	0.463	0.128
Trinidad and Tobago	-0.191	0.376	17	0.034	0.053
Israel	-0.457***	0.147	18	0.302	0.153
Jordan	-0.476**	0.188	18	0.252	0.161
Egypt, Arab Rep.	-0.299**	0.113	19	0.140	0.089
Sri Lanka	0.039	0.171	19	0.003	-0.009
India	-0.249*	0.126	19	0.153	0.072
Indonesia	-0.590***	0.099	16	0.706	0.223
Korea, Rep.	-0.688***	0.110	19	0.780	0.291
Malaysia	-0.584***	0.121	19	0.421	0.219
Pakistan	-0.389**	0.147	8	0.343	0.123
Philippines	-0.558***	0.185	19	0.382	0.204
Thailand	-0.898***	0.268	14	0.541	0.571
Ghana	0.016	0.200	18	0.000	-0.004
Kenya	-0.047	0.144	17	0.005	0.012
Mauritius	-0.275	0.201	15	0.120	0.080
Tanzania	-0.533***	0.162	12	0.410	0.190
Fiji	-0.299*	0.148	15	0.156	0.089

Notes: Robust standard errors clustered in parentheses; ***: significant at 1%; **: significant at 5%; *: significant at 10%. This table reports the results of regressing the growth of estimated technology parameter $\left(T_n^j\right)^{1/\theta}$ over the period from the 1960s to the 2000s on its initial value, by country. The speed of convergence, per decade, is reported in the last column. Missing values are due to the convergence coefficient being larger than 1.

Table A5. Comparison of Estimates of T_n^j

Method	Mean	St. Dev.	Corr w/baseline	β	$s.e.(\beta)$
Baseline	0.737	0.275	..	-0.517***	(0.044)
Additional gravity	0.728	0.270	0.999	-0.518***	(0.045)
Poisson	0.720	0.271	0.969	-0.534***	(0.046)
im_{nt}^j in d_{nit}^j	0.527	0.240	0.890	-0.339***	(0.051)
r: Caselli-Feyrer	0.702	0.295	0.989	-0.487***	(0.046)
r: Euler	0.694	0.265	0.954	-0.539***	(0.047)
r: Direct	0.744	0.273	0.910	-0.541***	(0.145)
r: Fin. Integration	0.682	0.264	0.960	-0.519***	(0.046)
Country-Specific IO	0.766	0.267	0.987	-0.480***	(0.042)
Country-Specific IO, α, β	0.805	0.272	0.903	-0.646***	(0.043)
$\theta = 4$	0.726	0.352	0.942	-0.600***	(0.045)
θ Sector-Specific	0.749	0.350	0.870	-0.691***	(0.047)

Notes: This table the results of comparing the baseline estimates of T_n^j to alternative estimation approaches. The first and second columns report the mean and the standard deviation of $\left(T_n^j\right)^{1/\theta}$ relative to the US. The third column reports the correlation between the baseline $\left(T_n^j\right)^{1/\theta}$ relative to the US and the alternative estimate. The fourth and fifth columns report the coefficient and standard errors from estimating the convergence regression (6) using each set of $\left(T_n^j\right)^{1/\theta}$ estimates.

Table A6. Zero Trade Observations: Model vs. Data

Sector Name	ISIC code	1960s	1970s	1980s	1990s	2000s
All Sectors Combined		0.007	0.006	0.006	0.001	0.009
Food and Beverages	15	0.000	0.000	0.000	0.000	0.000
Tobacco Products	16	0.075	0.100	0.015	0.015	0.026
Textiles	17	0.000	0.000	0.000	0.002	0.005
Wearing Apparel, Fur	18	0.011	0.015	0.000	0.000	0.004
Leather, Leather Products, Footwear	19	0.011	0.016	0.028	0.001	0.031
Wood Products (Excl. Furniture)	20	0.001	0.000	0.000	0.000	0.013
Paper and Paper Products	21	0.000	0.000	0.000	0.000	0.005
Printing and Publishing	22	0.017	0.021	0.000	0.000	0.009
Coke, Refined Petroleum Products, Nuclear Fuel	23	0.003	0.003	0.023	0.008	0.011
Chemical and Chemical Products	24	0.000	0.000	0.000	0.000	0.004
Rubber and Plastics Products	25	0.000	0.001	0.000	0.000	0.010
Non-Metallic Mineral Products	26	0.000	0.000	0.000	0.000	0.001
Basic Metals	27	0.003	0.001	0.000	0.000	0.011
Fabricated Metal Products	28	0.000	0.000	0.036	0.000	0.020
Office, Accounting, Computing, and Other Mach.	29C	0.001	0.000	0.000	0.000	0.013
Electrical Machinery, Communication Equipment	31A	0.000	0.000	0.000	0.000	0.011
Medical, Precision, and Optical Instruments	33	0.022	0.020	0.003	0.006	0.023
Transport Equipment	34A	0.012	0.000	0.005	0.000	0.011
Furniture and Other Manufacturing	36	0.012	0.015	0.005	0.002	0.012

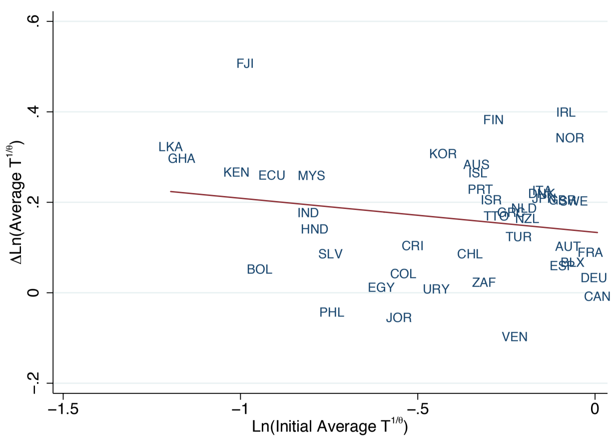
Notes: This table reports the share of global absorption taken up by importer-exporter-sector observations for which actual imports are zero in the data.

Table A7. The Fit of the Baseline Model with the Data

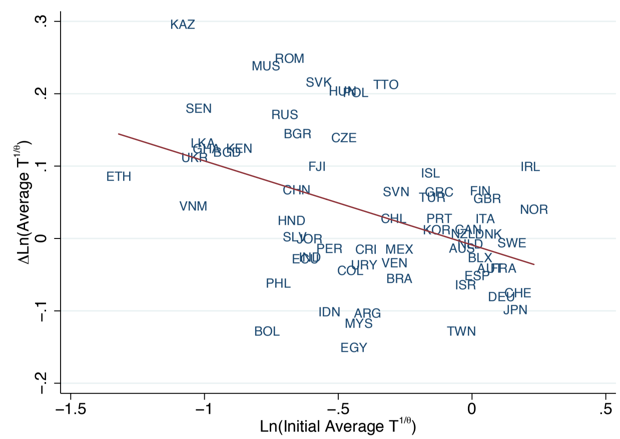
	model	data
Wages:		
mean	0.464	0.400
median	0.277	0.172
corr(model, data)	0.952	
Return to capital:		
mean	0.173	0.172
median	0.160	0.154
corr(model, data)	0.588	
π^j_{nn}:		
mean	0.638	0.570
median	0.710	0.614
corr(model, data)	0.922	
π^j_{ni}, $i \neq j$:		
mean	0.0051	0.0060
median	0.0002	0.0002
corr(model, data)	0.904	

Notes: This table reports the means and medians of wages relative to the US (top panel); return to capital relative to the US (second panel), share of domestically produced goods in overall spending (third panel), and share of goods from country i in overall spending (bottom panel) in the model and in the data. Wages and return to capital in the data are calculated as described in Section A.4.

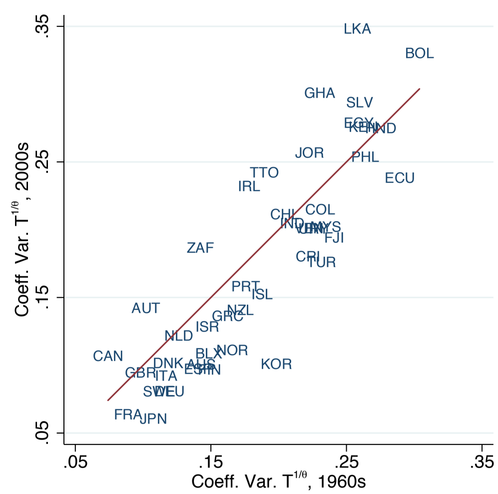
Figure A1. Absolute and Relative Convergence



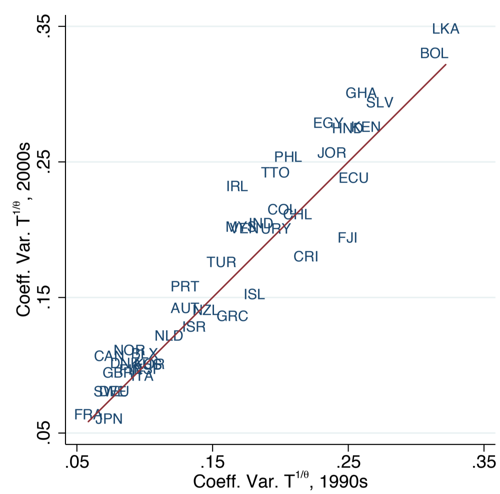
(a) 1960s to 2000s: Absolute Convergence and Initial Average



(b) 1990s to 2000s: Absolute Convergence and Initial Average



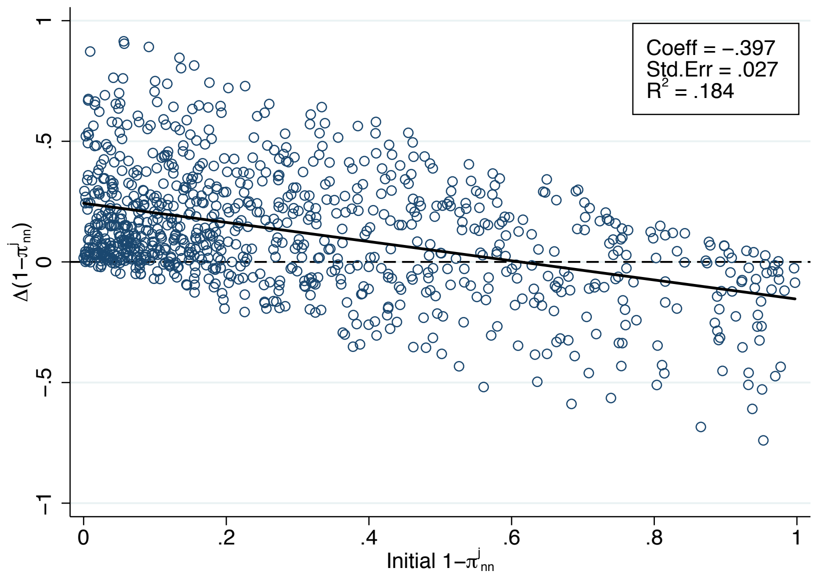
(c) 1960s and 2000s: Coefficient of Variation



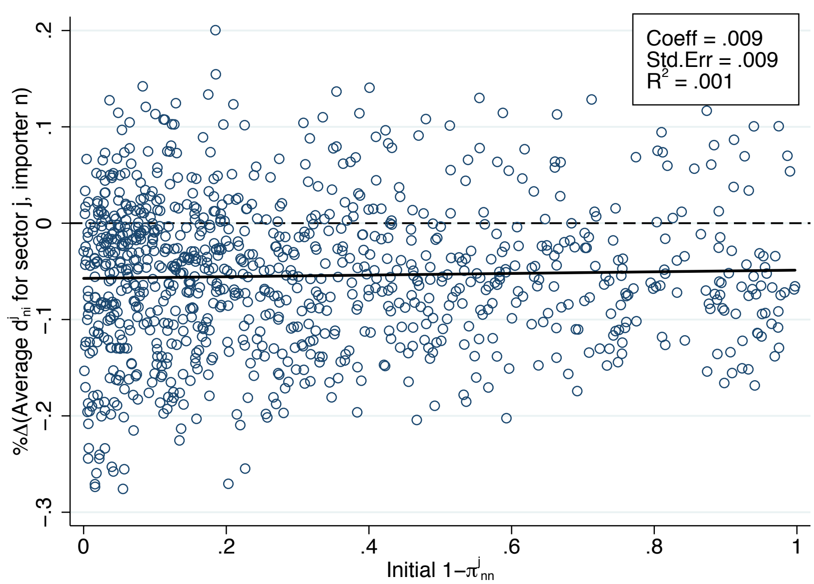
(d) 1990s and 2000s: Coefficient of Variation

Notes: The top panel of this figure presents the bivariate plots of absolute convergence from the 1960s (left panel) and the 1990s (right panel) against log initial average $T^{1/\theta}$ relative to the US. The bottom panel plots the coefficient of variation in $T^{1/\theta}$ relative to the US in the 2000s against this value in the 1960s (left panel) and the 1990s (right panel). In the bottom 2 panels, the line through the data is the 45-degree line.

Figure A2. Heuristic Evidence: Initial Import Shares, Changes in Import Shares, and Changes in Trade Costs



(a) Initial Import Shares and Changes in Import Shares



(b) Initial Import Shares and Changes in Trade Costs

Notes: This figure plots the change in the import share between the 1960s and 2000s $\Delta(1-\pi^j_{nn})$ (top panel), and the percentage change in import-weighted average import costs d^j_{ni} between the 1960 and the 2000s (bottom panel), against the import share of sector j in country n in the 1960s on the x-axis. The figure pools country-sectors. All of the productivities are expressed relative to the US values in that sector.