

The Evolution of Comparative Advantage: Measurement and Welfare Implications*

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Abstract

Using an industry-level dataset of production and trade spanning 75 countries and 5 decades, and a fully specified multi-sector Ricardian model, we estimate productivities at sector level and examine how they evolve over time in both developed and developing countries. We find that in both country groups, comparative advantage has become weaker: productivity grew systematically faster in sectors that were initially at the greater comparative disadvantage. The global welfare implications of this phenomenon are significant. Relative to the counterfactual scenario in which an individual country's comparative advantage remained the same as in the 1960s, and technology in all sectors grew at the same country-specific average rate, welfare today is 1.9% lower at the median. The welfare impact varies greatly across countries, ranging from -0.5% to 6% among OECD countries, and from -9% to 27% among non-OECD countries. Remarkably, for the OECD countries, nearly all of the welfare impact is driven by changes in technology in OECD countries, and for the non-OECD countries, nearly all of the welfare impact is driven by changes in technology in non-OECD countries.

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1 Introduction

How does technology evolve over time? This question is important in a variety of 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 comparative advantage, 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. Plainly, greater *relative* technology differences lead to larger gains from trade, and thus welfare is 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.¹

This suggests that in order to fully account for the impact of technological progress on economic outcomes, we must understand not just the changes in average country-level TFP, but also how relative technology evolves across sectors. Or, in the vocabulary of international trade, it is important to know what happens to both absolute and comparative advantage. However, until now the literature has focused almost exclusively on estimating absolute technology differences. In this paper, we examine the evolution of comparative advantage over time and its welfare consequences. We first use a large-scale industry-level dataset on production and bilateral trade, spanning 75 countries, 19 manufacturing sectors, and 5 decades, to estimate productivity in each country, sector, and decade, and document the changes in comparative advantage in this set of countries between the 1960s and today. We then use these estimates in a fully specified Ricardian model of production and trade to assess the welfare consequences of the patterns seen in the data.

Our main results can be summarized as follows. First, we find strong evidence that comparative advantage has become weaker. Controlling for the average productivity growth of all sectors in a country, sectors that were at the greater initial comparative disadvantage grew systematically faster. This effect is present in all time periods, and is similar in magnitude in both developed and developing countries. The speed of convergence implied by the estimates is about 25% per

¹Other papers that explore technological change in Ricardian models are, among many others, Jones (1979), Krugman (1979), Brezis, Krugman and Tsiddon (1993), and Hymans and Stafford (1995).

decade.

Second, counterfactual exercises reveal that the welfare impact of changes in comparative advantage is large. We compare welfare in each country during the 2000s to the counterfactual scenario in which productivity grows at the same country-specific average rate between the 1960s and the 2000s, but its comparative advantage remains as it was in the 1960s. Because we allow average productivity to grow in each country, this exercise reveals the welfare effects of the evolution of comparative advantage.

For the median country, welfare today is 1.9% lower than it would have been had comparative advantage remained unchanged since the 1960s. Lower welfare is exactly what theory would predict, given the empirical result that a typical country's comparative advantage has become weaker over this period. Indeed, we find that countries with a more pronounced weakening of comparative advantage tended to experience a larger welfare loss, and countries whose comparative advantage strengthened tended to gain in welfare. The median welfare impact corresponds to roughly 40% of the median gains from trade relative to complete autarky, 4.5%, implied by the model.

When considered in isolation, the median country thus appears to lose from its own changes in comparative advantage. In an alternative counterfactual, we evaluate the welfare impact of technological change in all the countries simultaneously. The median country today has a 1% lower welfare compared to the counterfactual scenario in which the *worldwide* comparative advantage had remained the same as in the 1960s. In addition, it appears that the overall welfare impact of global changes in comparative advantage is largely driven by what happens in similar countries. That is, in the sample of OECD countries, overall welfare changes are driven almost exclusively by comparative advantage changes in the OECD countries. The same is true in the non-OECD sample: nearly all of the variation in total welfare impact in that group is driven by what happens to comparative advantage of the non-OECD countries, rather than the OECD.

The basic difficulty in measuring sectoral productivity growth in a large sample of countries and over time is the lack of comparable data on sectoral output and inputs. In addition, estimates of productivity must take into account each country's participation in exports and imports, both of the final output, and of intermediate inputs used in production. In the absence of sufficiently detailed input and output price indices, such an exercise would be impractical in a large set of countries. To overcome this problem, we use the methodology developed by Eaton and Kortum (2002), and extended to a multi-sector framework by Shikher (2004), Chor (2010), and Costinot and Komunjer (2008), among many others. This approach uses the structure of the model to estimate the unobserved productivity parameters within a framework that takes explicit account of prices and international trade, both in sectoral output, as well as in intermediate inputs. Our model features many aspects that would be important for estimating underlying technology reli-

ably: multiple factors of production (labor and capital), a realistic input-output matrix between the sectors, both inter- and intra-sectoral trade, and a non-traded sector.

We are not the first to use international trade and production data within the Eaton and Kortum (2002) framework to estimate technology parameters. Eaton and Kortum (2002) and Waugh (2009) perform this analysis in a one-sector model at a point in time, an exercise informative of the cross-section of countries' overall TFP but not their comparative advantage.² Shikher (2004, 2005, 2009) obtains technology estimates by sector in the sample of OECD countries, while Caliendo and Parro (2010) analyze the impact of NAFTA in a multi-sector Eaton-Kortum model. A recent paper by Hsieh and Ossa (2010) examines the global welfare impact of sector-level productivity growth in China between 1993 and 2005, focusing on the uneven growth across sectors. Relative to existing contributions, we extend the multi-sector approach to a much greater set of countries, and, most importantly, over time. This allows us, for the first time, to examine not just the global cross-section of productivities, but its evolution over the past 5 decades and the welfare implications of those changes.

Changes in productivity at sector level have received comparatively less attention in the literature. Bernard and Jones (1996a, 1996b) use production data to study convergence in a sample of 15 OECD countries and 8 sectors. Proudman and Redding (2000) study the evolution of trade patterns in the G-5 countries, and find a great deal of heterogeneity in country experiences. Hausmann and Klinger (2007) examine changes in countries' revealed comparative advantage and how these are related to initial export patterns. Our paper is the first to use a fully specified model of production and trade to estimate changes in technology. In addition, we greatly expand the sample of countries and years relative to these studies.

Finally, our paper is related to 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, Cadot and Strauss-Kahn 2009). These studies typically find that countries have a tendency to diversify their production and exports as they grow, at least until they become quite developed. Our findings of weakening comparative advantage are consistent with greater diversification. Unlike diversification indices, which have no structural interpretation, our approach makes this phenomenon more precise, by calculating the magnitudes of technology changes that are responsible for the observed changes in diversification.³

The rest of the paper is organized as follows. Section 2 lays out the theoretical framework. Section 3 presents the estimation procedure and the data. Section 4 describes the patterns of

²Finicelli, Pagano and Sbracia (2009b) estimate the evolution of overall manufacturing TFP between 1985 and 2002 using a one-sector Eaton and Kortum model.

³Our paper is also related to the literature on international technology diffusion, surveyed by Keller (2004). While we document large and systematic changes in technology over time, our approach is, for now, silent on the mechanisms behind these changes.

the evolution of comparative advantage over time, and presents the main econometric results of the paper on relative convergence. Section 5 examines the welfare implications of the observed evolution of comparative advantage. Section 6 concludes.

2 Theoretical Framework

The world is comprised of N countries, indexed by n and i , and $J + 1$ sectors, indexed by j and k . There are two factors of production, labor (L) and capital (K). Each sector produces a continuum of goods. The first J sectors are tradable subject to barriers to trade, and the $J + 1$ -th sector is nontradable. Both capital and labor are mobile across sectors and immobile across countries. Trade is balanced each period. We suppress the time index for the ease of notation.

2.1 The Environment

Period utility of the representative consumer in country n is homothetic, given by

$$U_n = \frac{Y_n^{1-\sigma} - 1}{1-\sigma},$$

where Y_n denotes the final consumption in country n , and $\frac{1}{1-\sigma}$ denotes the intertemporal rate of substitution. The budget constraint (or the resource constraint) of the consumer is given by

$$P_n Y_n = w_n L_n + r_n K_n,$$

where P_n denotes the final good price, K_n is the exogenous endowment of capital, L_n is the exogenous labor supply, and w_n and r_n are the wage rate and the rental return of capital, respectively.

The production of the final good Y_n in country n is given by

$$Y_n = \left(\sum_{j=1}^J \omega_j^{\frac{1}{\eta}} (Y_n^j)^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1} \xi_n} (Y_n^{J+1})^{1-\xi_n},$$

where ξ_n denotes the Cobb-Douglas weight for the tradable sector composite good, η is the elasticity of substitution between the tradable sectors, ω_j denotes the weight of each tradable sector in final consumption, Y_n^{J+1} is the nontradable-sector composite good, and Y_n^j is the composite good in tradable sector j . Thus, the price of the final good in country n is given by:

$$P_n = B_n \left(\sum_{j=1}^J \omega_j (p_n^j)^{1-\eta} \right)^{\frac{1}{1-\eta} \xi_n} (p_n^{J+1})^{1-\xi_n},$$

where p_n^j is the price of the sector j composite, and $B_n = \xi_n^{-\xi_n} (1 - \xi_n)^{-(1-\xi_n)}$.

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

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

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

$$p_n^j = \left[\int_0^1 p_n^j(q)^{1 - \varepsilon_j} dq \right]^{\frac{1}{1 - \varepsilon_j}}.$$

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:

$$c_n^j = \left(w_n^{\alpha_j} r_n^{1 - \alpha_j} \right)^{\beta_j} \left(\prod_{k=1}^{J+1} \left(p_n^k \right)^{\gamma_{k,j}} \right)^{1 - \beta_j}.$$

That is, production in sector j requires labor, capital, and a bundle of intermediate inputs, coming from all sectors $k = 1, \dots, J + 1$. 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, $\gamma_{k,j}$ vary by output industry j as well as input industry k .

Productivity $z_n^j(q)$ for each $q \in [0, 1]$ in each sector j 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 $z_n^j(q)$ is random and comes from the Fréchet distribution that has the cumulative distribution function

$$F_n^j(z) = e^{-T_n^j z^{-\theta_j}}.$$

In this distribution, the absolute advantage term T_n^j varies by both country and sector, and the dispersion parameter θ_j may potentially vary by sector as well.

The cost of producing one unit of good q in sector j and country n is $c_n^j / z_n^j(q)$. International trade is subject to iceberg costs: in order for one unit of good q produced in sector j to arrive at country n from country i , $d_{ni}^j > 1$ units of the good must be shipped. We normalize $d_{nn}^j = 1$ for country n in tradable sector j . Note that the trade costs will vary by destination pair, by sector, and by time, and in general will not be symmetric: d_{ni}^j need not equal d_{in}^j . Under perfect competition, the price at which country i can supply tradable good q in sector j to country n is

equal to:

$$p_{ni}^j(q) = \left(\frac{c_i^j}{z_i^j(q)} \right) d_{ni}^j.$$

Buyers of each good q in tradable sector j in country n will select to buy from the cheapest source country. Thus, the price actually paid for this good in country n will be:

$$p_n^j(q) = \min_{i=1, \dots, N} \left\{ p_{ni}^j(q) \right\}.$$

Following the standard EK approach, define the “multilateral resistance” term

$$\Phi_n^j = \sum_{i=1}^N T_i^j \left(c_i^j d_{ni}^j \right)^{-\theta_j}.$$

This value summarizes, for country n , the access to production technologies in sector j . Its value will be higher if in sector j , country n 's trading partners have high productivity (T_i^j) or low cost (c_i^j). It will also be higher if the trade costs that country n faces in this sector are low. Standard steps lead to the familiar result that the probability of importing good q from country i , π_{ni}^j is equal to the share of total spending on goods coming from country i , X_{ni}^j/X_n^j , and is given by:

$$\frac{X_{ni}^j}{X_n^j} = \pi_{ni}^j = \frac{T_i^j \left(c_i^j d_{ni}^j \right)^{-\theta_j}}{\Phi_n^j}.$$

In addition, the price of good j in country n is simply

$$p_n^j = \Gamma_j \left(\Phi_n^j \right)^{-\frac{1}{\theta_j}},$$

where $\Gamma_j = \left[\Gamma \left(\frac{\theta_j + 1 - \varepsilon_j}{\theta_j} \right) \right]^{\frac{1}{1 - \varepsilon_j}}$, with Γ the Gamma function.

2.2 Equilibrium

The **competitive equilibrium** of this model world economy consists of a set 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) given the prices, the consumer's demand satisfies the first-order conditions; (iii) the prices ensure the market clearing conditions for labor, capital, tradable goods and nontradable goods; (iv) trade shares ensure balanced trade for each country.

The set of prices includes the wage rate w_n , the rental rate r_n , the sectoral prices $\{p_n^j\}_{j=1}^{J+1}$, and the aggregate price P_n in each country n . The allocation rule includes the capital and labor allocation across sectors $\{K_n^j, L_n^j\}_{j=1}^{J+1}$, final consumption demand $\{Y_n^j\}_{j=1}^{J+1}$, and total demand $\{Q_n^j\}_{j=1}^{J+1}$

(both final and intermediate goods) for each sector. The trade shares include the expenditure share π_{ni}^j of country n from country i in sector j .

Characterization of Equilibrium

Given the set of prices $\{w_n, r_n, P_n, \{p_n^j\}_{j=1}^{J+1}\}_{n=1}^N$, we first characterize the optimal allocations from final demand. The optimal allocations solve the following equivalent problem:

$$\max Y_n = \left(\sum_{j=1}^J \omega_j^{\frac{1}{\eta}} (Y_n^j)^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1} \xi_n} (Y_n^{J+1})^{1-\xi_n}$$

subject to

$$\sum_{j=1}^{J+1} p_n^j Y_n^j = P_n Y_n = w_n L_n + r_n K_n.$$

The first order conditions associated with this optimization problem imply the following final demand:

$$p_n^j Y_n^j = \xi_n (w_n L_n + r_n K_n) \frac{\omega_j (p_n^j)^{1-\eta}}{\sum_{k=1}^J \omega_k (p_n^k)^{1-\eta}}, \text{ for all } j = \{1, \dots, J\}$$

and

$$p_n^{J+1} Y_n^{J+1} = (1 - \xi_n) (w_n L_n + r_n K_n).$$

We next characterize the production and factor allocations across the world. Let Q_n^j denote the total sectoral demand of country n in sector j . Q_n^j is used as final goods in final demand and as intermediate goods for domestic production of all sectors. That is,

$$p_n^j Q_n^j = p_n^j Y_n^j + \sum_{k=1}^J (1 - \beta_k) \gamma_{j,k} \left(\sum_{i=1}^N \pi_{in}^k p_i^k Q_i^k \right) + (1 - \beta_{J+1}) \gamma_{j,J+1} p_n^{J+1} Q_n^{J+1}$$

for tradeable sectors $j = 1, \dots, J$, and

$$p_n^{J+1} Q_n^{J+1} = p_n^{J+1} Y_n^{J+1} + \sum_{k=1}^{J+1} (1 - \beta_k) \gamma_{j,k} p_n^k Q_n^k$$

in the non-tradeable sector. In particular, the domestic production value in sector $j = 1, 2, \dots, J$ of country n is the sum of (i) domestic final expenditure $p_n^j Y_n^j$ and (ii) all countries' expenditure on country n 's sector j goods as intermediate inputs in all tradable sectors: $\sum_{k=1}^J (1 - \beta_k) \gamma_{j,k} \left(\sum_{i=1}^N \pi_{in}^k p_i^k Q_i^k \right)$, and (iii) expenditure on the j 's sector intermediate inputs in the domestic non-traded sector $(1 - \beta_{J+1}) \gamma_{j,J+1} p_n^{J+1} Q_n^{J+1}$. 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, Ishii and Yi 2001); and two-way input linkages between the tradeable and the non-tradeable sectors.

In each tradable sector, some goods q are imported from abroad and some goods q are exported to the rest of the world. The exports in sector j of country n is $EX_n^j = \sum_{i=1}^N \mathbb{1}_{i \neq n} \pi_{in}^j p_i^j Q_i^j$, and the imports in sector j and country n is $IM_n^j = \sum_{i=1}^N \mathbb{1}_{i \neq n} \pi_{ni}^j p_n^j Q_n^j$. The total exports of country n is $EX_n = \sum_{j=1}^J EX_n^j$, and the total imports of country n is $IM_n = \sum_{j=1}^J IM_n^j$. The trade balance condition requires that for any country n , $EX_n - IM_n = 0$.

We now study the factor allocations across sectors. The total production of tradable sector j in country n is given by $\sum_{i=1}^N \pi_{in}^j p_i^j Q_i^j$. The optimal sectoral factor allocations in country n and tradable sector j must satisfy

$$\sum_{i=1}^N \pi_{in}^j p_i^j Q_i^j = \frac{w_n L_n^j}{\alpha_j \beta_j} = \frac{r_n K_n^j}{(1 - \alpha_j) \beta_j}.$$

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

$$p_n^{J+1} Q_n^{J+1} = \frac{w_n L_n^{J+1}}{\alpha_{J+1} \beta_{J+1}} = \frac{r_n K_n^{J+1}}{(1 - \alpha_{J+1}) \beta_{J+1}}.$$

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

$$\sum_{j=1}^{J+1} L_n^j = L_n \text{ and } \sum_{j=1}^{J+1} K_n^j = K_n.$$

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

3 Estimating Model Parameters

Using data on sectoral production, bilateral sector-level trade, relative prices, GDP, as well as information on trade barriers, we estimate the technology parameters T_i^j for a large set of countries in two steps. First, we estimate the technology parameters T_i^j of the tradable sectors for each country and each sector relative to the U.S.. Second, we estimate the technology parameters for the U.S., including the nontradable sector, and T_i^{J+1} for all other countries.

3.1 Tradable Sector Relative Technology

We now focus on the tradable sectors. Following the standard EK approach, first divide trade shares by their domestic counterpart:

$$\frac{\frac{X_{ni}^j}{X_n^j}}{\frac{X_{nn}^j}{X_n^j}} = \frac{X_{ni}^j}{X_{nn}^j} = \frac{T_i^j (c_i^j d_{ni}^j)^{-\theta_j}}{T_n^j (c_n^j)^{-\theta_j}},$$

which in logs becomes:

$$\ln \left(\frac{X_{ni}^j}{X_{nn}^j} \right) = \ln \left(T_i^j (c_i^j)^{-\theta_j} \right) - \ln \left(T_n^j (c_n^j)^{-\theta_j} \right) - \theta_j \ln d_{ni}^j.$$

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

$$\ln d_{ni}^j = d_k^j + b_{ni}^j + CU_{ni}^j + RTA_{ni}^j + ex_i^j + \nu_{ni}^j,$$

where d_k^j is an indicator variable for a distance interval (following EK, we set the distance intervals, in miles, to $[0, 350]$, $[350, 750]$, $[750, 1500]$, $[1500, 3000]$, $[3000, 6000]$, $[6000, \text{maximum}]$). Additional variables are whether the two countries share a common border (b_{ni}^j), belong to a currency union (CU_{ni}^j), or to a regional trade agreement (RTA_{ni}^j). Following the arguments in Waugh (2009), we include an exporter fixed effect ex_i^j . Finally, there is an error term ν_{ni}^j . Note that all the variables have a sector superscript j : we allow all the trade cost proxy variables to affect true iceberg trade costs d_{ni}^j differentially across sectors. There is a range of evidence that trade volumes at sector level vary in their sensitivity to distance or common border (see, among many others, Do and Levchenko 2007, Berthelon and Freund 2008).

This leads to the following final estimating equation:

$$\ln \left(\frac{X_{ni}^j}{X_{nn}^j} \right) = \underbrace{\ln \left(T_i^j (c_i^j)^{-\theta_j} \right) - \theta_j ex_i^j}_{\text{Exporter Fixed Effect}} - \underbrace{\ln \left(T_n^j (c_n^j)^{-\theta_j} \right)}_{\text{Importer Fixed Effect}} \\ - \underbrace{\theta_j d_k^j - \theta_j b_{ni}^j - \theta_j CU_{ni}^j - \theta_j RTA_{ni}^j}_{\text{Bilateral Observables}} - \underbrace{\theta_j \nu_{ni}^j}_{\text{Error Term}}.$$

It is clear from this expression that estimating this relationship will yield, for each country, an estimate of its technology-cum-unit-cost term in each sector j , $T_n^j (c_n^j)^{-\theta_j}$, which is obtained by exponentiating the importer fixed effect. The available degrees of freedom imply that these estimates are of each country's $T_n^j (c_n^j)^{-\theta_j}$ relative to a reference country, which in our estimation

is the U.S.. We denote this estimated value by S_n^j :

$$S_n^j = \frac{T_n^j}{T_{us}^j} \left(\frac{c_n^j}{c_{us}^j} \right)^{-\theta_j}.$$

It is immediate from this expression that estimation delivers a convolution of technology parameters T_n^j and cost parameters c_n^j . Both will of course affect trade volumes, but we would like to extract technology T_n^j from these estimates. In order to do that, we follow the approach of Shikher (2004). In particular, for each country n , the share of total spending going to home-produced goods is given by

$$\frac{X_{nn}^j}{X_n^j} = T_n^j \left(\frac{\gamma^j c_n^j}{p_n^j} \right)^{-\theta_j}.$$

Dividing by its U.S. counterpart:

$$\frac{X_{nn}^j/X_n^j}{X_{us,us}^j/X_{us}^j} = \frac{T_n^j}{T_{us}^j} \left(\frac{c_n^j p_{us}^j}{c_{us}^j p_n^j} \right)^{-\theta_j} = S_n^j \left(\frac{p_{us}^j}{p_n^j} \right)^{-\theta_j},$$

where the subscript us denotes the United States, and thus the ratio of price levels in sector j relative to the U.S. becomes:

$$\frac{p_n^j}{p_{us}^j} = \left(\frac{X_{nn}^j/X_n^j}{X_{us,us}^j/X_{us}^j} \frac{1}{S_n^j} \right)^{\frac{1}{\theta_j}}.$$

The entire right-hand side of this expression is either observable or estimated. Thus, we can impute the price levels relative to the U.S. in each country and each tradable sector.

The cost of the input bundles relative to the U.S. can be written as:

$$\frac{c_n^j}{c_{us}^j} = \left(\frac{w_n}{w_{us}} \right)^{\alpha_j \beta_j} \left(\frac{r_n}{r_{us}} \right)^{(1-\alpha_j) \beta_j} \left(\prod_{k=1}^J \left(\frac{p_n^k}{p_{us}^k} \right)^{\gamma_{k,j}} \right)^{1-\beta_j} \left(\frac{p_n^{J+1}}{p_{us}^{J+1}} \right)^{\gamma_{J+1,j} (1-\beta_j)}.$$

Using information on relative wages, returns to capital, price in each tradable sector, and the nontradable sector price relative to the U.S., we can thus impute the costs of the input bundles relative to the U.S. in each country and each sector. Armed with those values, it is straightforward to back out the relative technology parameters:

$$\frac{T_n^j}{T_{us}^j} = S_n^j \left(\frac{c_n^j}{c_{us}^j} \right)^{\theta_j}.$$

3.2 Complete Estimation

So far we have estimated TFP of the tradable sectors relative to the United States. To complete our estimation, we still need to find the TFP levels for the tradable sectors in the United States.

To do that we use the NBER-CES Manufacturing Industry Database for the U.S. (Bartelsman and Gray 1996). We also need to estimate the TFP levels of the nontradable sector for all sample countries. The information we will use is the sectoral final demand in each country in the sample.

We start by measuring the observed TFP levels for the tradable sectors in the U.S.. The form of the production function gives

$$\ln Y_{us}^j = \ln \Lambda_{us}^j + \beta_j \alpha_j \ln L_{us}^j + \beta_j (1 - \alpha_j) \ln K_{us}^j + (1 - \beta_j) \sum_{k=1}^{J+1} \gamma_{k,j} \ln M_{us}^{k,j},$$

where Λ^j denotes the measured TFP in sector j , Y^j denotes the output, L^j denotes the labor input, K^j denotes the capital input, and $M^{k,j}$ denotes the intermediate input from sector k . The NBER-CES Manufacturing Industry Database offers information on output, labor input, capital input, and intermediate good input. Thus, we can estimate the observed TFP level for each manufacturing tradable sector using the above equation.

If the U.S. were a closed economy, the observed TFP level for sector j would be given by $\Lambda_{us}^j = (T_{us}^j)^{\frac{1}{\theta_j}}$. 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, Pagano and Sbracia (2009a). We use our model to back out the true TFP level of each tradable sector in the United States. Here we follow Finicelli et al. (2009a) and use the following relationship:

$$(\Lambda_{us}^j)^{\theta_j} = T_{us}^j + \sum_{i \neq us} T_i^j \left(\frac{c_i^j d_{us,i}^j}{c_{us}^j} \right)^{-\theta_j}.$$

Thus, we have

$$(\Lambda_{us}^j)^{\theta_j} = T_{us}^j \left[1 + \sum_{i \neq us} \frac{T_i^j}{T_{us}^j} \left(\frac{c_i^j d_{us,i}^j}{c_{us}^j} \right)^{-\theta_j} \right] = T_{us}^j \left[1 + \sum_{i \neq us} S_i^j \left(d_{us,i}^j \right)^{-\theta_j} \right].$$

This equation can be solved for underlying technology parameters T_{us}^j in the U.S., given estimated observed TFP Λ_{us}^j , and all the S_i^j 's and $d_{us,i}^j$'s estimated in the previous subsection.

We next estimate the preference shares $\{\omega_j\}_{j=1}^J$. We start with a guess of $\{\omega_j\}_{j=1}^J$ and find sectoral prices p_n^k as follows.

1. Start with a guess of $\{p_n^j\}_{j=1}^J$ for all country n .
2. Compute the tradable sector aggregate price $p_n^T = \left(\sum_{k=1}^J \omega_k (p_n^k)^{1-\eta} \right)^{\frac{1}{1-\eta}}$ for all n .
3. Compute p_n^{J+1} using the data on the ratio of the relative nontradable price for all n .

4. Compute sectoral unit costs c_n^j and Φ_n^j .
5. Update prices $p_n^j = \Gamma_j \left(\Phi_n^j \right)^{-\frac{1}{\theta_j}}$ and repeat the above procedures until the prices converge.

We then update the preference shares using the final sectoral expenditure share of the U.S.:

$$\omega_j = \frac{p_{us}^j Y_{us}^j}{\xi_{us}(w_{us} L_{us} + r_{us} K_{us})} \left(\frac{p_{us}^j}{p_{us}^T} \right)^{\eta-1}, \text{ for any } j = \{1, \dots, J\}.$$

We normalize the vector of ω to have a sum of one. Repeat the above procedures until the sectoral preference shares converge.

We then estimate the nontradable sector TFP using the relative prices. In the model, the nontradable sector price is given by

$$p_n^{J+1} = \gamma^{J+1} (T_n^{J+1})^{-\frac{1}{\theta^{J+1}}} c_n^{J+1}.$$

Since we know p_n^T , c_n^{J+1} , and the relative price of nontradables (which we take from the data), we can back out $T_n^{J+1} \forall n$ from the equation above.

3.3 Data Description and Implementation

In order to carry out estimation, we assemble data on production and trade for a sample of up to 75 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 comes from the COMTRADE database compiled by the UN. 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. 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.

The distance and common border variables were 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 were used to estimate production function parameters α^j and β^j . To compute α^j for each sector, we calculated the share of the total wage bill in value added, and took a simple median across countries (taking the mean yields essentially the same results). To compute intermediate input intensity, β^j , we took the median of value added divided by total output.

The intermediate input coefficients $\gamma_{k,j}$ 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 k required to produce one dollar of final output in column j . Thus, it is the direct counterpart of the input coefficients $\gamma_{k,j}$. Note that we assume these to be the same in all countries. di Giovanni and Levchenko (2010) provide suggestive evidence that at such a coarse level of aggregation, Input-Output matrices are indeed similar across countries. In addition, we use the U.S. I-O matrix to obtain the shares of total final consumption expenditure going to each sector, which we use to pin down taste parameters ω_j in traded sectors $1, \dots, J$; as well as α_{J+1} and β_{J+1} in the non-tradeable sector, which cannot be obtained from UNIDO.⁴

The computation of relative costs of the input bundle requires information on wages and the returns to capital. To compute wages, we divided the total manufacturing sector wage bill by total manufacturing employment in each country, and took that value relative to the U.S.. Consistent with the model, this procedure delivers wages that differ by country but not by sector.⁵

Obtaining information on the return to capital, r_n , is less straightforward, since it is not observable directly. In the baseline analysis, we assume that the wage-rental ratio is determined by the aggregate capital-labor ratio through an aggregate market clearing condition:

$$\frac{r_n}{w_n} = \frac{(1 - \alpha)L_n}{\alpha K_n},$$

where α is the aggregate share of labor in GDP, which we set to $2/3$.⁶

⁴The U.S. I-O matrix provides an alternative way of computing α^j and β^j . These parameters calculated based on the U.S. I-O table are very similar to those obtained from UNIDO, with the correlation coefficients between them above 0.85 in each case. The U.S. I-O table implies greater variability in α^j 's and β^j 's across sectors than does UNIDO.

⁵In less than 1% of country-decade observations, either the total wage bill or employment were missing from the UNIDO data. In those cases, the wage relative to the U.S. was proxied by the GDP per capita relative to the U.S.

⁶The return to capital will be affected by country characteristics other than capital abundance, such as the quality of the country's regulatory environment, corruption, and expropriation risk, among other factors. Indeed, Caselli and Feyrer (2007) document that the marginal product of capital is remarkably similar across a wide range of countries. Alternatively, the return to capital will be the same in all countries under international capital mobility. None of the results below are affected if we assume instead that the return to capital, r_n , does not differ across countries.

The price of non-tradeables relative to the U.S., p_n^{J+1}/p_{us}^{J+1} , and the price of non-tradeables relative to tradeables in each country, p_n^{J+1}/p_n^T , 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 were extrapolated using a simple linear fit to log PPP-adjusted per capita GDP from the Penn World Tables 6.3 (Heston, Summers and Aten 2002).

The total labor force in each country, L_n , and the total capital stock, K_n , are obtained from the Penn World Tables 6.3. Following the standard approach in the literature (see, e.g. Hall and Jones 1999, Bernanke and Gurkaynak 2001, Caselli 2005), the total labor force is calculated from the data on the total GDP per capita and per worker.⁷ The total capital is calculated using the perpetual inventory method that assumes a depreciation rate of 6%: $K_{n,t} = (1 - 0.06)K_{n,t-1} + I_{n,t}$, where $I_{n,t}$ is total investment in country n in period t . For most countries, investment data start in 1950, and the initial value of K_n is set equal to $I_{n,0}/(\gamma + 0.06)$, where γ is the average growth rate of investment in the first 10 years for which data are available.

In order to estimate the relative TFP's in the tradable sectors in the U.S., we use the 2009 version of the NBER-CES Manufacturing Industry Database, that 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 TFP's for the U.S. in each tradeable sector $j = 1, \dots, J$ and each decade.

The share of expenditure on traded goods, ξ_n in each country and decade is sourced from Yi and Zhang (2010), who compile this information for 30 developed and developing countries. For countries unavailable in the Yi and Zhang data, values of ξ_n were 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 linear relationship was typically quite good, with R^2 's of 0.30 to 0.80 across decades.

Finally, for now we assume that the dispersion parameter θ_j does not vary across sectors. There are no reliable estimates of how it varies across sectors, and thus we do not model this variation. We pick the value of $\theta = 8.28$, which is the preferred estimate of EK.⁸ It is important to assess how the results below are affected by the value of this parameter. One may be especially concerned about how the results change under lower values of θ . Lower θ implies greater within-

⁷Using the variable name conventions in the Penn World Tables, $L_n = 1000 * pop * rgdpch/rgdpwoc$.

⁸Shikher (2004, 2005, 2009), Burstein and Vogel (2009), and Eaton, Kortum, Neiman and Romalis (2010), among others, follow the same approach of assuming the same θ across sectors. Caliendo and Parro (2010) use tariff data and triple differencing to estimate sector-level θ . However, their approach may impose too much structure and/or be dominated by measurement error: at times the values of θ they estimate are negative. In addition, in each sector the restriction that $\theta > \varepsilon - 1$ must be satisfied, and it is not clear whether Caliendo and Parro (2010)'s estimated sectoral θ 's meet this restriction in every case. Our approach is thus conservative by being agnostic on this variation across sectors.

sector heterogeneity in the random productivity draws. Thus, trade flows become less sensitive to the costs of the input bundles (c_i^j), and the gains from intra-sectoral trade become larger relative to the gains from inter-sectoral trade. We repeated the entire analysis in the paper assuming instead a value of $\theta = 4$, which is at or near the bottom of the range that has been used in the literature. Overall, the results are remarkably similar. The correlation between estimated T_i^j 's under $\theta = 4$ and the baseline is above 0.95, and there is actually somewhat greater variability in T_i^j 's under $\theta = 4$. Appendix Tables A5 through A7 report the main econometric and quantitative results of the paper under this alternative value of θ . Comparing them to the baseline results, it is clear that the two are remarkably similar.

We choose the elasticity of substitution between broad sectors within the tradeable bundle, η , to be equal 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 non-tradeable goods, which is set to 1 by the Cobb-Douglas assumption. The elasticity of substitution between varieties within each tradeable sector, ε_j , is set to 4.

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.

4 Evolution of Comparative Advantage

In this section, we describe the basic patterns in how estimated sector-level technology varies across countries and over time, focusing especially on whether comparative advantage has become stronger or weaker. Going through the steps described in Section 3.1 yields, for each country n , tradeable sector j , and decade, the state of technology relative to the U.S., T_n^j/T_{us}^j . Since the choice of the U.S. as the reference country is arbitrary, we present the stylized facts based not on each country's difference with respect to the U.S., but with respect to the global frontier. In each sector and decade, we select the 2 highest values of T_n^j/T_{us}^j , take their geometric mean, and label that the global frontier. We then re-normalize each country's technology parameter to be expressed relative to the frontier, rather than the U.S.. In addition, since mean productivity in each sector is equal to $T^{1/\theta}$, we carry out the analysis on this value, rather than T .

Table 1 presents summary statistics for the OECD and non-OECD countries in each decade. The first column reports the mean distance to the frontier across all sectors in a country, a measure that can be thought of as *absolute advantage*. Not surprisingly, the OECD countries as a group catch up to the frontier between the 1960s and the 2000s, with productivities going up from 0.65 to 0.84 of the frontier value. The non-OECD countries' position shows no clear upward or downward pattern. The second column in each panel summarizes the magnitude of

within-country differences in productivity across sectors. Namely, it reports the mean ratio of productivities in the two most productive sectors relative to the two least productive ones, by country group and decade. This measure can be thought of as *comparative advantage* across sectors. For the OECD, this measure is on the order of 1.4–1.5, and decreasing monotonically over time. For the non-OECD countries, it fluctuates around 2, showing no clear trend. Not surprisingly, the non-OECD countries tend to have stronger comparative advantage.

The evolution of these averages over time masks a great deal of heterogeneity among countries. Table 2 reports top 10 and bottom 10 countries ranked according to how fast their average productivity changed relative to the frontier. The left panel presents the changes from the 1960s to 2000s, and the right panel from the 1980s to 2000s. Over the period 1960s–2000s, the countries that caught up to the frontier the fastest are for the most part peripheral OECD countries, such as Norway, Portugal, and Greece. Countries slowest to catch up (or fastest to fall behind) are developing countries, that surprisingly include two of the more successful East Asian economies, Thailand and Malaysia. This is of course not inconsistent with high rate of economic growth experienced by these countries. First, these are measures of average technology, and part of the growth in those countries would have been driven by factor accumulation. More importantly, these are measures of distance to the technological frontier. Thus, even if these countries experienced overall productivity growth, our procedure shows that the frontier grew even faster. Since the 1980s, the composition of countries changes somewhat, but the patterns are broadly similar.

In addition to absolute advantage, we can assess how the countries comparative advantage evolved. Table 3 reports the top 10 and bottom 10 countries in how much the dispersion in the country’s technology across sectors changed. In particular, for each country and decade, we compute the coefficient of variation in $T^{1/\theta}$ across sectors, and record how much this coefficient of variation changed over time. Thus, larger negative changes imply greater reductions in productivity dispersion across sectors, and thus greater *relative* catch-up. Conversely, positive values imply that a country’s comparative advantage has gotten stronger, as its productivity dispersion increased.

It is clear from comparing Tables 2 and 3 that absolute and relative convergence are closely related: most of the fastest converging countries on average are also those that catch up disproportionately in their weakest sectors. This can be due in part to the fact that the best sectors in those countries are already at the frontier, thus the only sectors that can catch up are the weak ones. However, the rankings are very similar if we instead do not normalize by the frontier, and assess the changes relative to the reference country. This way, there is no mechanical ceiling for a country’s strongest sectors. Less obviously, the bottom countries tend to be similar as well. Thus, countries that fell behind the most on average also tend to experience greater dispersion across sectors: their weakest sectors fall disproportionately more than their strongest ones. Figure 1

presents the correlation between relative and absolute convergence graphically. There is a strong association between these two measures.

Table 4 reports the correlation coefficients between absolute and relative convergence measures, and the corresponding changes in real PPP-adjusted per capita income and overall trade openness, sourced from the Penn World Tables. In addition to the high positive correlation (0.61-0.64) between our two measures, the table reveals that neither is particularly strongly correlated with changes in income or openness. There is a positive correlation (around 0.25) between income growth and average convergence, the correlation with relative convergence is close to zero and mildly negative. Growth in trade openness is actually negatively correlated with average convergence, and virtually uncorrelated with relative convergence. Figure 2 presents the scatterplots of absolute and relative convergence against income growth and openness.

The summary statistics so far reveal a great deal of variation in how countries' absolute and comparative advantage evolved between the 1960s and today. To shed further light on whether comparative advantage has gotten stronger or weaker over time, we estimate a convergence specification in the spirit of Barro (1991) and Barro and Sala-i-Martin (1992):

$$\Delta \log (T_n^j)^{1/\theta} = \beta \text{Initial log } (T_n^j)^{1/\theta} + \delta_n + \delta_j + \epsilon_{nj} \quad (1)$$

Unlike the classic cross-country convergence regression, our 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 effects, which affects the interpretation of the coefficient. The country effect captures the average change in productivity across all sectors in each country – the absolute advantage. Thus, β picks up the impact of the initial relative productivity on the relative growth of a sector within a country – the evolution of comparative advantage. In particular, a negative value of β implies that relative to the country-specific average, the most backward sectors grew fastest.

Table 5 reports 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, underneath each one we report 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 years 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, and we do not report those standard errors to conserve space.⁹

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: even with clustering the t -statistic is over 13. The speed of convergence implied by this coefficient is 24% per decade. As a benchmark, the classic Barro and Sala-i-Martin (1992) rate of convergence is 2% per year, or 22% per decade, strikingly close to what we find 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, 12.4% per decade. The rest of the columns report the results decade-by-decade. Though there is statistically significant convergence in each decade, it is striking that the speed of convergence trends downward, from nearly 30% from the 1960 to the 1970s, to 16.5% 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. (Note that we do not recalculate subsample-specific frontier productivities, so the frontier is the same across subsamples.) Breaking it down produces slightly faster convergence rates than in the full sample. With the exception of the 1980s to the 2000s long difference, the non-OECD countries are catching up somewhat faster, which is not surprising.

Appendix Tables A3 and A4 report the results of estimating the convergence equation (1) country by country, for the periods starting in the 1960s and the 1980s, respectively. 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. Starting in the 1960s, there is considerable evidence of convergence in these country-specific estimates. In all countries, the convergence coefficient is

⁹If the initial T 's tend to be measured with error, it has been noted that the convergence regression of the type estimated here will produce bias in favor of finding convergence (Quah 1993). We ran a number of checks to assess the relevance of this effect in our setting. First, we estimated a number of panel specifications with a variety of interacted fixed effects: country \times sector, country \times decade, and sector \times decade included together in estimation. These additional fixed effects will help control for measurement error that varies mainly at country-sector, country-time, or sector-time level, respectively. We also implemented the Arellano-Bond and Blundell-Bond dynamic panel estimators, that difference the data and use lagged values of T to instrument for current changes in T . All of these alternative estimates actually imply a *faster* speed of convergence than the estimates in Table 5. Second, to check how much measurement error is needed to generate our results, we ran a simulation in which we started with artificial data exhibiting zero convergence across sectors within a country, and added measurement error to the right-hand side variable until the OLS coefficient was equal to the coefficient found in our estimates. It turns out that in order for measurement error to produce coefficient magnitudes found in the data when the truth is zero convergence, it must be the case that 62% of the cross-sectoral variation in the right-hand side variable is due to measurement error.

negative, and significant at the 10% level or below in 39 out of 51 available countries (76%). The evidence starting in the 1980s is weaker: though the large majority of the coefficients are still negative, only 25 out of 61 countries (41%) are showing statistical significance. In addition, most of the countries with a significant coefficient are actually the OECD. Thus, consistent with the pooled results that show a slowdown in convergence starting in the 1980s, these results are less striking than those starting in the 1960s.

All in all, our results provide remarkably robust evidence of relative convergence: in all time periods and broad sets of countries we consider, relatively weak sectors grow faster, with sensible rates of convergence. This implies that Ricardian comparative advantage is getting weaker, at least when measured at the level of broad manufacturing sectors.

5 Welfare Analysis

This section computes the welfare impact of changes in comparative advantage documented in the previous section. In order to do this, we solve the full model laid out in Section 2 for a variety of values of technology parameters. The baseline corresponds to the actual values of T_n^j estimated for the 2000s. Before running the counterfactual experiments, we assess the fit of the baseline model in a number of dimensions. The values of technology parameters are estimated based on the gravity relationship in sectoral trade flows and actual factor endowments, thus the model fits bilateral sector-level trade flows as well as the least-squares gravity relationship can deliver. A more important question is whether the levels of factor prices – w and r – implied by the model are close to the values from the data used in calculating technology parameters. Table 6 compares w 's and r 's in the model and in the data for 2000s.¹⁰ It is clear that the two are very close: the means and the medians match up quite well, and the correlation between model and data wages is 0.987. The correlation in r 's is slightly lower, but still quite high at 0.918.

Another metric by which to evaluate the model is overall trade flows. Though the model is based on matching bilateral sector-level trade flows, it may be that aggregating across different sectors and adding a non-tradeable sector leads to biases when it comes to overall trade openness. The bottom panel compares manufacturing imports as a share of GDP in the model to the data.¹¹ We can see that the averages are extremely close, with both means and medians in the model and the data at roughly 20-22%. The correlation is not perfect, but very high at 0.74. Figure 3 presents the comparison of the three variables between the model and the data graphically.

The first counterfactual assumes that between the 1960s and today, each country's T 's relative to the world frontier grew at their geometric average rate, but their comparative advantage

¹⁰Comparisons based on earlier decades deliver nearly identical results.

¹¹The data on manufacturing imports as a share of GDP come from the World Bank's World Development Indicators.

remained the same as it was in the 1960s. Precisely, the counterfactual T 's are calculated as:

$$\frac{\left(T_n^j\right)_{\text{counterfactual}}}{\left(T_F^j\right)_{2000s}} = \frac{\left(T_n^j\right)_{1960s}}{\left(T_F^j\right)_{1960s}} \times \frac{\left(\prod_{k=1}^J\left(T_n^k / T_F^k\right)_{2000s}\right)^{\frac{1}{J}}}{\left(\prod_{k=1}^J\left(T_n^k / T_F^k\right)_{1960s}\right)^{\frac{1}{J}}},$$

where T_F^j is the world frontier in sector j , calculated as in Section 4. The use of geometric averages has two appealing features. The first is that even though the counterfactual T 's are calculated to keep their distance to the frontier, the geometric average of counterfactual T 's is equal to the geometric average of the country's actual T 's in the 2000s. This ensures that the normalization to the frontier does not induce movements up or down of the average productivity in the country, which would confound the meaning of our counterfactual exercise. The second appealing feature is that this formulation produces identical counterfactual T 's whether the experiment is carried out on absolute T 's or $T^{1/\theta}$'s, which are the mean productivities.¹²

We begin by evaluating the impact of each country's changes in comparative advantage on its own welfare in isolation. In order to do this, we solve the model while keeping comparative advantage fixed to the 1960s for one country at a time, and record the change in welfare for that country in the counterfactual relative to the baseline. Table 7 summarizes the results, separating the OECD and the non-OECD countries. The table reports the percentage changes in welfare, for the counterfactual relative to the benchmark. Thus, the positive median values in the first column indicate that on average, welfare would have been higher had comparative advantage not changed since the 1960s. This accords well with what is predicted by theory, given the pronounced weakening of comparative advantage we found in the data in Section 4. However, now we can quantify these effects: for the median OECD country, welfare would have been 1.7% higher had its comparative advantage not weakened. For the non-OECD, the impact very similar, 1.9% at the median.

The second notable aspect of the results is the large dispersion. Among the OECD countries, the standard deviation of welfare changes is 1.8%, while for the non-OECD, it is 2.5 times higher, 5.5%. Correspondingly, the OECD changes range from -0.5% to 5.6%, while for the non-OECD, the range is from -9.3% to 27%. Importantly, among the non-OECD countries, welfare changes range from large negative to large positive, indicating that heterogeneity across countries is first-order.

To cross-check these results and compare magnitudes, the bottom panel of Table 7 reports the same summary statistics for the overall gains from trade compared to autarky for the 2000s in the baseline model. It appears that the welfare impact of the evolution of comparative advantage is

¹²We keep productivity in the nontradeable sector at the benchmark value in all the counterfactual experiments, since our focus is on the welfare impact of changes in comparative advantage.

on average of the same order of magnitude as the total gains from trade. For the median OECD country, the median gains from trade are 5.2%, while for the non-OECD countries, the median total gains from trade are 4.4%. In addition, there are important differences in the extent of variation of welfare gains from trade compared to welfare changes due to technological changes. In both groups of countries, the gains from trade have a standard deviation of about 3% and a range of about 11%: from a minimum of 1 to a maximum of 12%. For the OECD countries, the range of welfare changes due to technology is much smaller, with a standard deviation of less than 2%, and a range of 6 percentage points. However, for the non-OECD countries, technology changes matter much more: they have a standard deviation of 5.5%, and a range of nearly 40 percentage points. In addition, while gains from trade are – of course – always positive, the welfare impact of technological changes takes on both positive and negative values.

How can we make sense of such a wide variation? Theory predicts that on average, countries experiencing a weakening in comparative advantage should see a reduction in welfare, and countries with a strengthening comparative advantage should be better off. We can verify this by correlating the welfare change implied by the counterfactual exercise to our empirical measures of weakening/strengthening of comparative advantage. Figure 4 presents the results. It plots the change in welfare in the counterfactual relative to the benchmark against the percentage change in the coefficient of variation in a country's $T^{1/\theta}$'s calculated in the previous section. An fall in the coefficient of variation implies that dispersion across sectoral productivities decreased in a country over time – a weakening of comparative advantage. We should expect these countries to on average have higher welfare in the counterfactual that instead fixes comparative advantage to its initial value. Figure 4 confirms this conjecture: there is a pronounced negative relationship between these two variables, with a correlation of -0.5.¹³

The preceding counterfactual describes the impact of changes in comparative advantage in an individual country on welfare in the country itself. Consistent with the simple intuition gleaned from theory, our empirical finding of weakening comparative advantage also implies that on average, a country would have been better off keeping its 1960s comparative advantage, given the technological change actually observed elsewhere in the world. A complementary, and equally interesting question is what would have happened to all countries had comparative advantage been stuck in the 1960s in every country in the world. Panel A of Table 8 reports the welfare results of this counterfactual. It summarizes the percentage change in welfare that would have resulted had the entire world kept its comparative advantage the same as in the 1960s. Once again, a positive number means that welfare is higher in the counterfactual relative to the benchmark: in this case a country is better off living in the counterfactual world.

On average, while we still find that countries are worse off, these welfare losses are smaller

¹³This correlation is virtually unchanged if outlier Indonesia is excluded.

than those in the previous counterfactual, in which only one country's comparative advantage was fixed at the 1960s. The median welfare loss to the OECD is 1.2%, and for the non-OECD 0.6%. The range of outcomes is similar, however. For the non-OECD countries, welfare in the counterfactual ranges from a 9.7% gain to a 22.3% loss. For the OECD, the range of outcomes narrows somewhat.

The preceding two sets of results point to the first-order role of trading partners' evolution of comparative advantage for each country's welfare: the welfare loss from technological change is smaller if everyone's technology is evolving, compared to the case in which only one country is changing its comparative advantage. In the next exercise, we sort out which types of trading partners turn out to be most important for a country's welfare. For instance, it is often suggested that changes in comparative advantage in developing countries can reduce welfare in developed ones (see Samuelson 2004, for a recent example). In order to evaluate this claim, we break up the overall welfare effect into two large groups: that driven by technology changes in the OECD, and in the non-OECD. To do this, we run two additional counterfactual exercises: in the first, we keep the comparative advantage in the OECD countries fixed as in the 1960s, and let the non-OECD countries' comparative advantage evolve as it did in the data. This exercise reveals the welfare changes in all of the countries in the world that are due to the evolution of comparative advantage in the OECD only. In the second counterfactual, we keep the non-OECD comparative advantage fixed to the 1960s instead, and let the OECD technology evolve as it did in the data.

Panels B and C of Table 8 report the results. Once again, a positive number means that the country is worse off under the counterfactual compared to the benchmark, that is, the actual observed changes in comparative advantage decreased welfare. The patterns are striking: observed changes in OECD comparative advantage tended to hurt the OECD countries, but had virtually no effect on the non-OECD countries. The median impact of OECD technological change on the non-OECD countries is 0.0%, and the range is also tiny, from -0.5% to 0.7%. The same is true of the non-OECD technical change: it tended to lower welfare within that group, and had virtually no impact on the OECD.

Figure 5(a) plots for the OECD countries the welfare changes implied by the evolution of comparative advantage in the OECD only on the y-axis against the total welfare changes from the evolution of comparative advantage in the entire world. Figure 5(b) plots instead the changes in welfare in the OECD due to the non-OECD countries' evolution of comparative advantage. For ease of interpretation, we add a 45-degree line to both plots. The results are striking. Virtually all of the total welfare change in the OECD is driven by changes in comparative advantage in the OECD itself, as shown in Figure 5(a). By contrast, the non-OECD impact on the OECD is virtually zero for almost all countries. These results imply that while it is true that changes in comparative advantage can lower welfare, for the OECD welfare is driven almost exclusively by

what happens within that group of countries.

These results could be driven in part by the fact that the trade between the OECD countries accounts for majority of world trade, and thus the OECD countries are almost always each others' largest trading partners. Figure 6 repeats the exercise for the non-OECD country group. In 6(a), we plot the welfare change in the non-OECD that is due to the OECD comparative advantage changes against the total welfare change. In 6(b), we instead plot the welfare change due to the non-OECD changes. The results are remarkable: among the non-OECD countries, most welfare changes are driven by the non-OECD comparative advantage changes. This result cannot be explained by the preponderance of trade in this group of countries, since the non-OECD-non-OECD trade is the smallest category of world trade, much lower than the OECD-non-OECD trade. For these results, multilateral effects are clearly important.

5.1 Changes in Comparative Advantage and Trade Volumes

A related aspect of weakening comparative advantage is its impact on trade volumes. Intuition based on simple theory tells us that when comparative advantage weakens, trade volumes should decrease. We confirm this in Table 9. It reports the absolute change in the ratio of imports to GDP in the counterfactual compared to the benchmark. Panel A reports the results for the change in the imports/GDP ratio under the first counterfactual, in which only one country's comparative advantage is kept fixed to the 1960s, while all other countries' sectoral productivities are the same as estimated in the data. For the OECD countries, imports are 1.9 percentage points of GDP higher in the counterfactual compared to the baseline, a proportional increase of about 10% relative to what is observed in the data. For the non-OECD countries, the change is even larger, 4.2 percentage points of GDP, or about a 20% change in trade openness compared to the baseline. Panel B of Table 9 reports the results for the second counterfactual, in which the worldwide relative technology is fixed to the 1960s. Here, the increase is slightly more subdued, 1.8 percentage points of GDP for the OECD, and 2.6 percentage points of GDP for the non-OECD.

6 Conclusion

How does technology evolve over time, and what are the consequences of technological change? In the growth literature, it is widely recognized that economic growth is driven in large part by productivity growth, making it the key force for improvements in welfare. However, when *relative* technology differences are a source of international trade as in the Ricardian world, the welfare impact of technological progress depends on which sectors grow in which countries.

This paper starts by estimating comparative advantage in a sample of some 75 countries, 19 sectors, and 5 decades, 1960s to today. We document a striking pattern in the data: in the

world as a whole, comparative advantage is getting weaker over time. 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. This empirical finding opens the door to the theoretical possibility that this type of uneven technological progress can actually reduce welfare in the trading countries. Calibrating the model and solving for the counterfactual scenario in which comparative advantage is instead fixed at its initial-period values, we indeed find that welfare was reduced by weakening comparative advantage. The average impact is large, roughly the same order of magnitude as the total gains from trade for these countries in the 2000s.

In developed countries, the typical worry is that rapid technological catch-up in developing world can lower welfare through this channel. However, we find that nearly all of the welfare impact for the OECD countries comes from changes in comparative advantage within the OECD. Thus, while the negative welfare impact of uneven technological change is very much a feature of the data, for developed countries the culprit is not the poor countries, but rather the rich countries themselves.

Appendix A Solution Algorithm

Given $\{L_n, K_n, \{T_n^j\}_{j=1}^{J+1}, \xi_n\}_{n=1}^N$, $\{\varepsilon_j, \alpha_j, \theta_j, \beta_j, \{\gamma_{k,j}\}_{k=1}^{J+1}, \{d_{ni}^j\}_{N \times N}\}_{j=1}^{J+1}$, and η , we compute the competitive equilibrium of the model as follows.

1. Guess $\{w_n, r_n\}_{n=1}^N$.

- Compute prices from the following equations:

$$c_n^j = \left(w_n^{\alpha_j} r_n^{1-\alpha_j} \right)^{\beta_j} \left(\prod_{k=1}^{J+1} (p_n^k)^{\gamma_{k,j}} \right)^{1-\beta_j} \quad \text{for any } n \in \{1, \dots, N\} \text{ and } j \in \{1, \dots, J+1\},$$

$$\Phi_n^j = \sum_{i=1}^N T_i^j \left(c_i^j d_{ni}^j \right)^{-\theta_j} \quad \text{for any } n \in \{1, \dots, N\} \text{ and } j \in \{1, \dots, J\},$$

$$\Phi_n^{J+1} = T_n^{J+1} (c_n^{J+1})^{-\theta_{J+1}} \quad \text{for any } n \in \{1, \dots, N\},$$

$$p_n^j = \Gamma_j (\Phi_n^j)^{-\frac{1}{\theta_j}} \quad \text{for any } n \in \{1, \dots, N\} \text{ and } j \in \{1, \dots, J+1\},$$

$$P_n = B_n \left(\sum_{j=1}^J \omega_j (p_n^j)^{1-\eta} \right)^{\frac{1}{1-\eta} \xi_n} (p_n^{J+1})^{1-\xi_n}.$$

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

$$Y_n^j = \xi_n \frac{w_n L_n + r_n K_n}{p_n^j} \frac{\omega_j (p_n^j)^{1-\eta}}{\sum_{k=1}^J \omega_k (p_n^k)^{1-\eta}}, \quad \text{for any } j = \{1, \dots, J\},$$

$$Y_n^{J+1} = (1 - \xi_n) \frac{w_n L_n + r_n K_n}{p_n^{J+1}}.$$

- Compute the trade shares π_{ni}^j as follows:

$$\pi_{ni}^j = \frac{T_i^j \left(c_i^j d_{ni}^j \right)^{-\theta_j}}{\Phi_n^j}.$$

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

$$p_n^j Y_n^j + \sum_{k=1}^J \left(\sum_{i=1}^N Q_i^k p_i^k \pi_{in}^k \right) (1 - \beta_k) \gamma_{j,k} + Q_n^{J+1} p_n^{J+1} (1 - \beta_{J+1}) \gamma_{j,J+1} = p_n^j Q_n^j.$$

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

$$\sum_{i=1}^N p_i^j Q_i^j \pi_{in}^j = \frac{w_n L_n^j}{\alpha_j \beta_j} = \frac{r_n K_n^j}{(1 - \alpha_j) \beta_j}, \quad \text{for any } j = \{1, \dots, J\},$$

$$p_n^{J+1} Q_n^{J+1} = \frac{w_n L_n^{J+1}}{\alpha_{J+1} \beta_{J+1}} = \frac{r_n K_n^{J+1}}{(1 - \alpha_{J+1}) \beta_{J+1}}.$$

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

$$\sum_{j=1}^{J+1} L_n^j = L_n, \quad \sum_{j=1}^{J+1} K_n^j = K_n.$$

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

References

- Barro, Robert J.**, “Economic Growth in a Cross Section of Countries,” *Quarterly Journal of Economics*, May 1991, 106 (2), 407–443.
- and **Xavier Sala-i-Martin**, “Convergence,” *Journal of Political Economy*, April 1992, 100 (2), 223–251.
- Bartelsman, Eric J. and Wayne Gray**, “The NBER Manufacturing Productivity Database,” October 1996. NBER Technical Working Paper 205.
- Bernanke, Ben and Refet Gurkaynak**, “Is Growth Exogenous? Taking Mankiw, Romer, and Weil Seriously,” *NBER Macroeconomics Annual*, 2001, 16, 11–57.
- Bernard, Andrew B. and Charles I. Jones**, “Technology and Convergence,” *Economic Journal*, July 1996a, 106, 1037–1044.
- and —, “Comparing Apples to Oranges: Productivity Convergence and Measurement Across Industries and Countries,” *American Economic Review*, December 1996b, 86, 1216–1238.
- Berthelon, Matias and Caroline Freund**, “On the Conservation of Distance in International Trade,” *Journal of International Economics*, July 2008, 75 (2), 310–320.
- Brezis, Elise S., Paul R. Krugman, and Daniel Tsiddon**, “Leapfrogging in International Competition: A Theory of Cycles in National Technological Leadership,” *American Economic Review*, December 1993, 83 (5), 1211–1019.
- Burstein, Ariel and Jonathan Vogel**, “Globalization, Technology, and the Skill Premium,” October 2009. mimeo, UCLA and Columbia University.
- Caliendo, Lorenzo and Fernando Parro**, “Estimates of the Trade and Welfare Effects of NAFTA,” January 2010. mimeo, University of Chicago.
- Carrère, Céline, Olivier Cadot, and Vanessa Strauss-Kahn**, “Export Diversification: What’s behind the Hump?,” November 2009. Forthcoming, *Review of Economics and Statistics*.
- Caselli, Francesco**, “Accounting for Cross-Country Income Differences,” in Steven Durlauf Philippe Aghion, ed., *Handbook of Economic Growth*, Vol. 1, Elsevier-North Holland, 2005, chapter 9, pp. 679–741.
- and **James Feyrer**, “The Marginal Product of Capital,” *Quarterly Journal of Economics*, May 2007, 122 (2), 535–568.
- Chor, Davin**, “Unpacking Sources of Comparative Advantage: A Quantitative Approach,” June 2010. Forthcoming, *Journal of International Economics*.
- Costinot, Arnaud and Ivana Komunjer**, “What Goods Do Countries Trade? A Structural Ricardian Model,” November 2008. Mimeo, MIT and U.C. San Diego.
- di Giovanni, Julian and Andrei A. Levchenko**, “Putting the Parts Together: Trade, Vertical Linkages, and Business Cycle Comovement,” *American Economic Journal: Macroeconomics*, April 2010, 2 (2), 95–124.
- Do, Quy-Toan and Andrei A. Levchenko**, “Comparative Advantage, Demand for External Finance, and Financial Development,” *Journal of Financial Economics*, December 2007, 86 (3).
- Eaton, Jonathan and Samuel Kortum**, “Technology, Geography, and Trade,” *Econometrica*, September 2002, 70 (5), 1741–1779.

- , **Sam Kortum**, **Brent Neiman**, and **John Romalis**, “Trade and the Global Recession,” July 2010. mimeo, Penn State University and University of Chicago.
- Finicelli, Andrea**, **Patrizio Pagano**, and **Massimo Sbracia**, “Ricardian Selection,” October 2009a. Bank of Italy *Temi di Discussione* (Working Paper) No. 728.
- , —, and —, “Trade-revealed TFP,” October 2009b. Bank of Italy *Temi di Discussione* (Working Paper) No. 729.
- Hall, Robert** and **Charles Jones**, “Why Do Some Countries Produce So Much More Output per Worker than Others,” *Quarterly Journal of Economics*, 1999, 114, 83–116.
- Hausmann, Ricardo** and **Bailey Klinger**, “The Structure of the Product Space and the Evolution of Comparative Advantage,” April 2007. CID Working Paper No. 146.
- Heston, Alan**, **Robert Summers**, and **Bettina Aten**, “Penn World Table Version 6.1,” October 2002. Center for International Comparisons at the University of Pennsylvania (CICUP).
- Hicks, John**, “An Inaugural Lecture,” *Oxford Economic Papers*, 1953, 5 (2), 117–135.
- Hsieh, Chang-Tai** and **Ralph Ossa**, “A global view of productivity growth in China,” June 2010. mimeo, University of Chicago.
- Hummels, David**, **Jun Ishii**, and **Kei-Mu Yi**, “The Nature and Growth of Vertical Specialization in World Trade,” *Journal of International Economics*, June 2001, 54, 75–96.
- Hymans, Saul H.** and **Frank P. Stafford**, “Divergence, Convergence, and the Gains from Trade,” *Review of International Economics*, 1995, 3 (1), 118–123.
- Imbs, Jean** and **Romain Wacziarg**, “Stages of Diversification,” *American Economic Review*, March 2003, 93 (1), 63–86.
- Jones, Ronald**, “Technical Progress and Real Income in a Ricardian Trade Model,” in Ronald Jones, ed., *International Trade: Essays in Theory*, Amsterdam: North-Holland, 1979.
- Keller, Wolfgang**, “International Technology Diffusion,” *Journal of Economic Literature*, September 2004, 42 (3), 752–782.
- Klenow, Peter J.** and **Andrés Rodríguez-Clare**, “The Neoclassical Revival in Growth Economics: Has It Gone Too Far?,” *NBER Macroeconomics Annual*, 1997, 12, 73–103.
- Krugman, Paul**, “A Model of Innovation, Technology Transfer, and the World Distribution of Income,” *Journal of Political Economy*, April 1979, 87 (2), 253–66.
- Proudman, James** and **Stephen Redding**, “Evolving Patterns of International Trade,” *Review of International Economics*, 2000, 8 (3), 373–396.
- Quah, Danny**, “Galton’s Fallacy and Tests of the Convergence Hypothesis,” *Scandinavian Journal of Economics*, December 1993, 95 (4), 427–443.
- Rose, Andrew K.**, “Do We Really Know That the WTO Increases Trade?,” *American Economic Review*, March 2004, 94 (1), 98–114.
- Samuelson, Paul A.**, “Where Ricardo and Mill Rebut and Confirm Arguments of Mainstream Economists Supporting Globalization,” *Journal of Economic Perspectives*, 2004, 18 (3), 135–146.
- Shikher, Serge**, “Putting industries into the Eaton-Kortum model,” July 2004. mimeo, Suffolk University.
- , “Accounting for International Trade,” August 2005. mimeo, Suffolk University.

—, “Capital, technology, and specialization in the neoclassical model,” February 2009. mimeo, Suffolk University.

Waugh, Michael, “International Trade and Income Differences,” 2009. Forthcoming, *American Economic Review*.

Yi, Kei-Mu and Jing Zhang, “Structural Change in an Open Economy,” April 2010. Mimeo, Federal Reserve Bank of Philadelphia and University of Michigan.

Table 1. Summary Statistics

	OECD			Non-OECD		
	Mean $T^{1/\theta}$	Top2/bottom2 $T^{1/\theta}$	Countries	Mean $T^{1/\theta}$	Top2/bottom2 $T^{1/\theta}$	Countries
1960s	0.651	1.502	21	0.453	2.066	33
1970s	0.692	1.434	21	0.471	1.775	37
1980s	0.776	1.412	22	0.509	1.922	42
1990s	0.808	1.395	22	0.378	2.136	53
2000s	0.838	1.394	22	0.410	2.088	53

Notes: This table reports the summary statistics for the average productivity relative to the frontier (mean $T^{1/\theta}$), the relative productivity of the two most productive tradeable sectors relative to the 2 least productive ones (top2/bottom2 $T^{1/\theta}$), 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 2. Average Convergence: Fastest and Slowest Countries

Since 1960s		Since 1980s	
Top 10: Fastest Converging Countries		Top 10: Fastest Converging Countries	
Iceland	0.618	Portugal	0.373
Norway	0.615	Greece	0.364
Korea, Rep.	0.566	Ireland	0.315
Ireland	0.525	Norway	0.258
Netherlands	0.449	Iceland	0.240
Finland	0.445	Korea, Rep.	0.240
Israel	0.384	Belgium-Luxembourg	0.182
Greece	0.382	Mauritius	0.162
Portugal	0.347	United Kingdom	0.159
Germany	0.337	Finland	0.138
Bottom 10: Slowest Converging Countries		Bottom 10: Slowest Converging Countries	
Malaysia	-0.163	Senegal	-0.226
Philippines	-0.166	Argentina	-0.236
Canada	-0.183	Brazil	-0.237
Turkey	-0.259	Peru	-0.270
Thailand	-0.271	India	-0.332
Venezuela, RB	-0.276	Iran, Islamic Rep.	-0.348
Honduras	-0.337	Venezuela, RB	-0.366
India	-0.358	Ethiopia	-0.395
Egypt, Arab Rep.	-0.372	Egypt, Arab Rep.	-0.405
Sri Lanka	-0.419	Honduras	-0.428

Notes: This table reports the 10 fastest and 10 slowest converging countries since the 1960s (left panel) and the 1980s (right panel), measured by the percent change in the mean absolute distance to the frontier across all tradeable sectors.

Table 3. Relative Convergence: Fastest and Slowest Countries

Since 1960s		Since 1980s	
Top 10: Fastest Converging Countries		Top 10: Fastest Converging Countries	
Norway	-0.654	Norway	-0.534
Indonesia	-0.396	Sweden	-0.379
Finland	-0.379	Greece	-0.264
Sweden	-0.343	Denmark	-0.231
Spain	-0.333	Iceland	-0.199
Korea, Rep.	-0.327	Finland	-0.185
Denmark	-0.299	Spain	-0.172
Belgium-Luxembourg	-0.290	Chile	-0.142
Iceland	-0.286	Germany	-0.133
Ireland	-0.271	Costa Rica	-0.111
Bottom 10: Slowest Converging Countries		Bottom 10: Slowest Converging Countries	
India	0.132	Trinidad and Tobago	0.301
Kenya	0.154	Saudi Arabia	0.308
Honduras	0.185	Italy	0.317
Thailand	0.260	El Salvador	0.352
Egypt, Arab Rep.	0.300	Canada	0.352
South Africa	0.315	Australia	0.419
Ghana	0.353	Venezuela, RB	0.584
Japan	0.448	Egypt, Arab Rep.	0.761
Canada	0.485	Iran, Islamic Rep.	0.785
Sri Lanka	0.744	Japan	0.880

Notes: This table reports the 10 fastest and 10 slowest converging countries since the 1960s (left panel) and the 1980s (right panel), measured by the percent change in the coefficient of variation across tradeable sectors in the distance to the frontier.

Table 4. Correlations Between Convergence Measures, Per Capita Income Growth, and Changes in Openness

Since the 1960s				
	Pct Chg in Average Abs. Distance	Pct Chg in Coeff. Var. of $T^{1/\theta}$	Pct Chg in Real Per Capita Income	Pct Chg in Trade Openness
Pct Chg in Average Abs. Distance	<i>0.270</i>			
Pct Chg in Coeff. Var. of $T^{1/\theta}$	-0.642	<i>0.263</i>		
Pct Chg in Real Per Capita Income	0.238	-0.140	<i>1.483</i>	
Pct Chg in Trade Openness	-0.293	-0.074	0.303	<i>0.981</i>
Since the 1980s				
	Average Abs. Distance	Pct Chg in Coeff. Var. of $T^{1/\theta}$	Pct Chg in Real Per Capita Income	Pct Chg in Trade Openness
Pct Chg in Average Abs. Distance	<i>0.195</i>			
Pct Chg in Coeff. Var. of $T^{1/\theta}$	-0.608	<i>0.263</i>		
Pct Chg in Real Per Capita Income	0.260	-0.052	<i>0.545</i>	
Pct Chg in Trade Openness	-0.331	0.048	0.121	<i>0.504</i>

Notes: This table reports the correlation coefficients (off-diagonal elements), and standard deviations (diagonal elements, in italics) between the measure of average convergence (Pct Chg in Average Abs. Distance), relative convergence (Pct Chg in Coeff. Var. of T), real PPP-adjusted per capita income, and overall trade openness. The latter two measures come from the Penn World Tables 6.3.

Table 5. Pooled Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var: Log Change in $T^{1/\theta}$	1960s to 2000s	1980s to 2000s	1960s to 1970s	1970s to 1980s	1980s to 1990s	1990s to 2000s
Panel A: All Countries						
Log(Initial $T^{1/\theta}$)	-0.618*** (0.046)	-0.220*** (0.030)	-0.254*** (0.029)	-0.168*** (0.027)	-0.195*** (0.029)	-0.152*** (0.040)
<i>NB:</i>						
<i>Speed of convergence, per decade</i>	<i>0.241</i>	<i>0.124</i>	<i>0.293</i>	<i>0.184</i>	<i>0.217</i>	<i>0.165</i>
Observations	929	1,122	991	1,074	1,183	1,335
R-squared	0.844	0.833	0.851	0.841	0.897	0.863
Panel B: OECD						
Log(Initial $T^{1/\theta}$)	-0.723*** (0.092)	-0.414*** (0.063)	-0.269*** (0.042)	-0.145*** (0.036)	-0.258*** (0.048)	-0.174*** (0.074)
<i>NB:</i>						
<i>Speed of convergence, per decade</i>	<i>0.321</i>	<i>0.267</i>	<i>0.313</i>	<i>0.157</i>	<i>0.298</i>	<i>0.191</i>
Observations	393	405	396	394	407	410
R-squared	0.860	0.847	0.874	0.839	0.799	0.834
Panel C: non-OECD						
Log(Initial $T^{1/\theta}$)	-0.731*** (0.056)	-0.269*** (0.046)	-0.378*** (0.041)	-0.227*** (0.040)	-0.264*** (0.042)	-0.206*** (0.054)
<i>NB:</i>						
<i>Speed of convergence, per decade</i>	<i>0.328</i>	<i>0.157</i>	<i>0.475</i>	<i>0.257</i>	<i>0.307</i>	<i>0.231</i>
Observations	536	717	595	680	776	925
R-squared	0.851	0.813	0.868	0.853	0.901	0.873
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 5%. This table reports the results of regressing the growth of estimated technology parameter ($T_t^{1/\theta}$) 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 6. Model Fit: Wages, Return to Capital, and Imports/GDP in the Model and the Data

		model	data
w :			
	mean	0.381	0.333
	median	0.125	0.145
	corr(model, data)	0.987	
r :			
	mean	0.830	0.919
	median	0.632	0.698
	corr(model, data)	0.918	
Imports/GDP:			
	mean	0.222	0.237
	median	0.212	0.200
	corr(model, data)	0.739	

Notes: This table reports the means and medians of imports as a share of GDP, wages relative to the U.S. (middle panel) and return to capital relative to the U.S., in the model and in the data. In the data, Imports/GDP are the manufacturing imports as a share of GDP in the 2000s, sourced from the World Bank's World Development Indicators. Wages and return to capital in the data are calculated as described in detail in the main text.

Table 7. Welfare in the Single-Country Counterfactual Relative to Baseline

	(1)	(2)	(3)	(4)	(5)
	Median	St. Dev.	Min	Max	Countries
Welfare gains in the counterfactual relative to baseline					
OECD	0.017	0.018	-0.005	0.056	22
Non-OECD	0.019	0.055	-0.093	0.270	53
<i>NB</i> : Overall gains from trade					
OECD	0.052	0.032	0.011	0.120	
Non-OECD	0.044	0.029	0.005	0.122	

Notes: This table reports the percentage change in welfare under the counterfactual scenario with respect to the baseline. The counterfactual assumes that for each individual country, comparative advantage remained as it was in the 1960s, while its T 's grew at the same country-specific average rate between the 1960s and the 2000s. All other countries' comparative advantage is taken from the data. In the baseline comparative advantage is as it is in the data for the 2000s. The lower panel reports the total gains from trade relative to autarky in the baseline for the 2000s

Table 8. Welfare in the Global Counterfactual Relative to Baseline

	(1)	(2)	(3)	(4)	(5)
	Median	St. Dev.	Min	Max	Countries
Welfare gains in the counterfactual relative to baseline					
<i>Panel A: CA fixed to 1960s in all countries</i>					
OECD	0.012	0.013	-0.008	0.038	22
Non-OECD	0.006	0.050	-0.097	0.223	53
<i>Panel B: CA fixed to 1960s in OECD countries only</i>					
OECD	0.013	0.014	-0.008	0.041	
Non-OECD	0.000	0.002	-0.005	0.007	
<i>Panel C: CA fixed to 1960s in non-OECD countries only</i>					
OECD	0.000	0.002	-0.002	0.006	
Non-OECD	0.013	0.054	-0.097	0.257	

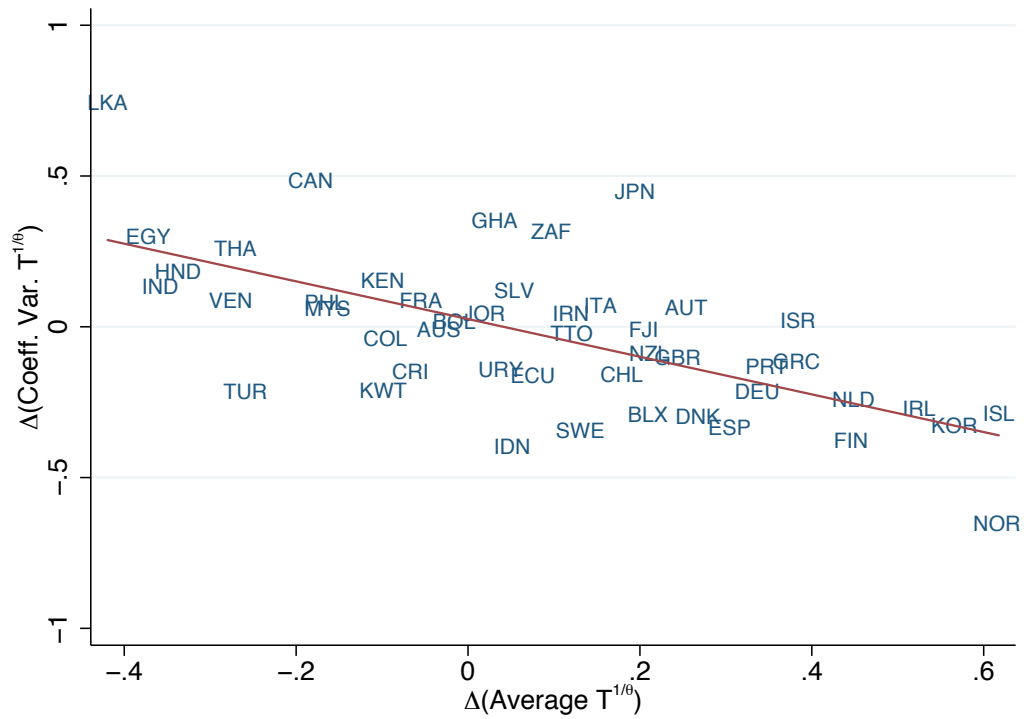
Notes: This table reports the percentage change in welfare under the counterfactual scenario with respect to the baseline. The counterfactual assumes that in all countries in the world (Panel A), in OECD (Panel B) and the non-OECD (Panel C), comparative advantage remained as it was in the 1960s, while its T 's grew at the same country-specific average rate between the 1960s and the 2000s. In the baseline comparative advantage is as it is in the data for the 2000s.

Table 9. Trade Volumes in the Counterfactuals Relative to Baseline

	(1)	(2)	(3)	(4)	(5)
	Median	St. Dev.	Min	Max	Countries
Absolute change in imports/GDP in the counterfactual relative to baseline					
<i>Panel A: Country-by-country counterfactual</i>					
OECD	0.019	0.039	-0.008	0.128	22
Non-OECD	0.042	0.079	-0.070	0.430	53
<i>Panel B: Global counterfactual</i>					
OECD	0.018	0.015	-0.004	0.048	
Non-OECD	0.026	0.039	-0.042	0.169	

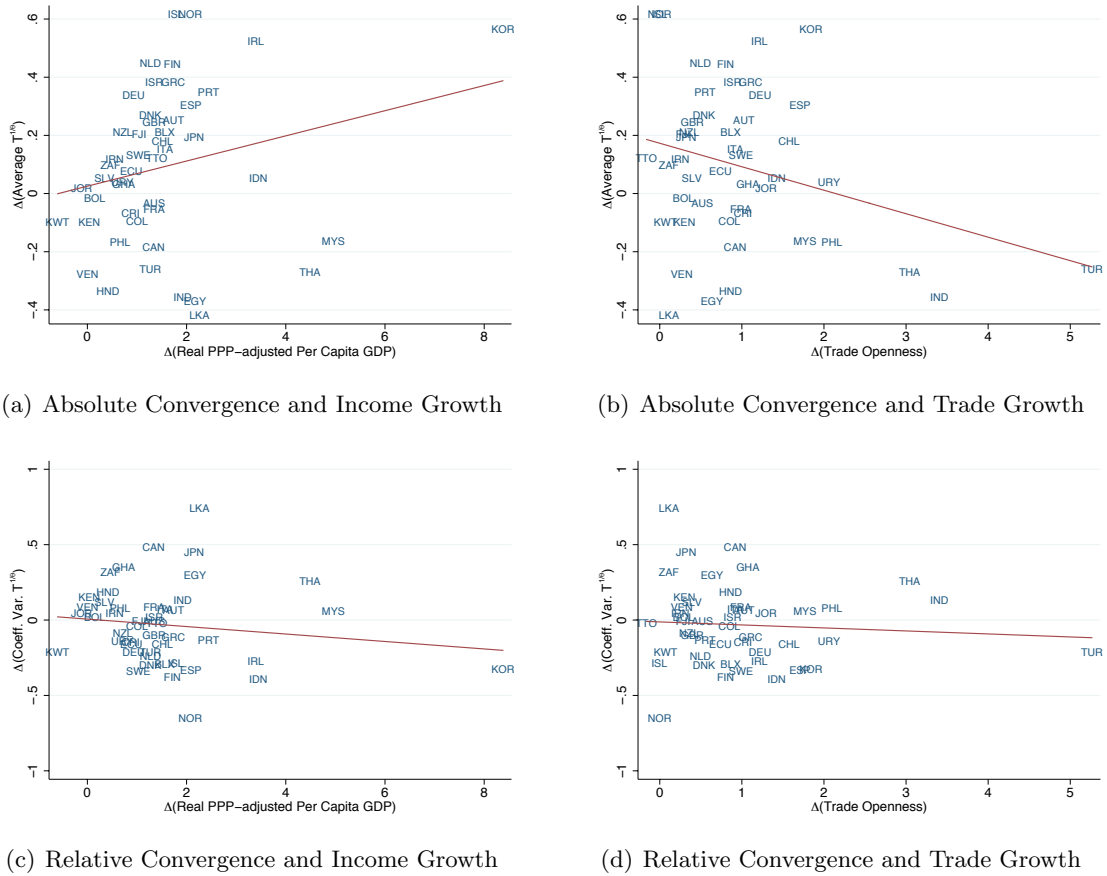
Notes: This table reports the absolute change in imports/GDP under the counterfactual scenarios with respect to the baseline. In Panel A, the counterfactual scenario assumes that a single country's comparative advantage is the same as in the 1960s, and evaluates the impact of this change for that country's trade volumes. In Panel B, the counterfactual scenario assumes that comparative advantage is fixed to the 1960s in every country in the world, and reports the summary statistics for the change in trade volumes in this sample of countries.

Figure 1. Absolute and Relative Convergence, 1960s – 2000s



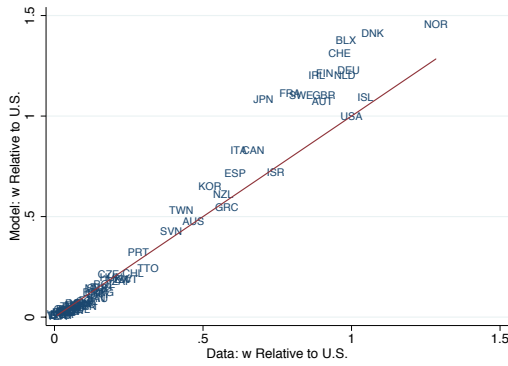
Notes: This figure displays the percentage change in a country's average distance to the world frontier (horizontal axis) against the percentage change in the coefficient of variation in distances to frontier across sectors (vertical axis), along with the least squares fit through the data.

Figure 2. Convergence, Income Growth, and Changes in Trade Openness, 1960s to 2000s

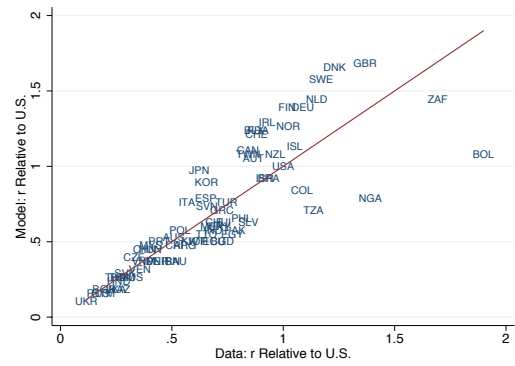


Notes: This figure presents the bivariate plots of absolute (top row) and relative convergence (bottom row), against contemporaneous changes in PPP-adjusted real per capita GDP and changes in trade openness (Imports + Exports)/GDP.

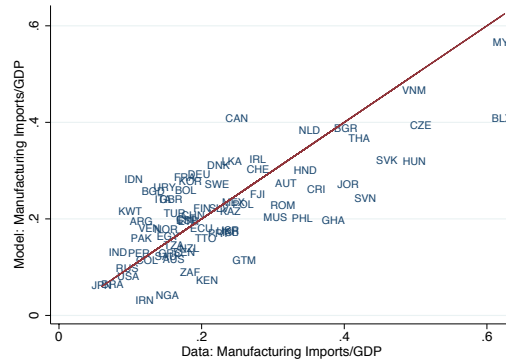
Figure 3. Model vs. Data: Wages, Return to Capital, and Trade Openness



(a) Wages



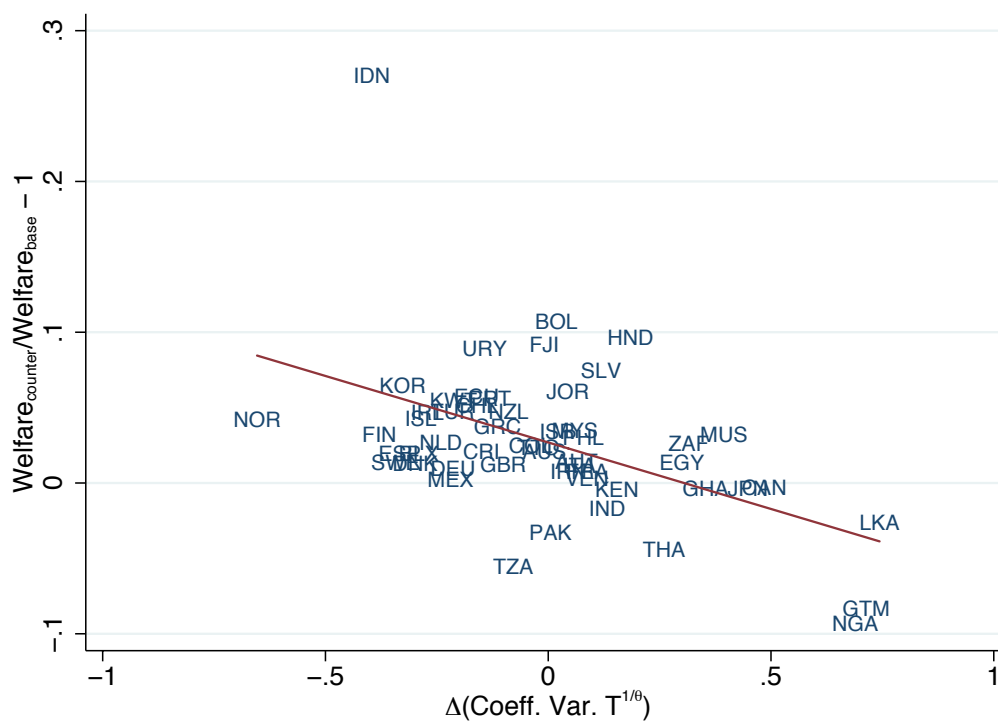
(b) Return to Capital



(c) Imports/GDP

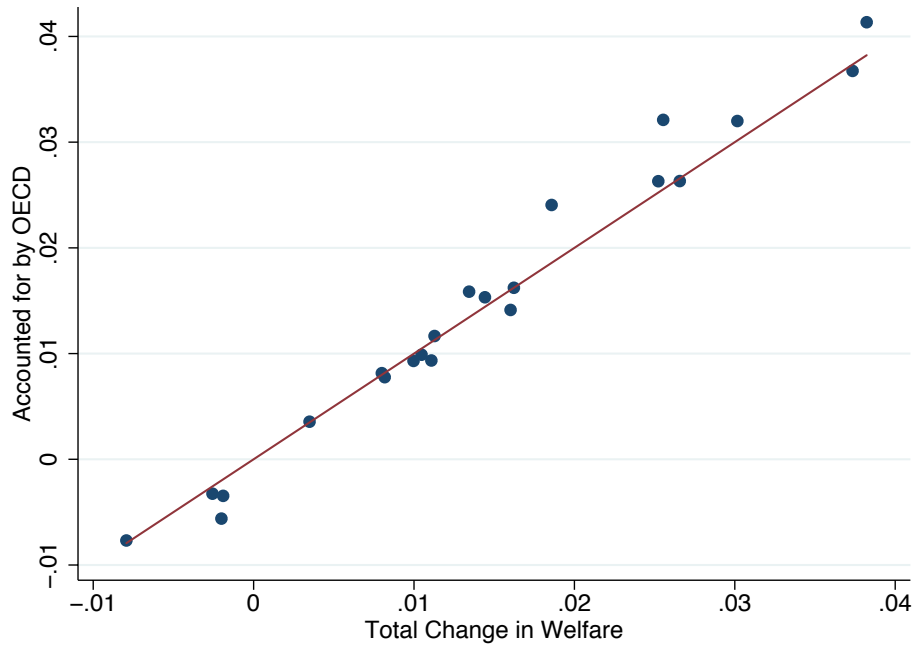
Notes: This figure presents the scatterplots of wages, return to capital, and manufacturing imports/GDP, for the model (y-axis) against the data (x-axis).

Figure 4. Welfare Changes and Relative Convergence

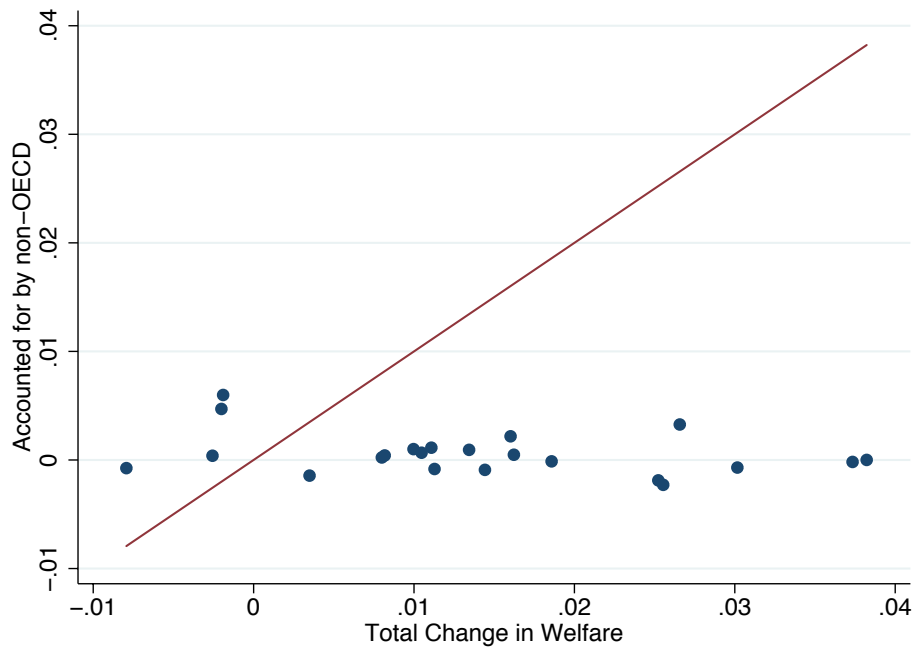


Notes: This figure displays the percentage change in a country's welfare in the counterfactual scenario in which its comparative advantage was fixed at its 1960s value relative to the baseline (y-axis), against the change in the coefficient of variation in the country's $T^{1/\theta}$ between the 1960s and the 2000s (x-axis). A larger value of the x-axis variable implies that comparative advantage has gotten stronger. A negative value implies that comparative advantage has gotten weaker.

Figure 5. Welfare Changes for OECD Countries



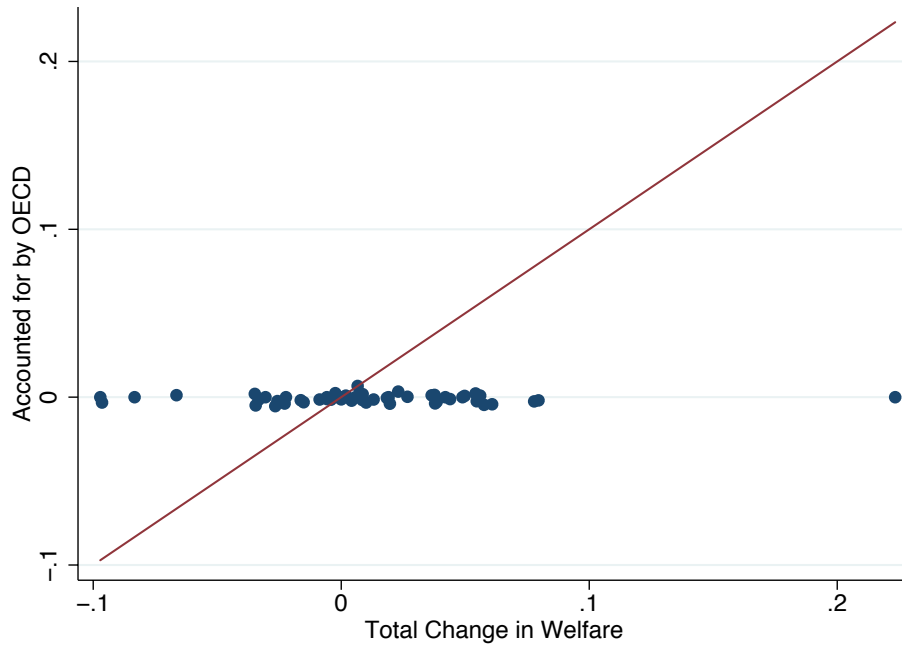
(a) Accounted for by OECD



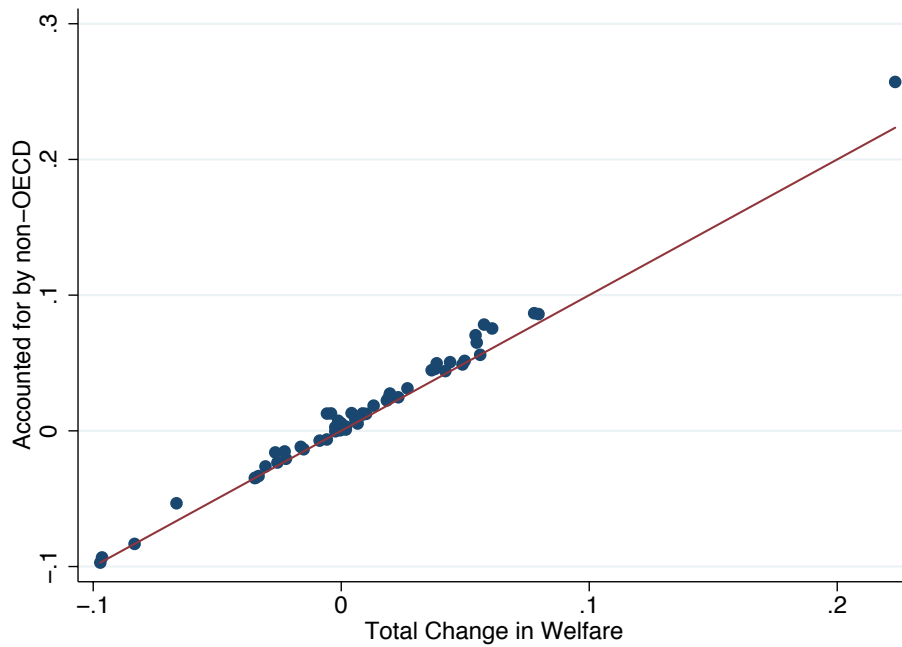
(b) Accounted for by non-OECD

Notes: This figure plots, for the OECD countries, the total welfare change in the counterfactual on the x-axis against the welfare change due to comparative advantage changes in the OECD only (top panel), and the non-OECD only (bottom panel). The straight line is the 45-degree line.

Figure 6. Welfare Changes for Non-OECD Countries



(a) Accounted for by OECD



(b) Accounted for by non-OECD

Notes: This figure plots, for the non-OECD countries, the total welfare change in the counterfactual on the x-axis against the welfare change due to comparative advantage changes in the OECD only (top panel), and the non-OECD only (bottom panel). The straight line is the 45-degree line.

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	Iran, Islamic Rep.	1960s–2000s
		Israel	1960s–2000s
		Jordan	1960s–2000s
		Kazakhstan	1990s–2000s
		Kenya	1960s–2000s
		Korea, Rep.	1960s–2000s
		Kuwait	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
		Saudi Arabia	1980s–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	0.303	0.209
16	Tobacco Products	0.264	0.520	0.527	0.010
17	Textiles	0.467	0.371	0.295	0.025
18	Wearing Apparel, Fur	0.493	0.377	0.320	0.089
19	Leather, Leather Products, Footwear	0.485	0.359	0.330	0.014
20	Wood Products (Excl. Furniture)	0.452	0.372	0.288	0.009
21	Paper and Paper Products	0.366	0.344	0.407	0.012
22	Printing and Publishing	0.484	0.469	0.407	0.004
23	Coke, Refined Petroleum Products, Nuclear Fuel	0.244	0.243	0.246	0.092
24	Chemical and Chemical Products	0.308	0.373	0.479	0.008
25	Rubber and Plastics Products	0.385	0.387	0.350	0.014
26	Non-Metallic Mineral Products	0.365	0.459	0.499	0.071
27	Basic Metals	0.381	0.299	0.451	0.002
28	Fabricated Metal Products	0.448	0.398	0.364	0.012
29C	Office, Accounting, Computing, and Other Machinery	0.473	0.390	0.388	0.094
31A	Electrical Machinery, Communication Equipment	0.405	0.380	0.416	0.057
33	Medical, Precision, and Optical Instruments	0.456	0.428	0.441	0.036
34A	Transport Equipment	0.464	0.343	0.286	0.175
36	Furniture and Other Manufacturing	0.460	0.407	0.397	0.065
4A	Nontradeables	0.561	0.651	0.788	
	Mean	0.414	0.393	0.399	0.053
	Min	0.244	0.243	0.246	0.002
	Max	0.561	0.651	0.788	0.209

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 non-tradeable inputs in total intermediate inputs; ω_j is the taste parameter for tradeable sector j , estimated using the procedure described in Section 3.2. Variable definitions and sources are described in detail in the text.

Table A3. Country-by-Country Estimates Relative Convergence, 1960s to 2000s

Country	β	s.e.	Obs.	R ²	Speed of Convergence, by decade
United Kingdom	-0.831***	0.188	19	0.469	0.444
Austria	-0.964**	0.336	19	0.450	0.828
Belgium-Luxembourg	-0.872***	0.188	19	0.660	0.515
Denmark	-1.025***	0.166	19	0.692	–
France	-0.738***	0.198	19	0.343	0.335
Germany	-0.753***	0.138	19	0.527	0.350
Italy	-0.320	0.208	19	0.160	0.096
Netherlands	-0.772***	0.182	19	0.563	0.370
Norway	-1.028***	0.062	19	0.917	–
Sweden	-0.890***	0.178	18	0.544	0.552
Canada	-0.293	0.275	19	0.046	0.087
Japan	-0.831**	0.304	18	0.296	0.444
Finland	-0.684**	0.275	19	0.607	0.288
Greece	-0.507**	0.189	19	0.343	0.177
Iceland	-0.588**	0.215	15	0.439	0.222
Ireland	-1.280***	0.117	19	0.795	–
Portugal	-0.435**	0.180	19	0.306	0.143
Spain	-0.424***	0.106	19	0.626	0.138
Turkey	-0.379***	0.128	18	0.350	0.119
Australia	-0.242	0.166	19	0.110	0.069
New Zealand	-0.199	0.126	19	0.165	0.055
South Africa	-0.046	0.295	18	0.002	0.012
Bolivia	-0.368***	0.123	17	0.319	0.115
Chile	-0.303***	0.102	19	0.241	0.090
Colombia	-0.308*	0.148	19	0.178	0.092
Costa Rica	-0.441**	0.152	17	0.302	0.145
Ecuador	-0.259***	0.088	19	0.228	0.075
El Salvador	-0.265*	0.131	18	0.097	0.077
Honduras	-0.394*	0.216	17	0.144	0.125
Mexico	-0.577**	0.193	13	0.391	0.215
Uruguay	-0.270**	0.113	19	0.285	0.079
Venezuela, RB	-0.309	0.181	19	0.222	0.093
Trinidad and Tobago	-0.382	0.264	17	0.207	0.120
Iran, Islamic Rep.	-0.461*	0.234	19	0.158	0.155
Israel	-0.273	0.243	18	0.107	0.080
Jordan	-0.521**	0.204	18	0.284	0.184
Kuwait	-0.688***	0.173	17	0.514	0.291
Egypt, Arab Rep.	-0.328*	0.158	19	0.089	0.099
Sri Lanka	0.252	0.247	19	0.068	-0.056
India	-0.326*	0.186	19	0.117	0.099
Indonesia	-0.615***	0.162	16	0.553	0.239
Korea, Rep.	-0.801***	0.135	19	0.628	0.404
Malaysia	-0.708***	0.192	19	0.308	0.308
Pakistan	-0.379**	0.147	8	0.265	0.119
Philippines	-0.582**	0.217	19	0.291	0.218
Thailand	-1.151*	0.579	14	0.382	–
Ghana	-0.041	0.203	18	0.002	0.010
Kenya	-0.173	0.188	17	0.035	0.048
Mauritius	-0.108	0.246	15	0.010	0.028
Tanzania	-0.612**	0.227	12	0.419	0.237
Fiji	-0.269*	0.150	15	0.091	0.078

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 $(T_n^j)^{1/\theta}$ 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 A4. Country-by-Country Estimates Relative Convergence, 1980s to 2000s

Country	β	s.e.	Obs.	R ²	Speed of Convergence, by decade
United Kingdom	-0.836***	0.203	19	0.478	0.904
Austria	-0.617*	0.316	19	0.354	0.480
Belgium-Luxembourg	-0.841***	0.219	19	0.489	0.919
Denmark	-0.778***	0.188	19	0.516	0.754
France	-1.164***	0.222	19	0.493	–
Germany	-0.698***	0.172	19	0.451	0.598
Italy	-0.303	0.355	19	0.074	0.181
Netherlands	-0.465**	0.217	19	0.244	0.312
Norway	-0.856***	0.108	19	0.781	0.969
Sweden	-0.519***	0.114	18	0.514	0.366
Switzerland	-1.106***	0.177	13	0.687	–
Canada	-0.516*	0.280	19	0.138	0.363
Japan	0.156	0.300	19	0.012	-0.073
Finland	-0.419*	0.212	19	0.343	0.271
Greece	-0.432***	0.128	19	0.531	0.283
Iceland	-0.706**	0.287	13	0.534	0.613
Ireland	-0.797**	0.313	19	0.320	0.797
Portugal	-0.230**	0.081	19	0.160	0.131
Spain	-0.401*	0.200	19	0.390	0.257
Turkey	-0.079	0.078	19	0.023	0.041
Australia	-0.015	0.255	19	0.000	0.008
New Zealand	0.022	0.171	19	0.001	-0.011
South Africa	-0.120	0.176	18	0.030	0.064
Argentina	-0.017	0.087	19	0.001	0.008
Bolivia	0.008	0.079	19	0.001	-0.004
Brazil	-0.273	0.250	16	0.131	0.160
Chile	-0.222**	0.081	19	0.252	0.125
Colombia	0.019	0.115	19	0.003	-0.010
Costa Rica	-0.356**	0.129	17	0.243	0.220
Ecuador	-0.222	0.136	19	0.126	0.125
El Salvador	0.023	0.240	18	0.001	-0.011
Honduras	-0.275	0.174	19	0.095	0.161
Mexico	-0.395*	0.189	18	0.165	0.251
Peru	0.150	0.100	19	0.099	-0.070
Uruguay	-0.137*	0.072	19	0.203	0.073
Venezuela, RB	0.249	0.187	19	0.072	-0.111
Trinidad and Tobago	0.031	0.154	18	0.002	-0.015
Iran, Islamic Rep.	0.536*	0.295	19	0.153	-0.215
Israel	0.094	0.124	18	0.032	-0.045
Jordan	-0.056	0.173	19	0.006	0.029
Kuwait	-0.259	0.201	17	0.091	0.150
Saudi Arabia	0.020	0.414	18	0.000	-0.010
Egypt, Arab Rep.	0.389	0.241	19	0.133	-0.164
Bangladesh	-0.024	0.146	17	0.002	0.012
Sri Lanka	0.031	0.063	19	0.008	-0.015
Taiwan Province of China	-0.115	0.258	19	0.014	0.061
India	-0.059	0.212	19	0.005	0.030
Indonesia	-0.241*	0.124	19	0.166	0.138
Korea, Rep.	-0.533*	0.282	19	0.235	0.380
Malaysia	-0.118	0.231	19	0.012	0.063
Pakistan	-0.188	0.253	8	0.074	0.104
Philippines	-0.158	0.229	19	0.024	0.086
Thailand	0.161	0.268	15	0.022	-0.075
Ethiopia	-0.246*	0.136	17	0.183	0.141
Ghana	-0.200	0.139	18	0.075	0.112
Kenya	0.068	0.124	17	0.015	-0.033
Mauritius	-0.019	0.130	18	0.001	0.010
Senegal	0.086	0.160	17	0.013	-0.041
Tanzania	0.157	0.292	12	0.044	-0.073
Fiji	-0.124	0.157	16	0.027	0.066
China	-0.160	0.190	19	0.037	0.087

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 $(T_n^j)^{1/\theta}$ over the period from the 1980s 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. $\theta = 4$: Pooled Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var: Log Change in $T^{1/\theta}$	1960s to 2000s	1980s to 2000s	1960s to 1970s	1970s to 1980s	1980s to 1990s	1990s to 2000s
$\text{Log}(\text{Initial}T^{1/\theta})$	-0.665*** (0.045)	-0.265*** (0.031)	-0.278*** (0.030)	-0.176*** (0.025)	-0.230*** (0.029)	-0.141*** (0.039)
<i>NB:</i>				Panel A: All Countries		
<i>Speed of convergence, per decade</i>	<i>0.273</i>	<i>0.154</i>	<i>0.326</i>	<i>0.194</i>	<i>0.261</i>	<i>0.152</i>
Observations	929	1,122	991	1,074	1,183	1,335
R ²	0.680	0.647	0.678	0.666	0.743	0.672
				Panel B: OECD		
$\text{Log}(\text{Initial}T^{1/\theta})$	-0.730*** (0.094)	-0.406*** (0.071)	-0.267*** (0.043)	-0.155*** (0.031)	-0.247*** (0.046)	-0.176*** (0.072)
<i>NB:</i>						
<i>Speed of convergence, per decade</i>	<i>0.327</i>	<i>0.260</i>	<i>0.311</i>	<i>0.168</i>	<i>0.284</i>	<i>0.194</i>
Observations	393	405	396	394	407	410
R ²	0.755	0.709	0.785	0.662	0.627	0.673
				Panel C: non-OECD		
$\text{Log}(\text{Initial}T^{1/\theta})$	-0.739*** (0.054)	-0.295*** (0.044)	-0.398*** (0.041)	-0.220*** (0.034)	-0.285*** (0.040)	-0.173*** (0.053)
<i>NB:</i>						
<i>Speed of convergence, per decade</i>	<i>0.336</i>	<i>0.175</i>	<i>0.507</i>	<i>0.248</i>	<i>0.335</i>	<i>0.190</i>
Observations	536	717	595	680	776	925
R ²	0.733	0.632	0.708	0.687	0.754	0.683
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 5%. This table reports the results of regressing the growth of estimated technology parameter $(T_n^i)^{1/\theta}$ on its initial value over different time periods and subsamples. The values of $(T_n^i)^{1/\theta}$ are estimated under the assumption that $\theta = 4$. The speed of convergence, per decade, is reported (in italics) underneath each coefficient estimate.

Table A6. $\theta = 4$: Welfare in the Single-Country Counterfactual Relative to Baseline

	(1)	(2)	(3)	(4)	(5)
	Median	St. Dev.	Min	Max	Countries
Welfare gains in the counterfactual relative to baseline					
OECD	0.014	0.025	-0.018	0.086	22
Non-OECD	0.045	0.106	-0.098	0.602	53
<i>NB</i> : Overall gains from trade					
OECD	0.112	0.072	0.020	0.266	
Non-OECD	0.086	0.057	0.010	0.258	

Notes: This table reports the percentage change in welfare under the counterfactual scenario with respect to the baseline, under the assumption that $\theta = 4$. The counterfactual assumes that for each individual country, comparative advantage remained as it was in the 1960s, while its T 's grew at the same country-specific average rate between the 1960s and the 2000s. All other countries' comparative advantage is taken from the data. In the baseline comparative advantage is as it is in the data for the 2000s. The lower panel reports the total gains from trade relative to autarky in the baseline for the 2000s

Table A7. $\theta = 4$: Welfare in the Global Counterfactual Relative to Baseline

	(1)	(2)	(3)	(4)	(5)
	Median	St. Dev.	Min	Max	Countries
Welfare gains in the counterfactual relative to baseline					
<i>Panel A: CA fixed to 1960s in all countries</i>					
OECD	0.015	0.022	-0.013	0.077	22
Non-OECD	0.031	0.102	-0.129	0.569	53
<i>Panel B: CA fixed to 1960s in OECD countries only</i>					
OECD	0.014	0.024	-0.018	0.080	
Non-OECD	0.000	0.003	-0.010	0.007	
<i>Panel C: CA fixed to 1960s in non-OECD countries only</i>					
OECD	0.001	0.003	-0.002	0.010	
Non-OECD	0.034	0.104	-0.129	0.589	

Notes: This table reports the percentage change in welfare under the counterfactual scenario with respect to the baseline, under the assumption that $\theta = 4$. The counterfactual assumes that in all countries in the world (Panel A), in OECD (Panel B) and the non-OECD (Panel C), comparative advantage remained as it was in the 1960s, while its T 's grew at the same country-specific average rate between the 1960s and the 2000s. In the baseline comparative advantage is as it is in the data for the 2000s.