Structural Development Accounting*

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Abstract

We construct and estimate a unified model combining three of the main sources of cross-country income disparities: differences in factor endowments, barriers to technology adoption and the inappropriateness of frontier technologies to local conditions. The key components are different types of workers, distortions to capital accumulation, directed technical change, costly adoption and spillovers from the world technology frontier. Despite its parsimonious parametrization, our empirical model provides a good fit of GDP data for up to 86 countries in 1970 and 122 countries in 2000. Removing barriers to technology adoption would increase the output per worker of the average non-OECD country relative to the US from 0.19 to 0.61, while increasing skill premia in all countries. Removing barriers to trade in goods amplifies income disparities, induces skill-biased technology adoption and increases skill premia in the majority of countries. These results are reverted if trade liberalization is coupled with international IPR protection.

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1 Introduction

New technologies do not diffuse instantaneously, and adoption lags are considered a major determinant of productivity differences across firms and nations. In a classic paper, Griliches (1957) documents that new more productive seeds of hybrid corn diffused slowly across US agricultural regions, with a 15-year lag between adoption in Iowa and Alabama, and that their diffusion was affected by local conditions, such as geography and market potential. The spread of more recent technologies follows a similar pattern. Kiessling (2009) reports evidence of slow adoption of information and communication technology diffusion both between and within countries. For instance, while personal computers became available in the early 1980s, in 2006 the percentage of the population using computers amounted to 80.6% in US, 36.3% in Spain, 5.6% in China and 2.7% in India. Cross-country studies confirm that technology adoption depends both on country-specific factors and on characteristics of new technologies. For example, a McKinsey (2001) report on India mentions among the main sources of inefficiencies the fact that firms are too small to benefit from the best technologies and that these may require skills that the country does not possess. The importance of local economic conditions is also stressed by Caselli and Wilson (2004), who show that countries import technologies complementing their abundant factors, and by Ciccone and Papaioannou (2009), who find that human capital fosters the adoption of skilled-labor augmenting technologies. At the aggregate level, there is evidence that differences in technology are a key determinant of cross-country income disparities. A large body of research measuring total factor productivity (TFP) as the Solow residual of an aggregate production function typically finds the latter to account for roughly 50% of observed differences in output per worker. Beyond being a measure of our ignorance, this residual is nothing but a generic notion of technology, i.e., the mapping from factors to aggregate production.

What all these pieces of evidence suggest is that, if we are to understand income disparities, we need a theory for how different types of technologies are developed and adopted across countries. In turn, this requires unbundling the concept of TFP into a set of heterogeneous technologies and to identify what country-specific factors facilitate the adoption of certain innovations more than others. To this end, a parsimonious description of technology is provided by the following aggregate production function:

$$Y = K^{\alpha}\left(\left[(A_L L)^{\frac{\upsilon-1}{\upsilon}} + (A_H H)^{\frac{\upsilon-1}{\upsilon}}\right]^{\frac{\upsilon}{\upsilon-1}}\right)^{1-\alpha}, \tag{1}$$

were Y, K, H and L are output, physical capital, skilled and unskilled labor, respectively. The state of technology is identified by the parameters A_L and A_H, which measure the efficiency with which the economy uses unskilled and skilled labor, respectively. The parameter v, instead, captures the elasticity of substitution between the two types of workers. Given data on factors and a value for v, any differences in Y can be generated by allowing technology, A_L and A_H, to vary. While accounting exercises based on (1) are certainly useful, the crucial question is to understand *how* technologies are developed and *why* they may differ across countries. Providing a theoretical answer to these questions and confronting it to the data is the main goal of this paper.

Building on Acemoglu and Zilibotti (2001) (henceforth, AZ01) and Gancia and Zilibotti (2009), we propose a theory of directed technical change and technology adoption that yields a micro-founded version of the aggregate production function (1). In the model, an advanced economy, identified with the US and called for simplicity the North, develops endogenously the world technology frontier, represented by the pair (A_{LN}, A_{HN}). As in models of horizontal innovation (see Gancia and Zilibotti (2005) for a survey), the world technology frontier is given by the stock of existing machines and, as in models of directed technical change (e.g., AZ01 and Acemoglu 2002), R&D effort can be devoted to develop H- or L-complement machines.[1] In the benchmark case, we assume that there is no trade in technology – e.g., due to the lack of international protection of intellectual property rights (IPR) – so that new machines are sold in the North only.[2] As a result, the equilibrium skill-bias of the world technology frontier is proportional to the skill-endowment of the North. To capture the advantage of backwardness emphasized, among others, by Nelson and Phelps (1966), and Acemoglu, Aghion and Zilibotti (2006) we assume that all other countries can *adopt* existing technologies at a cost which is decreasing in their distance from the frontier. Besides this cost, technology adoption - just like innovation - is profit-driven and depends on local economic conditions, such as the abundance of complementary factors (K, L and H) and the size of domestic markets. This combination of the theory of directed technical change with international knowledge spillovers allows us

[1] The notion of directed technical change stretches back to Kennedy (1964). Acemoglu (1998) constructs a quality-ladder model of directed technical change to study the patterns of wage inequality in the US in the 1970's and 1980's.

[2] We relax this assumption in an extension where we introduce international license contracts on the use of technology.

to build a tractable model of cross-country technology differences suitable for quantitative analysis.

The resulting model yields structural equations that can be used to estimate its two key parameters: the elasticity of substitution between the skilled and unskilled labor, ϵ, and the elasticity of the adoption cost to the technology gap, ξ, capturing exogenous barriers to knowledge flows. From these estimates, our methodology allows us to tease out the relative importance of two distinct sources of low productivity: technology inappropriateness and distance to frontier. To see why, note that when barriers to adoption are very low, a country will operate with the best technologies; yet, to the extent that frontier technologies are highly skill biased they will be of limited use in skill-scarce countries, thereby generating low aggregate productivity. On the contrary, countries well inside the frontier are free to choose a more optimal mix of technologies, so that their low productivity will be mostly explained by barriers to adoption, rather than the skill-technology mismatch.

To estimate the elasticity of substitution between the skilled and unskilled labor, we use time-series data on the skill premium and the relative skill supply in the US (the frontier economy). The second parameter, ξ, measuring barriers to technology adoption, is instead estimated from a micro-founded version of equation (1). That is, given data on Y, K, H and L, we search for the constant ξ (across all adopting countries and also for different income groups) that minimizes the sum of squared deviations between predicted and observed relative output. Despite the parsimonious parameterization, the fit of the model is remarkably good, indicating that the underlying theory of technological change and diffusion, which places skill endowment, domestic market size and international spillovers as the cornerstone, is broadly consistent with the data. Similarly to Caselli and Coleman (2006), we find that virtually all adopting countries are inside the world technology frontier, that skill scarce countries tend to adopt predominantly unskilled-labor complement innovations and that barriers to adoption are higher in less developed countries. We also find evidence that barriers to technology adoption are relatively stable over the period 1970-2000 among non-OECD economies, while they appear to have fallen for OECD countries. The extreme versions of the model, in which each country develops local technologies independently or in which all country share the same technology, are instead rejected by the data. We also compare the fit of the model under alternative specifications for the cost of adopting technologies that allow us to vary the strength of market size effects and under the assumption of free trade in goods.

With our preferred parameterization, we use the model to perform a series of counterfactuals. First, we show that removing barriers to technology adoption would increase gross domestic product per worker (GDP pw) relative to the US from 0.19 to 0.61 for the average non-OECD country and from 0.68 to 0.91 for the average OECD country. The effect is particularly strong for small countries, which lack the local market size required to benefit from expensive technologies. Second, we study the effect of institutional changes associated to the process of globalization, focusing on the integration of markets for goods and technology. As noted by AZ01 and Acemoglu (2003), trade liberalization may have triggered skill-biased technical change (SBTC) in the US during the last two decades of the 20th century and this may have amplified cross-country income differences. To illustrate the global impact of this phenomenon, we compute the effect both on the world technology frontier and on adopting countries of removing barriers to trade in goods. As trade with skill-scarce countries increase the relative price of skill-intensive goods in the skill-abundant North, it fosters the incentives to introduce skill-complement technologies. The effect on technology adoption is however ambiguous. On the one hand, the increase in the skill bias of the frontier technology makes the adoption of skill-complement technologies cheaper. On the other hand, the rise in the relative price of low-skill-intensive goods in skill-scarce countries promotes the adoption of less skill-biased technologies. We find that, given the estimated parameters, trade would induce most followers to adopt more skill-biased technologies than in the absence of trade. Thus, trade tends to exacerbate the inappropriateness of technologies to the local endowments of non-frontier economies. The result is a global increase in skill premia (a factor of 2.9 for the average country), but also in the cross-country income gap (on average, GDP pw relative to the US falls by 13 percentage points).[3] On the contrary, allowing trade in technology too (i.e., the leader can licence its technology to follower countries), by fostering the incentives to introduce unskilled-labor complement innovations, reduces wage inequality and induces income convergence worldwide.

The paper contributes to a large literature, surveyed in Caselli (2005), aimed at decomposing cross-country income disparities into input differences and unmeasured productivity. We depart from earlier works (e.g., Hall and Jones, 1999) by assuming, consistently with all

[3] We should stress that these very large effects correspond to the extreme experiment of moving from no trade to completely free trade. Clearly, partial trade liberalization would give smaller effects.

available evidence, a less than infinite elasticity of substitution between workers of different skill level and by endogenizing productivity. Among more recent contributions, the closest paper is Caselli and Coleman (2006), who also decompose income using the aggregate production function (1). There are two main differences, however. First, they back out the pair (A_L, A_H) using data on input, but also factor prices. On the contrary, our theoretical model delivers structural equations that can be used to estimate (1) without relying on cross-country factor prices, which are notoriously difficult to obtain for a large sample and not always of high quality. Second, when modelling technology choices, they do not endogenize the world technology frontier. Fadinger (2009) estimates productivity differences across trading countries by fitting both national statistics and the factor content of trade. Yet, he does not endogenize technologies and their diffusion, while in this paper we do not use information contained in trade data.

The paper is also related to the vast literature on international technology diffusion. The idea that countries may benefit from technologies developed elsewhere was first put forward by Nelson and Phelps (1966) and then formalized by Barro and Sala-i-Martin (1997), Howitt (2000) and Acemoglu, Aghion and Zilibotti (2006). Empirical evidence of international technology spillovers is provided, among others, by Keller (2004) and Caselli and Wilson (2004). Here, we follow closely the model in Gancia and Zilibotti (2009), to which we add capital accumulation. More importantly, one of the main contributions is to estimate the resulting model. The importance of barriers to technology adoption in explaining cross-county income disparities has been emphasized by Parente and Prescott (1994, 2005). Comin and Hobijn (2010) and Comin, Easterly and Gong (2009) document that major innovations diffuse slowly (on average, they are adopted 47 years after their invention), and that differences in the speed of technology adoption are not only large, but also surprisingly persistent over time.

The fact that technologies originating from advanced countries may be excessively skill biased for the endowments of less developed countries, and that this may act both as a barrier to adoption and as source of low productivity, has been put forward by Atkinson and Stiglitz (1969), Basu and Weil (1998), and AZ01. Our approach is most related to AZ01. The main difference is that they only focus on the case in which all countries share the same technology. In the current model, instead, aggregate productivity in less developed countries is relatively low both because of the technology-skill mismatch identified in AZ01 and because of costly adoption.

The paper is structured as follows. Section 2 builds the benchmark model of a world economy where a technology leader engages in directed innovation, while a large number of less advanced countries engage in directed technology adoption. It provides a microfoundation for the aggregate production function (1) and illustrates three main sources of low aggregate productivity: lack of capital, distance to frontier and technology inappropriateness. Section 3 extends the model by first allowing trade in goods and then in technology (IPR protection) too. Section 4 estimates the model and quantifies the relative importance of the three sources of income differences. The empirical model is then used to perform counterfactual exercises and sensitivity analysis. Section 5 concludes.

2 The Benchmark Model

In this section, we present a model of directed technical change closely related to Acemoglu, Gancia and Zilibotti (2011) and Gancia and Zilibotti (2009). The key ingredients are different types of labor (skilled and unskilled workers), cross-country differences in factor endowments and factor-biased (directed) technical progress. In addition, we consider physical capital accumulation, which was ignored in previous work. Moreover, we emphasize the distinction between the introduction of frontier technologies (*innovation*) which is carried out in the "North", and the sluggish process of imitation and adaptation of such technologies to less developed countries (the "South"). We refer to the latter as technology *adoption.* Adoption is assumed to be cheaper than innovation, creating a laggard advantage. However, since technical change is directed to the factor endowment of the North, the South faces a menu of technologies to imitate that are overly skill biased, given its lower skilled endowment.

2.1 Preferences

The world consists of a technology leader (the North), and a set of non-technological leaders (the South), all populated by infinitely lived agents endowed with logarithmic preferences. We denote by N the frontier economy and by $S \in \hat{S} = \{S_1, S_2, ..., S_n\}$ a generic Southern economy. More formally, the utility function of the representative agent in each country is given by:

$$U_J = \int_0^\infty e^{-\rho t} \log(c_{Jt}) dt,$$

where $J \in \{N, S\}$ and ρ is the discount rate. The optimal consumption plan satisfies the Euler equation, $\dot{c}_{Jt}/c_{Jt} = r_{Jt} - \rho$, where the interest rate r_{Jt} may be different across countries, since capital markets are not integrated. We remove time indexes when this is no source of confusion.

2.2 Technology

Final output, used for both consumption and investment, is produced by a representative competitive firm subject to the following production function:

$$Y_J = K_J^{\alpha} \left[Y_{LJ}^{\frac{\epsilon-1}{\epsilon}} + Y_{HJ}^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon(1-\alpha)}{\epsilon-1}}, \tag{2}$$

where K is capital, Y_L and Y_H are intermediate goods produced with unskilled and skilled labor, respectively, and $\epsilon > 1$ is the elasticity of substitution between them. Profit maximization implies that the rental rate of capital equals the marginal product of capital. More formally, after choosing Y as the *numéraire*, we have $K_J = \alpha Y_J / (r_J \chi_J)$, where χ_J is a wedge capturing distortions which open a gap between the private and social rate of returns to investments. When $\chi_J = 1$, there is no distortion, and the standard condition equating the interest rate to the marginal product of capital holds. Substituting back K_J into (2) yields:

$$Y_J = \left(\frac{\alpha}{r_J \chi_J} \right)^{\frac{\alpha}{1-\alpha}} \left[Y_{LJ}^{\frac{\epsilon-1}{\epsilon}} + Y_{HJ}^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon-1}}. \tag{3}$$

Profit maximization implies then the following inverse demand functions:

$$P_{HJ} = (1-\alpha) \left(\frac{\alpha}{r_J \chi_J} \right)^{\frac{(\epsilon-1)\alpha}{\epsilon(1-\alpha)}} \left(\frac{Y_J}{Y_{HJ}} \right)^{\frac{1}{\epsilon}} \text{ and } P_{LJ} = (1-\alpha) \left(\frac{\alpha}{r_J \chi_J} \right)^{\frac{(\epsilon-1)\alpha}{\epsilon(1-\alpha)}} \left(\frac{Y_J}{Y_{LJ}} \right)^{\frac{1}{\epsilon}}, \tag{4}$$

where P_L and P_H are the prices of Y_L and Y_H, respectively. Note that $P_{HJ}/P_{LJ} = [Y_{LJ}/Y_{HJ}]^{\frac{1}{\epsilon}}$.

The production function at the sector level is given by:

$$Y_{LJ} = E_{LJ} \left[\int_0^{A_{LJ}} y_{LJ}(i)^{\frac{\sigma-1}{\sigma}} di \right]^{\frac{\sigma}{\sigma-1}} \quad \text{and} \quad Y_{HJ} = E_{HJ} \left[\int_0^{A_{HJ}} y_{HJ}(i)^{\frac{\sigma-1}{\sigma}} di \right]^{\frac{\sigma}{\sigma-1}},$$

where (A_L, A_H) is the state vector consisting of the measure of intermediate inputs produced with unskilled and skilled labor, respectively. The terms $E_{LJ} \equiv (A_{LJ})^{\frac{\sigma-2}{\sigma-1}}$ and $E_{HJ} \equiv (A_{HJ})^{\frac{\sigma-2}{\sigma-1}}$ are externalities that make the model consistent with the existence of a balanced growth path (see Gancia and Zilibotti (2009) for a discussion of such externalities). Note that the externality vanishes at $\sigma = 2$.

The producers of Y_L and Y_H are also competitive. Their profit maximization yields the following relative demand equations:

$$\frac{y_{LJ}(i)}{y_{LJ}(j)} = \left[\frac{p_{LJ}(j)}{p_{LJ}(i)}\right]^{\sigma} \quad \text{and} \quad \frac{y_{HJ}(i)}{y_{HJ}(j)} = \left[\frac{p_{HJ}(j)}{p_{HJ}(i)}\right]^{\sigma},$$

where p_L and p_H denote the price of intermediates.

The intermediate good sector is monopolistic, with each producer holding the patent for a single variety. The production function for each intermediate input, $y_{LJ}(i)$ and $y_{HJ}(i)$, is linear in the type of labor employed,

$$y_{LJ}(i) = l_J(i) \text{ and } y_{HJ}(i) = Zh_J(i),$$

where $Z \geq 1$ is a parameter that will allow us to match the level of the skill premium in the benchmark case. The industry equilibrium is subject to the resource constraints $\int_0^{A_{LJ}} l_J(i)\, di \leq L_J$ and $\int_0^{A_{HJ}} h_J(i)\, di \leq H_J$, where L_J and H_J are assumed to be in fixed supply. As the monopolists face a demand curve with the constant price elasticity of σ, it is optimal for them to set prices equal to $p_{LJ}(i) = p_{LJ} = (1 - 1/\sigma)^{-1} w_{LJ}$ and $p_{HJ}(i) = p_{HJ} = (1 - 1/\sigma)^{-1} w_{HJ}/Z$, where w_L and w_H are the wage of unskilled and skilled workers, respectively. This pricing formula also implies that profits per firm are a fraction $1/\sigma$ of revenues:

$$\pi_{LJ}(i) = \frac{p_{LJ} l_J(i)}{\sigma} \quad \text{and} \quad \pi_{HJ}(i) = \frac{p_{HJ} Z h_J(i)}{\sigma}. \tag{5}$$

Using symmetry and labor market clearing yields $l_J(i) = L_J/A_{LJ}$ and $h_J(i) = H_J/A_{HJ}$, which in turn allows to express sectorial output as:

$$Y_{LJ} = A_{LJ} L_J \quad \text{and} \quad Y_{HJ} = A_{HJ} Z H_J. \tag{6}$$

Note that output in each sector is a linear function of labor and of the state of technology. Plugging (6) into (4) yields the relative price:

$$\tilde{P}_J \equiv \frac{P_{HJ}}{P_{LJ}} = \left[\tilde{A}_J Z \tilde{h}_J\right]^{-\frac{1}{\epsilon}}, \tag{7}$$

where $\tilde{A} \equiv A_H/A_L$ is the skill bias of the technology and $\tilde{h} \equiv H/L$ is the relative skill endowment. Note that "tilde" denotes relative (skill-to-unskill) variables. Relative wages and profits can be found using (7), and noting that $p_{LJ} L_J = P_{LJ} Y_{LJ}$ and $p_{HJ} Z H_J = P_{HJ} Y_{HJ}$:

$$\tilde{w}_J \equiv \frac{w_{HJ}}{w_{LJ}} = Z \frac{P_{HJ}}{P_{LJ}} \frac{A_{HJ}}{A_{LJ}} = \left[Z \tilde{A}_J\right]^{1-\frac{1}{\epsilon}} \left[\tilde{h}_J\right]^{-\frac{1}{\epsilon}} \tag{8}$$

$$\tilde{\pi}_J \equiv \frac{\pi_{HJ}}{\pi_{LJ}} = \frac{P_{HJ}}{P_{LJ}} \frac{Z H_J}{L_J} = \tilde{A}_J^{-\frac{1}{\epsilon}} \left(Z \tilde{h}_J\right)^{1-\frac{1}{\epsilon}}. \tag{9}$$

Equation (9) shows that the relative profitability, π_H/π_L, has two components: a "price effect", whereby rents are higher in sectors producing more expensive goods, and a "market size effect", whereby rents are higher in bigger sectors.

2.3 Innovation in the North

Frontier innovation is carried out in the North, and takes the form of the introduction of new varieties of intermediate inputs. We assume that the development of *any* new variety requires a fixed cost of μ units of the numéraire Y. The direction of innovation is endogenous, i.e., each innovator can decide to design a variety that can be used in the H or L sector. As patents are infinitely lived, the value of a firm – either V_L or V_H – is the present discounted value of its future profit stream. Free entry implies that neither V_L nor V_H can exceed the innovation cost, μ. Since in a balanced growth path (a *steady state*) P_L, P_H and the interest rate r are constant, then $V_{LN} = \pi_{LN}/r_N = V_{HN} = \pi_{HN}/r_N = \mu$, which implies in turn that $\tilde{\pi}_N = 1$. The equalization of profit flows yields the equilibrium skill bias of technology in the North:

$$\tilde{A}_N = \left(Z\tilde{h}_N\right)^{\epsilon-1}. \tag{10}$$

Substituting $\tilde{A}_N$ into (8) yields the steady-state skill premium:

$$\tilde{w}_N = Z^{\epsilon-1}\left(\tilde{h}_N\right)^{\epsilon-2}. \tag{11}$$

To find the growth rate, we note that the interest rate is pinned down by either of the two free entry conditions, e.g., $r_N = \pi_{HN}/\mu = P_{HN}ZH_N/(\mu\sigma)$. Using (3), (4) and (6) to eliminate P_{HN}, normalizing $\chi_N = 1$, and using the Euler equation yields the balanced growth rate of the economy,

$$g_N = r_N - \rho = (1-\alpha)^{1-\alpha}\alpha^{\alpha}\left[\frac{L_N^{\epsilon-1} + (ZH_N)^{\epsilon-1}}{(\sigma\mu)^{\epsilon-1}}\right]^{\frac{1-\alpha}{\epsilon-1}} - \rho. \tag{12}$$

It can be shown that, along the balanced growth path, Y_N, c_N, K_N, A_{HN} and A_{LN} all grow at the rate g_N.

2.4 Directed Technology Adoption in the South

Southern countries are assumed to be skill scarce, namely, $\tilde{h}_S < \tilde{h}_N$ for all $S \in \hat{S}$, and to start from a lower technology level in both the skilled and unskilled sector. They can adopt at a cost the technologies developed in the North. To begin with, we assume that there is neither trade in goods nor international protection of IPR. Each of these assumption will be relaxed later on. The lack of IPR implies that innovators in the North cannot sell their copyrights to firms located in the South, so that the only market they have access to is the domestic one. In the absence of trade, the equilibrium conditions in the North are unaffected by the presence of the South.

The equilibrium conditions of Southern economies are analogous to those of the North, except for technology adoption, which differs from the innovation process. In particular, Southern countries take the state of the frontier technology, A_{LN} and A_{HN}, as given. Technology adoption is modeled as a costly investment activity similar to innovation. Following the earlier literature, we assume that, due to technological spillovers, the cost of adopting a technology in a sector, c_{LS} and c_{HS}, is a negative function of the technological gap in that sector:

$$c_{LS} = \mu \left(\frac{A_{LS}}{A_{LN}} \right)^{\xi} \quad \text{and} \quad c_{HS} = \mu \left(\frac{A_{HS}}{A_{HN}} \right)^{\xi}, \quad \xi \geq 0, \tag{13}$$

where A_{LN} and A_{HN} represent the world technology frontiers in the two sectors. That is, the farther behind a country is relative to the skill-specific frontier, the cheaper it is to adopt technologies in that sector. With this formulation, the total cost of adopting the entire set of z-complement technologies (with $z \in \{H, L\}$) is:

$$\mu \int_0^{A_{zN}} \left(\frac{A_{zS}}{A_{zN}} \right)^{\xi} dA_{zS} = \frac{\mu A_{zN}}{1+\xi}.$$

This expression shows that ξ can be interpreted as an inverse measure of barriers to technology adoption in the South. All intermediate inputs adopted in the South are sold by local monopolists.

In steady state, free entry implies $\pi_{HS}/\pi_{LS} = c_{HS}/c_{LS}$. Using this condition together with equations (9), (10) and (13), we can solve for the skill bias of the technology in the South:

$$\tilde{A}_S = \left(Z\tilde{h}_S \right)^{\frac{\epsilon-1}{1+\epsilon\xi}} \tilde{A}_N^{\frac{\epsilon\xi}{1+\epsilon\xi}} = Z^{\epsilon-1} \left[\tilde{h}_S \cdot \tilde{h}_N^{\epsilon\xi} \right]^{\frac{\epsilon-1}{1+\epsilon\xi}}. \tag{14}$$

Technology adoption in the South depends on the skill endowment of the North and of the local economy. On the one hand, local skill abundance increases the profitability of adopting skill-complement innovations. On the other hand, skill abundance in the North means that the frontier technology is more skill biased, and that skilled technologies are cheaper to imitate. Note also that the skill bias of the technology in the adopting economy is increasing in ξ, capturing the speed of technology transfer. In particular, in the limit case of $\xi = 0$ (prohibitive barriers) each economy develops local technologies independently from the world frontier, and the skill abundance in the North becomes irrelevant: $\tilde{A}_S = \left(Z\tilde{h}_S\right)^{\epsilon-1}$. To the opposite case, as $\xi \to \infty$, adoption is free so that the South is using the technology of the North. In this case, it is the local skill endowment that does not matter: $\tilde{A}_S = \tilde{A}_N = \left(Z\tilde{h}_N\right)^{\epsilon-1}$. The latter is the case analyzed by AZ01.

2.5 Productivity Differences

As long as $\xi > 0$, a balanced growth path features $r_S = r_N \equiv r$, with the South and the North growing at the same rate, in spite of there being neither trade nor factor mobility. The model yields then predictions for steady-state output and productivity differences as functions of factor endowments and of exogenous parameters.

Proposition 1 *For any $S \in \hat{S}$, the steady-state output ratio relative to the frontier is*

$$\frac{Y_S}{Y_N} = \left(\left(\frac{K_S}{K_N}\right)^{\alpha} \left[\frac{L_S^{\frac{(\epsilon-1)(1+\xi)}{1+\epsilon\xi}} + \left(Z\tilde{h}_N\right)^{\frac{\xi(\epsilon-1)^2}{1+\epsilon\xi}} \times (ZH_S)^{\frac{(\epsilon-1)(1+\xi)}{1+\epsilon\xi}}}{L_N^{\frac{(\epsilon-1)(1+\xi)}{1+\epsilon\xi}} + \left(Z\tilde{h}_N\right)^{\frac{\xi(\epsilon-1)^2}{1+\epsilon\xi}} \times (ZH_N)^{\frac{(\epsilon-1)(1+\xi)}{1+\epsilon\xi}}} \right]^{\frac{(1-\alpha)(1+\epsilon\xi)}{(\epsilon-1)(1+\xi)}} \right)^{\frac{1+\xi}{\alpha+\xi}} \equiv f_S^{AUT}, \tag{15}$$

where $K_S/K_N = (Y_S/Y_N)\,/\,(\chi_S/\chi_N)$.

Proof. The production function, (2), yields

$$\frac{Y_S}{Y_N} = \left(\frac{A_{LS}}{A_{LN}}\right)^{1-\alpha} \left(\frac{K_S}{K_N}\right)^{\alpha} \left[\frac{L_S^{\frac{\epsilon-1}{\epsilon}} + \tilde{A}_S^{\frac{\epsilon-1}{\epsilon}} (ZH_S)^{\frac{\epsilon-1}{\epsilon}}}{L_N^{\frac{\epsilon-1}{\epsilon}} + \tilde{A}_N^{\frac{\epsilon-1}{\epsilon}} (ZH_N)^{\frac{\epsilon-1}{\epsilon}}} \right]^{\frac{\epsilon(1-\alpha)}{\epsilon-1}}. \tag{16}$$

To obtain the equilibrium expression for A_{LS}/A_{LN}, recall first that

$$\frac{\pi_{LS}}{\pi_{LN}} = \frac{c_{LS}}{\mu} = \left(\frac{A_{LS}}{A_{LN}}\right)^{\xi} \text{ and } \frac{\pi_{HS}}{\pi_{HN}} = \frac{c_{HS}}{\mu} = \left(\frac{A_{HS}}{A_{HN}}\right)^{\xi}, \tag{17}$$

where the relative profits can be written as

$$\frac{\pi_{LS}}{\pi_{LN}} = \frac{P_{LS} Y_{LS} A_{LN}}{P_{LN} Y_{LN} A_{LS}} = \frac{P_{LS} L_S}{P_{LN} L_N}, \tag{18}$$

using (5) and (6). Next, note that, since the price of Y_L equals its marginal product, then:

$$\frac{P_{LS}}{P_{LN}} = \left(\frac{A_{LS}}{A_{LN}}\right)^{-\alpha} \left(\frac{K_S}{K_N}\right)^{\alpha} \left[\frac{L_S^{\frac{\epsilon-1}{\epsilon}} + \tilde{A}_S^{\frac{\epsilon-1}{\epsilon}} (ZH_S)^{\frac{\epsilon-1}{\epsilon}}}{L_N^{\frac{\epsilon-1}{\epsilon}} + \tilde{A}_N^{\frac{\epsilon-1}{\epsilon}} (ZH_N)^{\frac{\epsilon-1}{\epsilon}}} \right]^{\frac{\epsilon(1-\alpha)}{\epsilon-1}-1} \left(\frac{L_S}{L_N}\right)^{-\frac{1}{\epsilon}}. \tag{19}$$

Next, (17), (18) and (19) imply that:

$$\frac{A_{LS}}{A_{LN}} = \left(\frac{L_S}{L_N}\right)^{\frac{\epsilon-1}{\epsilon(\xi+\alpha)}} \left(\frac{K_S}{K_N}\right)^{\frac{\alpha}{\xi+\alpha}} \left[\frac{L_S^{\frac{\epsilon-1}{\epsilon}} + \tilde{A}_S^{\frac{\epsilon-1}{\epsilon}} (ZH_S)^{\frac{\epsilon-1}{\epsilon}}}{L_N^{\frac{\epsilon-1}{\epsilon}} + \tilde{A}_N^{\frac{\epsilon-1}{\epsilon}} (ZH_N)^{\frac{\epsilon-1}{\epsilon}}}\right]^{-\frac{\alpha\epsilon-1}{(\epsilon-1)(\xi+\alpha)}}. \tag{20}$$

We can now use (20) to substitute away A_{LS}/A_{LN} into (16):

$$\frac{Y_S}{Y_N} = \left(\frac{L_S}{L_N}\right)^{\frac{(1-\alpha)(\epsilon-1)}{\epsilon(\xi+\alpha)}} \left(\frac{K_S}{K_N}\right)^{\alpha\frac{1+\xi}{\alpha+\xi}} \left[\frac{L_S^{\frac{\epsilon-1}{\epsilon}} + \tilde{A}_S^{\frac{\epsilon-1}{\epsilon}} (ZH_S)^{\frac{\epsilon-1}{\epsilon}}}{L_N^{\frac{\epsilon-1}{\epsilon}} + \tilde{A}_N^{\frac{\epsilon-1}{\epsilon}} (ZH_N)^{\frac{\epsilon-1}{\epsilon}}}\right]^{\frac{(1-\alpha)(1+\epsilon\xi)}{(\epsilon-1)(\alpha+\xi)}}. \tag{21}$$

Finally, eliminating $\tilde{A}_N$ and $\tilde{A}_S$ from (21) using (10) and (14), respectively, and rearranging terms, yields (15). ■

The formula of the output gap (15) resembles the ratio between two identical aggregate constant elasticity of substitution (CES) production functions. This is remarkable, since countries use in fact different technologies. However, the implied production function differs from standard CES functions such as (1) in two respects: First, it features increasing returns to scale, parameterized by the exponent $(1+\xi)/(\alpha+\xi) > 1$. Second, the structural parameter ξ implies a particular restriction between the *long-run* elasticity of substitution between high- and low-skill labor and the "weight" of the CES function, $\left(Z\tilde{h}_N\right)^{\frac{\xi(\epsilon-1)^2}{1+\epsilon\xi}}$. Given the structural parameters ϵ, α, ξ and Z, the right-hand side of the relative GDP equation is fully determined by the data of capital, low-skill labor and high-skill labor. Dividing both sides by the number of agents (workers) yields an accounting equation for GDP per capita (per worker).

As noted above, income differences depend on a scale effect, namely, larger countries are predicted to be *ceteris paribus* more productive. Interestingly, this effect disappears as barriers to adoption vanish and all countries converge to the technology frontier. Indeed, as $\xi \to \infty$, we have that $\tilde{A}_S \to \tilde{A}_N$ and

$$\lim_{\xi\to\infty} \frac{Y_S}{Y_N} = \left(\frac{K_S}{K_N}\right)^{\alpha} \left[\frac{L_S^{\frac{\epsilon-1}{\epsilon}} + \left(Z\tilde{h}_N\right)^{\frac{(\epsilon-1)^2}{\epsilon}} \times (ZH_S)^{\frac{\epsilon-1}{\epsilon}}}{L_N^{\frac{\epsilon-1}{\epsilon}} + \left(Z\tilde{h}_N\right)^{\frac{(\epsilon-1)^2}{\epsilon}} \times (ZH_N)^{\frac{\epsilon-1}{\epsilon}}}\right]^{\frac{\epsilon(1-\alpha)}{\epsilon-1}}, \tag{22}$$

which is the equation estimated by AZ01, who also set $\epsilon = 2$.

Figure 1 shows how different parameters affect productivity differences. The figure depicts economies with equally sized total labor forces and with $\epsilon = 2$. The parameters of the North are fixed at $\tilde{h}_N = \chi_N = 1$, and $Z = 1.5$, implying that $A_{HN}/A_{LN} = 1.5$. Then, we consider

Southern economies with different skill endowments, $\tilde{h}_S$, barriers to technology adoption, ξ, and investment wedges, χ_S. Panel (a) shows the pattern of technology adoption, i.e., the equilibrium proximity to the frontier in the L and H sector, respectively for different combinations of ξ and $\tilde{h}_S$, while holding constant $\chi_S = 1.2$. The figure plots three curves, each corresponding to a different relative skill endowment: $\tilde{h}_S = 0.9$ (highest curve), $\tilde{h}_S = 0.5$ (intermediate curve) and $\tilde{h}_S = 0.1$ (lowest curve). Moving along each curve from left to right yields points with increasing ξ. Dots single out some particular values of ξ. The parameter ξ affects both the distance to frontier (lower ξ implies a larger gap) and the skill bias of technology adoption. In particular, the lower ξ the more the technology will reflect local conditions. As we increase ξ the technology becomes more skill biased, as one can see by drawing rays from the origin through different dotted points along a line. For large levels of ξ, the technological differences between non-frontier economies with different endowments become very small, and are all well approximated by the case studied by AZ01 in which all countries adopt immediately the frontier technology. Panel (b) shows the same combination of parameters, but with a larger investment wedge $\chi_S = 1.5$. A larger χ_S reduces technology adoption, especially for countries with higher skill ratios. For example, a country with $\tilde{h}_S = 0.5$ and $\xi = 2$ adopts 85% of the high-skill and 98% of the low-skill technologies if $\chi_S = 1.2$, while it adopts 80% of the high-skill and 92% of the low-skill technologies if $\chi_S = 1.5$.

Panels (c) and (d) display the effect of ξ and $\tilde{h}_S$ on output per worker differences and the skill premium. As in panel (a), the investment wedge is fixed at $\chi_S = 1.2$ and each of the three curves represents a different $\tilde{h}_S$. Panel (c) shows that, as long as $\xi < 2$, barriers to technology adoption are important. However, for larger values of ξ the lion share of productivity differences originates from technology inappropriateness, i.e., the excessive skill bias of frontier technologies. For instance, if $\tilde{h}_S = 0.1$ and $\xi = 2$, removing all barriers would only reduce 18 percent of the distance to the frontier. In contrast, 74 percent of the productivity gap is due to technology mismatch, and 14 percent is due to the investment wedge. Moving back to panel (a), one can note that in this case more than 90 percent of the technologies used by low-skill workers are already in use when $\xi = 2$ and $\tilde{h}_S = 0.1$. Thus, slashing barriers triggers mainly the adoption of high-skill technologies (when $\xi = 2$ the Southern economy only adopts 60 percent of the high-skill technologies). However, this yields only modest productivity gains since only about 11% of the labor force is skilled.

The skill bias of technology is reflected in the wage inequality. The steady-state skill premium is given by $\tilde{w}_S = Z^{\epsilon-1}\tilde{h}_S^{\frac{\epsilon-\xi-2}{1+\epsilon\xi}}\tilde{h}_N^{\frac{(\epsilon-1)^2\xi}{1+\epsilon\xi}}$, where $\tilde{w}_S$ is increasing in ξ, ranging from $\tilde{w}_{S|\xi=0} = Z^{(\epsilon-1)}\tilde{h}_S^{\epsilon-2}$ to $\tilde{w}_{S|\xi\to\infty} = Z^{(\epsilon-1)}\tilde{h}_S^{-\frac{1}{\epsilon}}h_N^{\frac{(\epsilon-1)^2}{\epsilon}}$. Panel (d) of Figure 1 shows the long-run effect of ξ on wages for alternative relative skill endowments in the South. Increasing ξ induces a rise in the skill premium which is a direct consequence of the previous finding that a higher relative fraction of high-skill technologies are adopted as ξ increases. Moreover, starting from $\xi = 2$, the rise in the skill premium is steeper in countries with low skill ratios because there are more high-skill technologies left to adopt.

3 Extensions: Trade and IPR

So far, we have only allowed countries to interact through technological spillovers. In this section we extend the analysis first to economies that trade in goods and then to economies that, in addition, can import technologies through licensing contracts. We refer to the latter case as full IPR enforcement.

3.1 International Trade

In this section, we assume that the intermediate good Y_L and Y_H can be traded internationally without frictions. Under free trade, there is a single world price for P_L and P_H :

$$\tilde{P}^w \equiv \frac{P_H^w}{P_L^w} = \left[\frac{Y_L^w}{Y_H^w}\right]^{\frac{1}{\epsilon}} \tag{23}$$

where the superscript w refer to worldwide variables. Hence, $Y_L^w = A_{LN}L_N + \sum_{j=1}^n A_{LS_j}L_{S_j}$ and $Y_H^w = A_{HN}ZH_N + \sum_{j=1}^n A_{HS_j}ZH_{S_j}$. All equations in section 2.2 continue to hold, with local prices being now equal to the world price.

Consider, next, the innovation process in the North. The key observation is that the North continues to be the relevant market for new frontier technologies, since there is no IPR protection in the South. The profit flows of Northern firms are, then, $\pi_{LN} = P_L^w L_N/\sigma$ and $\pi_{HN} = P_H^w ZH_N/\sigma$. In a balanced-growth equilibrium, $\tilde{\pi}_N = 1$, which in turn implies that $\tilde{P}^w = \left(Z\tilde{h}_N\right)^{-1}$. Using (23) and rearranging terms (see proof below) leads to the following Lemma.

Lemma 1 *In a free trade environment, the skill bias of the frontier technology is given by:*

$$\tilde{A}_N = \tilde{A}_N^{trade} \equiv \frac{\left(Z\tilde{h}_N\right)^{\epsilon-1}}{\hat{h}} > \left(Z\tilde{h}_N\right)^{\epsilon-1}, \tag{24}$$

where

$$\hat{h} \equiv \frac{1+\sum_{j=1}^{n}\left(\frac{H_{S_j}}{H_N}\right)^{\frac{1+\xi}{\xi}}}{1+\sum_{j=1}^{n}\left(\frac{L_{S_j}}{L_N}\right)^{\frac{1+\xi}{\xi}}} < 1. \tag{25}$$

The skill bias of technology in country $S \in \hat{S}$ is given by

$$\tilde{A}_S = \tilde{A}_S^{trade} \equiv \frac{\left(Z\tilde{h}_N\right)^{\epsilon-1}}{\hat{h}}\left(\frac{\tilde{h}_S}{\tilde{h}_N}\right)^{\frac{1}{\xi}}. \tag{26}$$

Proof. Using (23) to substitute away $\tilde{P}^w$ from the equation $\tilde{P}^w = \left(Z\tilde{h}_N\right)^{-1}$ yields:

$$Z\tilde{h}_N = \left[Z\tilde{A}_N\left(\frac{\sum_{j=1}^{n}\frac{A_{HS_j}}{A_{HN}}H_{S_j}+H_N}{\sum_{j=1}^{n}\frac{A_{LS_j}}{A_{LN}}L_{S_j}+L_N}\right)\right]^{\frac{1}{\epsilon}}.$$

Solving out for $\tilde{A}_N$ yields:

$$\tilde{A}_N = \left(Z\tilde{h}_N\right)^{\epsilon-1} \times \left(\frac{1+\sum_{j=1}^{n}\frac{A_{LS_j}}{A_{LN}}\frac{L_{S_j}}{L_N}}{1+\sum_{j=1}^{n}\frac{A_{HS_j}}{A_{HN}}\frac{H_{S_j}}{H_N}}\right) \equiv \tilde{A}_N^{trade}. \tag{27}$$

We must now solve for the skill-specific distance-to-frontier terms. To this aim, note that, on the one hand, $\pi_{HS}/\pi_{HN} = H_S/H_N$ and $\pi_{LS}/\pi_{LN} = L_S/L_N$. On the other hand, in a balanced growth path, $\pi_{HS}/\pi_{HN} = c_{HS}/\mu$ and $\pi_{LS}/\pi_{LN} = c_{LS}/\mu$. Thus, $c_{HS} = \mu H_S/H_N$ and $c_{LS} = \mu L_S/L_N$. Then, using (13) to eliminate c_{HS} and c_{LS} yields:

$$\frac{A_{HS}}{A_{HN}} = \left(\frac{H_S}{H_N}\right)^{1/\xi}, \tag{28}$$

$$\frac{A_{LS}}{A_{LN}} = \left(\frac{L_S}{L_N}\right)^{1/\xi}. \tag{29}$$

Plugging (28)-(29) into (27) yields (24). Finally, (26) follows immediately from (24), (28) and (29). ■

The numerator of (24) is identical to its no-trade counterpart, (10). The denominator is smaller than unity, since Southern economies are skill scarce relative to the North. Thus, trade increases the skill bias of the frontier technology. This result generalizes the finding of AZ01 to an environment in which technology adoption is costly. Equation (24) also shows that the "trade multiplier" depends on ξ and on the relative market size and skill endowment of the two economies. $\tilde{A}_N$ increases with the difference in the skill endowment between the North and the South. Trade increases the relative price of the good that is intensive in the factor that is relatively abundant in each country (i.e., $\tilde{P}$ in the North) and the effect is larger the more different factor endowments are. Then, the stronger the increase in $\tilde{P}$ in the North relative to the no-trade environment, the larger the skill bias induced by trade. Barriers (i.e., a reduction in ξ) increase $\tilde{A}_N$. The intuition behind this result is that since the frontier technology is skill biased, technology transfer reduces the difference in effective endowments. In other words, barriers reduce the skill bias of adoption, thereby strengthening the North-South pattern of specialization in production. As a consequence, the price effect is larger when barriers are higher.

The effect of trade on the direction of technology adoption in the South (equation (26)) is instead ambiguous. On the one hand, trade increases the relative price of low-skill-intensive goods in the South, accelerating the adoption of low-skill technologies. On the other hand, the higher skill bias at the frontier makes it cheaper to adopt skilled technologies.[4]

The following proposition provides an expression for output differences – the analogue of equation (15) – under free trade.

Proposition 2 *Assume free international trade in the intermediate goods Y_H and Y_L. For any $S \in \hat{S}$, the steady-state output ratio relative to the frontier is:*

$$\frac{Y_S}{Y_N} = \left(\frac{K_S}{K_N}\right)^{\alpha} \left(\frac{L_S^{\frac{1+\xi}{\xi}} + \frac{\left(Z\tilde{h}_N\right)^{\frac{\xi(\epsilon-1)-(1+\xi)}{\xi}}}{\hat{h}} \times \left(ZH_S\right)^{\frac{1+\xi}{\xi}}}{L_N^{\frac{1+\xi}{\xi}} + \frac{\left(Z\tilde{h}_N\right)^{\frac{\xi(\epsilon-1)-(1+\xi)}{\xi}}}{\hat{h}} \times \left(ZH_N\right)^{\frac{1+\xi}{\xi}}} \right)^{1-\alpha} \equiv f_S^{trade}, \tag{30}$$

where $K_S/K_N = (Y_S/Y_N)/(\chi_S/\chi_N)$.

Proof. Rewrite the production function as $Y_J = (K_J)^{\alpha}\left(\hat{Y}_J\right)^{1-\alpha}$, where $\hat{Y}_J \equiv \left[\hat{Y}_{LJ}^{\frac{\epsilon-1}{\epsilon}} + \hat{Y}_{HJ}^{\frac{\epsilon-1}{\epsilon}}\right]^{\frac{\epsilon}{\epsilon-1}}$ and $\hat{Y}_{LJ}$ and $\hat{Y}_{HJ}$ denote the quantities used in final production in country J. Due to trade, these quantities differ from the respective local production levels (which we continue to denote by

[4] More formally, $\tilde{A}_S^{trade}/\tilde{A}_S = \hat{h}^{-1}\left(\tilde{h}_S/\tilde{h}_N\right)^{\frac{\xi+1}{\xi(\epsilon\xi+1)}}$, showing that trade increases (decreases) the skill bias of technology adoption if ξ is sufficiently large (small).

Y_{LJ} and Y_{HJ}). Balanced trade implies that

$$P^w_{\hat{Y}} \hat{Y}_J = P^w_{HJ} \hat{Y}_{HJ} + P^w_{LJ} \hat{Y}_{LJ} = P^w_{HJ} A_{HJ} Z H_J + P^w_{LJ} A_{LJ} L_J, \tag{31}$$

where $P^w_{\hat{Y}} = \left[(P^w_L)^{1-\epsilon} + (P^w_H)^{1-\epsilon} \right]^{1/(1-\epsilon)}$ is the same for all countries. Thus, for any $S \in \hat{S}$, we can write:

$$\frac{Y_S}{Y_N} = \left(\frac{K_S}{K_N} \right)^{\alpha} \left(\frac{\hat{Y}_S}{\hat{Y}_N} \right)^{1-\alpha} = \left(\frac{K_S}{K_N} \right)^{\alpha} \left(\frac{P^w_H A_{HS} Z H_S + P^w_L A_{LS} L_S}{P^w_H A_{HN} Z H_N + P^w_L A_{LN} L_N} \right)^{1-\alpha}, \tag{32}$$

where the second equality comes from (31) and from the fact that $\hat{Y}_S / \hat{Y}_N = P^w_{\hat{Y}} \hat{Y}_S / \left(P^w_{\hat{Y}} \hat{Y}_N \right)$. Rearranging terms yields:

$$\frac{Y_S}{Y_N} = \left(\frac{K_S}{K_N} \right)^{\alpha} \left(\frac{A_{LS} L_S}{A_{LN} L_N} \cdot \frac{1 + \tilde{P}^w \tilde{A}_S Z \tilde{h}_S}{1 + \tilde{P}^w \tilde{A}_N Z \tilde{h}_N} \right)^{1-\alpha}. \tag{33}$$

Then, using (29) and (23) to eliminate A_{LS}/A_{LN} and $\tilde{P}^w$, respectively, and rearranging terms, yields (30). ■

As emphasized in Ventura (2005) and Fadinger (2009), trade affects the shape of countries' aggregate production possibility frontier. In particular, for given technology, the elasticity of substitution between Y_{LS} and Y_{HS} $\left(\text{equivalently, between } L_S^{(1+\xi)/\xi} \text{ and } H_S^{(1+\xi)/\xi}\right)$ is now infinite, instead of ϵ, because all countries face the same world prices. The exponent $(1+\xi)/\xi \geq 1$ still captures the extent of the scale effect in adoption.

3.2 IPR (Licensing of Technologies)

In this section, we maintain free trade and also allow frontier technologies to be licensed from Northern to Southern (monopolist) firms in exchange of a perpetual royalty per unit produced in the South. For simplicity, we assume that when a technology is licensed there are no additional adoption costs. While some local firms could in principle choose to adopt frontier technologies that have not yet been licensed, in equilibrium all technologies will be licensed to the South as soon as they are introduced in the North.[5] Thus, no room is left for unlicensed technology adoption. Intuitively, this follows from the assumption that innovators can transfer technologies at zero costs. Therefore, no matter how low the cost of unlicensed adoption is, Northern producers will bid down the license cost and win the race. The discussion is summarized by the following Lemma.

[5] After a technology has been licensed to a firm in country S, there is no reason for a firm to pay a cost to produce the same variety, since Bertrand competition would bring the profit of the entrant first to zero.

Lemma 2 *Suppose that Northern producers can license their technology. Then, there exists a unique subgame perfect Nash equilibrium such that the South adopts instantaneously all technologies introduced in the North. All profits made in the Southern market are transferred to Northern firms as royalties.*

Full IPR protection entails both costs and benefits for the South. On the one hand, the South must transfer to the North the entire profit flow of intermediate producers. On the other hand, the South can adopt immediately all technologies (similar to the case of $\xi \to \infty$ in the benchmark model). In addition, IPR enforcement affects the direction of technical change, reducing the skill bias of the frontier technology. To see this, note that in steady state the present discounted value of the royalties paid by country S_j are $\varphi_{LS_j} = \pi_{LS_j}/r$ and $\varphi_{HS} = \pi_{HS_j}/r$. Including royalties, the zero-profit conditions for innovation yield:

$$\mu - \sum_{j=1}^{n} \varphi_{LS_j} = \frac{\pi_{LN}}{r}, \text{ and } \mu - \sum_{j=1}^{n} \varphi_{HS_j} = \frac{\pi_{HN}}{r}.$$

The equilibrium skill bias, $\tilde{A}_N$ (where $\tilde{A}_S = \tilde{A}_N$), is the determined implicitly by the following equation:

$$1 = \frac{\pi_{HN} + \sum_{j=1}^{n} \pi_{HS_j}}{\pi_{LN} + \sum_{j=1}^{n} \pi_{LS_j}} = \frac{P_H^w Z H_N + \sum_{j=1}^{n} P_H^w Z H_{S_j}}{P_L^w L_N + \sum_{j=1}^{n} P_L^w L_{S_j}} = \tilde{P}^w Z \tilde{h}^w,$$

where $\tilde{h}^w \equiv \left(H_N + \sum_{j=1}^{n} H_{S_j}\right) / \left(L_N + \sum_{j=1}^{n} L_{S_j}\right)$. This yields $\tilde{P}^w = \left(Z\tilde{h}^w\right)^{-1}$. Then, using (23), one obtains that $\tilde{A}_N = \tilde{A}_S = \tilde{A}_N^{IPR} \equiv \left(Z\tilde{h}^w\right)^{\epsilon-1}$, and $\tilde{w}_N = \tilde{w}_S = \tilde{w} = Z^{\epsilon-1}\left(\tilde{h}^w\right)^{\epsilon-2}$. That is, there is factor price equalization and both $\tilde{A}_N^{IPR}$ and $\tilde{w}_N$ are now smaller. Moreover, for given Z, the skill premium may even turn negative. To prevent this unreasonable outcome, we assume that skilled workers can take unskilled jobs and that a skilled worker produces Z times as much as an unskilled worker regardless of the sector of employment. This implies that there is a lower bound $\tilde{w} \geq Z$. When this lower bound is binding, the allocation of workers across the two sectors adjusts in order to keep $\tilde{w} = Z$. This leads to the following Proposition.

Proposition 3 *Assume free international trade in the intermediate goods Y_H and Y_L and IPR protection (licensing) in the South. For any $S \in \hat{S}$, the steady-state output ratio relative to the frontier is:*

$$\frac{Y_S}{Y_N} = \left(\frac{K_S}{K_N}\right)^{\alpha} \left(\frac{L_S + \tilde{w} H_S}{L_N + \tilde{w} H_N}\right)^{1-\alpha} \equiv f_S^{IPR}, \tag{34}$$

where $K_S/K_N = (Y_S/Y_N)/(\chi_S/\chi_N)$, $\tilde{h}^w = \left(H + \sum_{j=1}^{n} H_{S_j}\right) / \left(L + \sum_{j=1}^{n} L_{S_j}\right)$ *and* $\tilde{w} = \max\left\{Z^{\epsilon-1}(\tilde{h}^w)^{\epsilon-2},\ Z\right\}$.

Proof. The argument is parallel to the proof of Proposition 2. When $\tilde{w} > Z$, one obtains the analogue of expression (33),

$$\frac{Y_S}{Y_N} = \left(\frac{K_S}{K_N}\right)^{\alpha} \left(\frac{L_S}{L_N} \frac{1 + \tilde{P}^w \tilde{A}_N Z \tilde{h}_S}{1 + \tilde{P}^w \tilde{A}_N Z \tilde{h}_N}\right)^{1-\alpha}, \tag{35}$$

where the only differences between (33) and (35) is that in the latter $A_{LS} = A_{LN}$ and $\tilde{A}_N = \tilde{A}_S$. Next, substituting to $\tilde{P}^w$ and $\tilde{A}_N$ the respective expressions (i.e., $\tilde{P}^w = \left(Z\tilde{h}^w\right)^{-1}$ and $\tilde{A}_N = \left(Z\tilde{h}^w\right)^{\epsilon-1}$), and rearranging terms, leads to (34). When $\tilde{w} = Z$, a similar argument applies after noticing that:

$$\frac{P_H^w \hat{Y}_{HJ} + P_L^w \hat{Y}_{LJ}}{P_H^w \hat{Y}_{HN} + P_L^w \hat{Y}_{LN}} = \frac{w_H^w H_J + w_L^w L_J}{w_H^w H_N + w_L^w L_N} = \frac{Z H_J + L_J}{Z H_N + L_N}.$$

■

Cross-country productivity differences are smaller under full IPR. However, it becomes important to draw a distinction between GDP and (Gross National Product) GNP: the GNP of the North now includes the royalties paid by Southern firms. In general, it is ambiguous whether the GNP ratio increases with IPR. The growth rate of the world economy is unambiguously larger.

4 Empirical Analysis

In this section, we provide a quantitative assessment of the theory. The strategy is to use the no-trade economy of section 2 as the benchmark for a development accounting exercise. More precisely, we consider a relative production function of the form:

$$\frac{y_S}{y_N} = \frac{\Omega_S}{\Omega_N} \times \frac{H_N + L_N}{H_S + L_S} \times f_S^{AUT}, \tag{36}$$

where f_S^{AUT} is given by (15).[6] Equation (36) allows for exogenous Hicks-neutral TFP differences (i.e., the term Ω_S/Ω_N) that are alien to our theory. Therefore, the success of our theory is measured by the extent to which the empirical variation in output and productivity can be accounted for without resorting to differences in Ω.

In the spirit of the development accounting literature (e.g., Caselli, 2005), we calibrate the key parameters, whenever this is possible. In particular, we set $\alpha = 0.35$ to match the non-labor

[6] Recall that, although the countries use different technologies, our theory is consistent with a common representation of the aggregate CES production function featuring increasing returns to scale.

share of GDP in industrialized countries, calibrate ϵ and Z so as to match the time evolution of the skill premium in the frontier economy using the predictions of our theory, and estimate ξ so as to obtain the best fit of cross-country productivity differences in two cross-sections of up to 122 countries (see section 4.4.2 for more discussion). As it is customary, we use the no-trade scenario as the baseline case, and assess how successfully the benchmark model can account for the cross-country productivity distribution in 1970 and 2000. Then, we perform a number of theory-based counterfactuals including: (i) slashing all barriers to technology adoption, (ii) opening up the world economy to free trade, and (iii) allowing, in addition, perfect international IPR enforcement. We study the changes in the long-run distribution of productivity differences that each of these changes would trigger.

4.1 Data Description

Since our analysis focuses on balanced-growth equilibria, we do not attempt to fit high-frequency data, and focus on the distribution of cross-country productivity differences in 1970 and 2000. We assume the US to be the frontier economy, and calibrate ϵ and Z using the change in the skill premium and the skill ratio between 1970 and 2000 in the United States from the March Current Population Survey (CPS) cleaned by Autor, Katz, and Kearney (2008).[7] Like these authors, we only consider full-time, full-year workers aged 16 to 64 with 0 to 39 years of potential experience. We exclude female workers and workers with earnings below $67 per week in 1982 dollars, as well as workers with allocated earnings. We calculate relative wages as the ratio of the CPS sampling weighted average earnings for different education levels. In particular, we focus on high school graduates vs. non-high school graduates and college graduates vs. non-college graduates.

The data on output, investment, population and the labor force are from Heston, Summers and Aten (2009). The estimates of the capital stock are generated using the perpetual inventory method (see, e.g., Caselli (2005)). For the relative skill endowment, we use two data sets: Barro and Lee (2010) and Cohen and Soto (2007). These data sets contain information on the fraction of the population aged 25 and above with a high school or a college degree. The stock of skilled and unskilled workers is then simply calculated by multiplying the labor force

[7] In practice, we use the observations of 1971 and 2001 since the reported earnings are for the previous year. The two data sets are available online from David H. Autor's website.

with the corresponding skill fraction in the population. Following Hall and Jones (1999), we perform a natural resource correction on GDP by subtracting the fraction of value added in the mining and quarrying sector according to National Accounts Official Country Data accessed via UNdata. Because for some countries value added in the mining and quarrying sector is not reported on an annual basis, we linearly interpolate the missing data points for 1970 and 2000 if necessary. We drop Kuwait which is a strong outlier in terms of GDP pw in 1970.[8] We end up with a repeated cross-section of 86 (1970) to 122 (2000) countries when using the education data from Barro and Lee (2010), while we have 73 (1970) to 85 (2000) countries when using the data from Cohen and Soto (2007). In an appendix available from our webpages we repeat the analysis restricting the balanced sample of countries for which information is available both in 1970 and 2000 and find very similar results.

4.2 Calibration

4.2.1 Elasticity of Substitution

We identify ϵ and Z using equation (11) given the evolution of the skill premium in the US. More formally, we set ϵ and Z so as to match exactly the equation:

$$\log\left(\tilde{w}_{US,t}\right) = (\epsilon - 1)\log(Z) + (\epsilon - 2)\log\left(\tilde{h}_{US,t}\right), \tag{37}$$

where $t \in \{1970, 2000\}$. Hence

$$\epsilon = 2 + \frac{\log\left(\tilde{w}_{US,2000}\right) - \log\left(\tilde{w}_{US,1970}\right)}{\log\left(\tilde{h}_{US,2000}\right) - \log\left(\tilde{h}_{US,1970}\right)}. \tag{38}$$

The skill premia as well as the skill ratios are taken from the March CPS. As discussed above, we use two alternative measures of skill: secondary and tertiary school. The wage premium for high school graduates over non-high school graduates increased from 1.40 in 1970 to 2.02 in 2000, while the wage premium for college graduates over non-college graduates increased from 1.57 in 1970 to 1.88 in 2000. The ratio of high school graduates over non-high school graduates in the population in working age increased during the same period from 2.59 to 9.30, while the ratio of college graduates over non-college graduates increased from 0.21 to 0.43. Since in

[8] The inclusion of Kuwait does not change our main results. In Table 8 of the appendix we report the estimation results for a sample that includes Kuwait.

many OECD economies a large share of the population finishes secondary school, we regard tertiary education as the most appropriate measure of skill for our theory.

Equations (37)-(38) pin down ϵ and Z. Since both the skill ratio and the relative skill supply increased sharply in the United States during 1970–2000, the two equations imply that $\epsilon > 2$. Table 1 summarizes the baseline calibration for ϵ and Z conditional on the skill measure. In the table (and for future reference), *sec* stands for "secondary school completed" whereas *tert* stands for "tertiary school completed".

	Calibration	
Skill measure	ϵ	Z
sec	2.29	1.05
tert	2.25	1.96

Table 1: Baseline calibration

In our model, the parameter ϵ has the structural interpretation of a short-run elasticity between high- and low-skill labor. Other studies (e.g., Ciccone and Peri (2005)) provide estimates of such an elasticity of substitution in the interval $[1.4, 2]$. Since our estimate of ϵ falls outside of this range, we consider lower values in Section 4.4.1. Note that if we calibrate ϵ to lower values, we must allow Z to increase between 1970 and 2000, or else the theory would predict, counterfactually, a decline in the skill premium. In other words, our estimate $\epsilon > 2$ appears to be consistent with the prediction of our theory, whereas lower values of ϵ are rejected by our estimation unless we assume that there are other exogenous drivers of skill-biased technical change, captured by an increase in Z.

4.2.2 Barriers to Technology Adoption

Having calibrated α, Z and ϵ as described above, we estimate ξ by full information maximum likelihood (FIML) using the following econometric model:

$$\log\left(\frac{y_S}{y_{US}}\right) = \log\left[f_S^{AUT} \times \frac{H_N + L_N}{H_S + L_S}\right] + \log \varepsilon_S,$$

where f_S^{AUT} is given by (15), and $\log \varepsilon_S$ is an i.i.d. normally distributed disturbance with mean zero.

Table 2 shows the estimation results with robust standard errors in parentheses. The four rows refer to different skill categories (*sec* and *tert*) and data sets (Barro-Lee (BL) and Cohen-Soto (CS)). Columns 1 and 2 report the point estimate of ξ using the whole sample. Then, we allow ξ to vary between OECD (columns 3 and 4) and non-OECD countries (columns 5 and 6). The results show that ξ is significantly lower in non-OECD countries,[9] which is consistent with the interpretation that poor countries have larger barriers. Since there remains a great deal of heterogeneity within non-OECD countries, we split further the subsample into sub-Saharan (columns 7 and 8) and other non-OECD countries (columns 9 and 10).[10] The differences in barriers to technology adoption between both the sub-Saharan and other non-OECD countries and OECD and non-OECD countries are in all but one cases highly significant.[11]

Another pattern emerges from the table: The estimated ξ approximately doubles between 1970–2000 for OECD countries, while there is no big change for non-OECD countries. This suggests that technological integration increased mostly within the set of industrialized countries.

4.2.3 Results

Figure 2 plots the predicted GDP pw (log-difference from the US) against the actual GDP pw for all countries, using educational variables from the Barro-Lee data set and allowing ξ to differ across OECD, sub-Saharan and other non-OECD countries, as in Table 2. Panels

[9] We classify as OECD all countries that were OECD members in 2000 (same classification in both 1970 and 2000 to limit endogeneity issues). Including only countries that were OECD members in 1970 yields similar results. The estimates for OECD countries are then higher while those for non-OECD countries remain almost unchanged. For instance, the point estimate for OECD countries in the third row of Table 2 would be 6.61 (1.80) in 1970 and 21.50 (10.26) in 2000 instead of 5.91 (1.48) in 1970 and 11.71 (3.37) in 2000.

[10] We do not include Mauritius among the sub-Saharan countries, due to its special geographical and economic conditions (see Subramanian and Roy 2001). Including Mauritius would not cause dramatic changes in the point estimates. For instance, the third row in Table 2 would read 2.33 (0.20) in 1970 and 2.52 (0.30) for sub-Saharan countries and 3.83 (0.48) in 1970 and 3.94 (0.45) in 2000 for the other non-OECD countries.

[11] In 1970, the point estimate for sub-Saharan countries is lower than the point estimate for the other non-OECD countries at the 1 percent level of significance across all specifications. In 2000, barriers are significantly lower for the *tert* skill category at the 1 percent (BL) and 5 percent level (CS). For the *sec* skill category, the differences are significant at the 5 percent for BL and close to the 10 percent level of significance for CS. OECD countries have significantly lower barriers than non-OECD countries at the 1 percent level in 2000 for the *tert* skill category, while they are at least lower at the 5 percent level of significance for the *sec* skill category and in 1970 across all specifications.

		All countries		OECD		Non-OECD					
						All		Sub-Sahara		Others	
		1970	2000	1970	2000	1970	2000	1970	2000	1970	2000
Data	Skill	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
BL	sec	4.84	5.38	10.72	18.66	4.51	4.80	3.17	3.80	6.13	5.33
		(0.50)	(0.54)	(3.60)	(8.27)	(0.47)	(0.49)	(0.31)	(0.47)	(1.07)	(0.72)
CS	sec	3.78	3.98	6.40	11.32	3.75	3.48	2.25	3.00	4.90	3.77
		(0.35)	(0.38)	(1.09)	(2.47)	(0.35)	(0.34)	(0.24)	(0.32)	(0.60)	(0.52)
BL	tert	3.19	3.78	5.91	11.71	3.02	3.38	2.25	2.35	3.88	4.05
		(0.25)	(0.33)	(1.48)	(3.37)	(0.25)	(0.30)	(0.19)	(0.24)	(0.47)	(0.47)
CS	tert	3.23	2.83	5.53	8.41	3.05	2.46	1.97	1.86	4.14	2.92
		(0.28)	(0.24)	(0.96)	(1.37)	(0.28)	(0.21)	(0.19)	(0.13)	(0.45)	(0.36)
Obs.	(BL/CS)	85/71	121/83	19/17	29/23	66/54	92/60	23/19	23/19	43/35	69/41

Table 2: Baseline estimation

(a)-(c) use the secondary school educational measure for years 1970 and 2000, respectively, whereas Panels (b)-(d) use the tertiary education measure for the same years. In an appendix available from our webpages we plot the corresponding figure that is obtained by imposing a common ξ over the entire sample. Whenever a point lies on the 45-degree line, the theory fits the data perfectly. Whenever a point lies above (below) the 45-degree line, the model underpredicts (overpredicts) the productivity differences between that country and the US. The fit is altogether good, although there are some outliers, among them, Malta, Cyprus and Hong-Kong which lie significantly below the 45-degree line. This is not surprising, since these countries are classified as non-OECD countries (and thus pooled in the estimation of ξ with poorer economies), although they are very open economies sharing more commonalities with the OECD countries than with the rest of non-OECD countries. Since the estimation forces them to have large barriers, the model largely overpredicts their productivity difference relative to the US. If one merges these three countries with the OECD, they cease to be outliers. Likewise, Bahrain, Barbados, Brunei, Mauritius and Qatar (also below the 45-degree line) are small economies with special characteristics that make them atypical non-OECD economies. Among the countries lying significantly above the 45-degree line, one notices Japan, Korea and

China in year 2000. The large population size and/or the high physical capital per worker are behind this finding.

It is useful to compare the results with those that would obtain if we estimated productivity differences assuming no barriers to technology adoption, as in AZ01. More formally, we let $\xi \to \infty$ – see equation (22) – while keeping all other parameters unchanged. AZ01 find that their model yields a significantly better fit than a neoclassical one-sector model such as the one used by Hall and Jones (1999). Since our model encompasses their specification as a particular case, we can quantify the importance of barriers, separating their effect from that of "inappropriate technology". Figure 3 is the analogue of Figure 2 but letting $\xi \to \infty$. It shows that the model without barriers underestimates significantly the cross-country productivity differences.

To compare the goodness of fit of the two models more formally, we use the statistic proposed by AZ01:

$$\Re^2 = 1 - \sum_{j=1}^{n} \left(\log(y_{S_j}/y_{US}) - \widehat{\log}(y_{S_j}/y_{US}) \right)^2 / \sum_{j=1}^{n} \left(\log(y_{S_j}/y_{US}) \right)^2,$$

where $\log(y_{S_j}/y_{US})$ denotes the log-difference in output per worker from the US in the data and $\widehat{\log}(y_{S_j}/y_{US})$ the prediction of the model for the same country. $\Re^2$ would be equal to 1, if all points were aligned on the 45-degree line. In this case, the model would fit the data perfectly. Note that $\Re^2$ is not a standard R-squared, and can be negative if the fit is sufficiently low. Table 3 reports the $\Re^2$ for the three specifications of Table 2, and for comparison also the case of no barriers (column 4). In column 1 all countries are constrained to have the same ξ. In column 2 ξ is allowed to differ between OECD and non-OECD countries. Finally, in 3, we also allow ξ to differ between sub-Saharan and other non-OECD countries. In all cases, the model with barriers attains a much better fit than the model with no barriers.[12] The model with no barriers is also rejected in a formal Wald test.

A concern is that our estimation may imply $A_{LS}/A_{L,US}$ and/or $A_{HS}/A_{H,US}$ larger than unity, violating the assumption that the US is the technology leader in both sectors. To address

[12] The results are not directly comparable with those of AZ01. First their model implies $\epsilon = 2$, and they set $Z \in \{1.5, 1.8\}$ to match the skill premium. Second, they use data for 1990. To make the comparison more direct, we re-estimated our model after calibrating $\epsilon = 2$ and $Z = 1.8$, using the two educational measures from BL for the year of 2000. The $\Re^2$ of the model without barriers is 0.871 and 0.766 using *sec* and *tert*, respectively. In contrast, the $\Re^2$ of column 3 in Table 3 would be 0.940 and 0.922, respectively.

		Baseline estimation						No barriers	
		(1)		(2)		(3)		(4)	
Data	Skill	1970	2000	1970	2000	1970	2000	1970	2000
BL	sec	0.926	0.930	0.929	0.936	0.938	0.938	0.829	0.855
CS	sec	0.934	0.944	0.937	0.951	0.953	0.952	0.807	0.856
BL	tert	0.905	0.903	0.910	0.913	0.923	0.921	0.690	0.763
CS	tert	0.924	0.922	0.927	0.936	0.947	0.942	0.746	0.761

Table 3: Goodness of fit

this concern, Figure 4 plots the implied cross-country distribution of the sectoral productivities, $A_{LS}/A_{L,US}$ and $A_{HS}/A_{H,US}$, using our estimate of the baseline model in the case of tertiary education with BL data. The hypothesis that the US is the technology leader is never rejected in the skilled sector. More formally, $A_{HS}/A_{H,US} < 1$ for all S. This is not surprising. More interesting, the hypothesis that the US is the technology leader in the low-skill sector is only contradicted in the case of China and India in 2000. This is due to the large market for low-skill technologies available in those two countries. Since it seems empirically implausible that China and India use all technologies currently in use in the US in the low-skill sector, this finding suggests that the model may exaggerate the role of market size effect in technology adoption. Alternatively, the assumption that large developing economies such as China and India have frictionless internal markets may be incorrect. Altogether, we find it reassuring that – with only two (important) exceptions – the assumption that the US is the leader is consistent with our estimation, without the need of imposing any additional restriction.

4.3 Counterfactuals

In this section we use our model as a lab to perform three counterfactual experiments. We assume the economies to be initially in the no-trade steady state of year 2000, and study the long-run effect of institutional changes on cross-country inequality. The three experiments consist of, respectively: (i) removing all barriers to technology adoption, (ii) opening up the world economy to frictionless international trade, and (iii) introducing, in addition, full international IPR enforcement. We focus on steady-state effects.

We limit our discussion to the *tert* skill measure from the Barro-Lee data set and to the case in which ξ differs between OECD, sub-Saharan and other non-OECD countries (column 3 to 4 and 7 to 10 in Table 2). The parameters α, Z, ϵ and ξ are held constant across experiments at the levels of section 4.2 (with the exception of experiment (i) when we let $\xi \to \infty$). Since physical capital is endogenous, we allow the capital-output ratio to respond to institutional changes. We do so by first inferring from the observed capital-output ratios the cross-country distribution of the deep parameter χ (the "investment wedge") in the benchmark no-trade case. Next, we calculate the capital-output ratio that would obtain in each of the counterfactual steady states (no barriers, free trade and trade with full IPR enforcement) assuming no change in χ. Since our target is to estimate relative productivities, we focus on the distribution of investment wedges relative to the North. For country S such ratio is given by:

$$\frac{\chi_S}{\chi_N} = \frac{Y_S/K_S}{Y_N/K_N}, \tag{39}$$

where the right hand-side term is the capital-output ratio in the data, and we continue to assume the US to be the frontier economy. Next, letting variables indexed by the superscript *count* $\in \{nobarr, trade, IPR\}$ denote theoretical steady-state levels in each counterfactual, we obtain:

$$\frac{K_S^{count}}{K_N^{count}} = \frac{Y_S^{count}/\chi_S}{Y_N^{count}/\chi_N} = \frac{Y_S^{count}}{Y_N^{count}} \frac{K_S/Y_S}{K_N/Y_N}. \tag{40}$$

Replacing K_S/K_N by $K_S^{nobarr}/K_N^{nobarr}$, K_S^{trade}/K_N^{trade} and K_S^{IPR}/K_N^{IPR}, respectively, into equations (22), (30) and (34), and rearranging terms, yields the steady-state expressions for output and productivity reported in each of the subsections below.

4.3.1 No Barriers

In this section, we experiment with slashing all technology barriers. Such experiment differs from the analysis in Section 4.2.3, as there we treated the no-barrier model as an alternative model and estimated equation (22) taking the capital ratio directly from the data. In contrast, here we infer the χ from the benchmark case and let capital adjust in each country to the new steady state, as discussed above. The gains in output per worker will be larger for countries with smaller investment wedges, since slashing barriers induces a stronger increase in investments in physical capital in those countries.

We obtain the following counterfactual steady-state output gaps:

$$\begin{aligned}
\frac{Y_S^{nobarr}}{Y_N^{nobarr}} &= \left(\frac{K_S^{nobarr}}{K_N^{nobarr}}\right)^{\alpha} \times \left[\frac{L_S^{\frac{\epsilon-1}{\epsilon}} + \left(Z\tilde{h}_N\right)^{\frac{(\epsilon-1)^2}{\epsilon}} \times (ZH_S)^{\frac{\epsilon-1}{\epsilon}}}{L_N^{\frac{\epsilon-1}{\epsilon}} + \left(Z\tilde{h}_N\right)^{\frac{(\epsilon-1)^2}{\epsilon}} \times (ZH_N)^{\frac{\epsilon-1}{\epsilon}}}\right]^{\frac{\epsilon(1-\alpha)}{\epsilon-1}} \\
&= \left(\frac{K_S/Y_S}{K_N/Y_N}\right)^{\frac{\alpha}{1-\alpha}} \times \left[\frac{L_S^{\frac{\epsilon-1}{\epsilon}} + \left(Z\tilde{h}_N\right)^{\frac{(\epsilon-1)^2}{\epsilon}} \times (ZH_S)^{\frac{\epsilon-1}{\epsilon}}}{L_N^{\frac{\epsilon-1}{\epsilon}} + \left(Z\tilde{h}_N\right)^{\frac{(\epsilon-1)^2}{\epsilon}} \times (ZH_N)^{\frac{\epsilon-1}{\epsilon}}}\right]^{\frac{\epsilon}{\epsilon-1}},
\end{aligned}$$

where K_S/Y_S and K_N/Y_N are the observed capital output ratios. Panel (a) in Figure 5 plots the counterfactual log GDP pw relative to the US, $\widehat{\log}(y_S^{nobarr}/y_{US}^{nobarr})$, against the productivity differences predicted by the benchmark model. There are significant gains for most countries, which are especially large for those with small investment wedges. Among the OECD economies making largest gains, one notices New Zealand, Korea, Hungary, Czech Repulic, Slovak Republic and Switzerland. On average, the GDP pw relative to the US improves for an OECD country from 0.68 to 0.91 while non-OECD countries increase from 0.19 to 0.61. The effect is particularly strong for small countries, which lack the local market size required to benefit from expensive technologies (for instance, Cyprus improves from 0.34 to 1.05 while the United Kingdom only increases from 0.68 to 0.77).

4.3.2 Trade

In this section we consider the effects of opening up the world economy to free trade. The counterfactual steady-state output differences are given by equation (30), after replacing K_S/K_N by K_S^{trade}/K_N^{trade}, as given by equation (40). This yields:

$$\frac{Y_S^{trade}}{Y_N^{trade}} = \left(\frac{K_S/Y_S}{K_N/Y_N}\right)^{\frac{\alpha}{1-\alpha}} \times \frac{L_S^{\frac{1+\xi}{\xi}} + \frac{(Z\tilde{h}_N)^{\frac{\xi(\varepsilon-1)-(1+\xi)}{\xi}}}{\hat{h}} \times (ZH_S)^{\frac{1+\xi}{\xi}}}{L_N^{\frac{1+\xi}{\xi}} + \frac{(Z\tilde{h}_N)^{\frac{\xi(\varepsilon-1)-(1+\xi)}{\xi}}}{\hat{h}} \times (ZH_N)^{\frac{1+\xi}{\xi}}}.$$

As discussed in section 3.1, trade increases the skill bias of the frontier technology, while its effect on the skill bias of technology adoption is ambiguous.

Panel (b) in Figure 5 plots $\widehat{\log}(y_S^{trade}/y_{US}^{trade})$ against the predictions of the benchmark model. Cross-country income inequality increases significantly, and so does the distance of most countries from the US frontier. The GDP pw relative to the US decreases for the average

OECD country from 0.68 to 0.41, while the non-OECD countries fall from 0.19 to 0.10. Among the OECD countries that realize the largest losses are Italy, Luxembourg, Austria, France, and Finland. However, it is also important to remind that trade implies an increase in the growth rate of all economies, so a loss in relative terms does not imply a welfare loss.

4.3.3 Trade and IPR

In this section, we focus on trade with perfect IPR protection, following the theoretical analysis of section 3.2. The counterfactual steady-state output differences are given by equation (34), after replacing K_S/K_N by K_S^{IPR}/K_N^{IPR} as given by (40). This yields:

$$\frac{Y_S^{IPR}}{Y_N^{IPR}} = \left(\frac{K_S/Y_S}{K_N/Y_N}\right)^{\frac{\alpha}{1-\alpha}} \times \frac{L_S + \tilde{w}H_S}{L_N + \tilde{w}H_N},$$

where $\tilde{w} = \max\left\{Z^{\epsilon-1}(\tilde{h}^w)^{\epsilon-2},\ Z\right\}$. As discussed in section 3.2, all countries use now the frontier technology, as in the case of no barriers. However, the frontier technology is now less skill biased. Panel (c) in Figure 5 plots $\widehat{\log}(y_S^{IPR}/y_{US}^{IPR})$ against the productivity differences predicted by the benchmark model. The results are similar to those in panel (a), but the relative gains of non-frontier economies are larger. Many economies – including most European countries – would now surpass the US. The reason is twofold. First, the skill bias of the technology targets the average world endowment so innovation is too little skill biased for the most skilled rich countries such as the US. Second, many countries have a higher capital output ratio than the US. However, it is important to remember that non-frontier countries must transfer to the US a significant share of their GDP as license fees. So, the differences in GNP may be significantly larger than the differences in GDP.

Overall, these results are in line with AZ01 and Bonfiglioli and Gancia (2008), who show in more specific models that trade opening with no global IPR protection may induce a wave of technological progress which favors disproportionately the North, while stronger IPR protection in the South can speed up technology transfer and reduce income differences.

4.3.4 Wage Inequality

Finally, we consider the prediction of the theory for the changes in wage inequality in the three counterfactual scenarios relative to the benchmark case. Recall $\tilde{w}_S = Z \cdot \tilde{P}_S \cdot \tilde{A}_S$. In autarky, $\tilde{P}_S$ and $\tilde{A}_S$ are given by (7) and (14), respectively. The same expressions hold with no barriers to adoption after letting $\xi \to \infty$. In the free-trade case, prices are equalized worldwide to $\tilde{P}^w = \left(Z\tilde{h}_N\right)^{-1}$ and $\tilde{A}_S = \hat{h}^{-1}\left(Z\tilde{h}_N\right)^{\epsilon-1}\left(\tilde{h}_S/\tilde{h}_N\right)^{1/\xi}$, where $\hat{h}$ is given by (25). Finally, in the case of trade with IPR, we have $\tilde{w}_S = \max\left\{Z^{\epsilon-1}(\tilde{h}^w)^{\epsilon-2},\ Z\right\}$, where $\tilde{h}_w$ is the world average relative skill endowment.

Figure 6 plots the log-change in the steady-state skill premium for tertiary school against GDP per worker relative to the US when barriers are removed starting from the benchmark steady state equilibrium. Removing barriers implies an increase in the skill premia of non-frontier economies, since costly adoption reduces the skill bias of the technology adoption. The effect is stronger the farther away from the frontier a country is. For the average non-OECD country the skill premium increases by 25 percent, while it rises only by 3 percent among OECD countries. Figure 7 plots the corresponding log-change in the steady-state skill premium when an economy switches to free trade. Opening up to free trade in goods raises the skill premium in skill-abundant countries and lowers it in skill-scarce countries, as predicted by the Stolper-Samuelson theorem. However, by also inducing skill-biased technical change at the frontier, it generates an upward pressure on the skill premium worldwide. As a result, wage inequality increases in the majority of countries, particularly in skill-abundant and low-barriers countries. The conventional result that trade liberalization lowers inequality in skill-scarce countries holds only in the group of economies facing the highest barriers to technology adoption (for instance, in sub-Saharan countries the skill premium falls on average by 42 percent), while wage inequality rises even in India and China.

Finally, when IPR are also protected (no figure), the relevant market for new technologies becomes the world economy. This promotes the development of low-skill technologies and thus a fall in the skill premium. Moreover, since all countries now use the same technologies, all wages become the same everywhere. Given the large endowment of unskilled labor of the world economy, we find that with trade and IPR protection $\tilde{A}$ falls so much that the constraint $\tilde{w}_S \geq Z$ becomes binding. Thus, in the new steady state wage inequality drops to $\tilde{w} = Z$ in all countries. Before concluding, it is important to emphasize that these large changes in skill premia reflect the rather extreme nature of our counterfactual scenarios. The effect of partial integration of the markets for goods and technology would certainly be smaller. It is also important to stress that our model abstracts from differences in labor market institutions and policies which are likely to affect the cross-country pattern of skill premia and its change under the alternative scenarios.

4.4 Robustness

In this section we analyze the robustness of our results. First, we study the robustness of the model to different calibrations of ϵ. Then, we compare our results with those that would obtain from an atheoretical development accounting exercise. Next, we test the robustness of the results to a weaker form of the market size effect. Last, we estimate the model under the alternative assumption that in year 2000 all economies are open to international trade.

4.4.1 Lower Short-Run Elasticity of Substitution

In this part, we study the robustness of our model to a different calibration of ϵ. Earlier studies find the short-run elasticity of substitution between skilled and unskilled labor to be in the range $\epsilon \in [1.5, 2]$. It is important to stress that $\epsilon < 2$ is inconsistent in our model with the observation of increasing skill premia in the US during 1970-2000. To reconcile lower ϵ's with the evolution of the skill premium in the US, we must then allow for an exogenous increase in Z. The new calibration is summarized in Table 4, where we restrict attention to *tert* from the Barro-Lee dataset which is our preferred measure of skill.

	$\epsilon = 2$		$\epsilon = 1.5$	
Skill	Z_{1970}	Z_{2000}	Z_{1970}	Z_{2000}
tert	1.57	1.88	0.51	1.52

Table 4: Robustness calibration

Table 5 shows the new estimates of ξ. When $\epsilon = 2$, the results are qualitative similar to those of the benchmark case, although the estimates of ξ are somewhat larger. The $\Re^2$ are still above 0.9, and the differences in ξ across groups and time remain at the significance level of the baseline estimation in Table 2. In summary, our analysis is not affected by setting $\epsilon = 2$. When $\epsilon = 1.5$, the results continue to be similar to the benchmark case. The estimates go further up, and the level of significance reduces to 5 percent between OECD and non-OECD countries in 2000. In spite of this, the goodness of fit stays above 0.9.

		All countries		OECD		Non-OECD					
						All		Sub-Sahara		Others	
		1970	2000	1970	2000	1970	2000	1970	2000	1970	2000
Data	Skill	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\epsilon = 2$											
BL	tert	3.31	3.90	6.17	12.09	3.13	3.50	2.33	2.47	4.03	4.16
		(0.27)	(0.35)	(1.57)	(3.54)	(0.26)	(0.31)	(0.19)	(0.25)	(0.50)	(0.49)
$\epsilon = 1.5$											
BL	tert	3.74	4.38	7.00	13.53	3.54	3.94	2.65	2.93	4.56	4.58
		(0.31)	(0.40)	(1.86)	(4.22)	(0.30)	(0.36)	(0.22)	(0.30)	(0.61)	(0.56)
	Obs.	85	121	19	29	66	92	23	23	43	69

Table 5: Robustness estimation

4.4.2 Alternative Specifications

A number of papers (discussed in the introduction) perform development accounting exercises based on reduced form aggregate production functions such as equation (1). The wisdom of this literature is that the model can replicate the empirical cross-country productivity distribution as long as one imposes sufficiently low elasticities of substitution between factors of production. For instance, Caselli (2005) shows that if one calibrates a production function with physical and human capital allowing for very low values of the elasticity of substitution, one can fit arbitrarily well the cross-country data. In this paper, we allow ourselves no freedom in the choice of the elasticity of substitution between capital and labor, which we taken to be unit as it is standard in the growth accounting literature. In addition, we estimate the short-run elasticity of substitution between high- and low-skill labor using the time-series implication of the theory. The only parameter on which we impose no *a priori* restriction is ξ. We should note, though, that our theory imposes that the *long-run* elasticity of substitution between high- and low-skill labor be larger than the short-term elasticity. Thus, estimating ξ does not imply a degree of freedom in the choice of the elasticity of substitution, and our theory precludes that a good fit can arise from low elasticities.

Nevertheless, it is interesting to compare the success of our theory with that of a reduced form production function approach.[13] For the sake of such comparison, we estimate the following alternative (reduced form) model:

$$\frac{Y_S}{Y_N} = \left(\frac{K_S}{K_N}\right)^{\alpha} \left(\frac{L_S^{\frac{\upsilon-1}{\upsilon}} + \left(\frac{\bar{A}_H}{\bar{A}_L} H_S\right)^{\frac{\upsilon-1}{\upsilon}}}{L^{\frac{\upsilon-1}{\upsilon}} + \left(\frac{\bar{A}_H}{\bar{A}_L} H_N\right)^{\frac{\upsilon-1}{\upsilon}}}\right)^{\frac{\upsilon(1-\alpha)}{\upsilon-1}}, \tag{41}$$

subject to the restriction that labor markets are competitive, implying that:

$$\frac{\bar{A}_H}{\bar{A}_L} = (\tilde{w}_{US})^{\frac{\upsilon}{\upsilon-1}} \left(\frac{H_N}{L_N}\right)^{\frac{1}{\upsilon-1}},$$

where $\tilde{w}_{US}$ is the observed skill premium in the US and $\upsilon \geq 0$ is the elasticity of substitution between low- and high-skill labor.

Consistent with previous studies, we find that the best fit of this model obtains with low elasticities of substitution between high- and low-skill workers. For instance, if we measure skill by tertiary school from the Barro-Lee data set the best estimates yield $\upsilon_{1970} = 1.07$ and $\upsilon_{2000} = 0.50$. With such low elasticities, the model fits quite well the data. In particular, we obtain $\Re^2_{1970} = 0.771$ and $\Re^2_{2000} = 0.916$. However, the estimated elasticities are clearly outside of the consensus range. If we impose that $\upsilon \geq 1.5$, the goodness of fit falls significantly. For instance, with tertiary education and $\upsilon = 1.5$ one obtains $\Re^2_{1970} = 0.726$ and $\Re^2_{2000} = 0.802$ with BL and $\Re^2_{1970} = 0.785$ and $\Re^2_{2000} = 0.800$ with CS. For comparison, the corresponding $\Re^2$s of Table 3 range between 0.903 and 0.952. In addition, the reduced form model systematically underpredicts the cross-country productivity differences for reasonable values of υ. On both grounds, the reduced form model performs significantly worse than our structural model with tertiary education. In sum, a reduced form model without market-size effects does not outperform our structural model.

4.4.3 Weaker Market Size Effect

Our model implies a strong market size effect. In this section, we test the robustness of the results to a more general functional form for technology adoption implying that the cost of

[13] It is important to note that our model is *not* observationally equivalent to a standard aggregate constant returns to scale CES production function like (1) for two reasons. First, the parameter ξ implies a cross-restriction between the skill bias of the adopted technology and the long-run elasticity of substitution between high- and low-skill labor. Second, it features a market-size effects in the process of technology adoption, parameterized by the exponent $(1+\xi)/(\alpha+\xi) > 1$ in the right-hand side of (15).

adopting new technologies may increase in market size. We assume that:

$$c_{LS} = \mu \left(\frac{A_{LS}}{A_{LN}} \right)^{\xi} (L_S)^{\phi} \quad \text{and} \quad c_{HS} = \mu \left(\frac{A_{HS}}{A_{HN}} \right)^{\xi} (ZH_S)^{\phi},$$

where $\phi \geq 0$. This model nests the benchmark case in (13) when $\phi = 0$. This specification scales up the relative cost of technology adoption by the factor $(ZH_S/L_S)^{\phi}$ compared to the benchmark case and (partly) compensates for the market size effect in relative profits if $\phi > 0$. This allows us to analyze models with a weaker market size effect. Relative output is then given by

$$\frac{Y_S}{Y_N} = \left(\left(\frac{K_S}{K_N} \right)^{\alpha} \left[\frac{L_S^{\frac{(\epsilon-1)(1+\xi-\phi)}{1+\epsilon\xi}} + \left(Z\tilde{h}_N \right)^{\frac{\xi(\epsilon-1)(\varepsilon-1-\varepsilon\phi)}{1+\epsilon\xi}} \times (ZH_S)^{\frac{(\epsilon-1)(1+\xi-\phi)}{1+\epsilon\xi}}}{L_N^{\frac{(\epsilon-1)(1+\xi-\phi)}{1+\epsilon\xi}} + \left(Z\tilde{h}_N \right)^{\frac{\xi(\epsilon-1)(\varepsilon-1-\varepsilon\phi)}{1+\epsilon\xi}} \times (ZH_N)^{\frac{(\epsilon-1)(1+\xi-\phi)}{1+\epsilon\xi}}} \right]^{\frac{(1-\alpha)(1+\epsilon\xi)}{(\epsilon-1)(1+\xi-\phi)}} \right)^{\frac{1+\xi-\phi}{\alpha+\xi}},$$

which shows that the long-run elasticity of substitution as well as the scale effect is affected by the parameter ϕ.

We estimate the model under this alternative specification. The constraint that $\xi \geq 0$ turns out to be binding for sub-Saharan countries. The estimated value of ϕ is 0.584 (s.e. 0.006) for year 1970 and 0.576 (s.e. 0.007) for year 2000. The estimated values of ξ for 1970 are 0.63 (s.e. 0.30) for OECD countries and 0.24 (s.e. 0.10) for non-OECD countries (excluding sub-Saharan countries). The corresponding values for year 2000 are 1.18 (s.e. 0.47) for OECD countries and 0.18 (s.e. 0.08) for non-OECD countries (excluding Sub-saharan countries). The goodness of fit, $\Re^2 = 0.934$ in 1970 and $\Re^2 = 0.926$ in 2000, is marginally higher than in the benchmark model.

The results are qualitatively consistent with those in the benchmark model: the estimate of ξ increases significantly (by a factor of two) between 1970 and 2000 for OECD countries, while there is no significant change (the point estimate being in fact somewhat lower) for non-OECD countries. However, the estimated barriers are significantly larger for all countries, or equivalently the elasticity of technology adoption to the distance to the frontier is lower. In addition, it appears as if there is no technology spillover to sub-Saharan countries that develop their technologies in complete isolation ($\xi = 0$). It is worth remarking that the improvement in the fitness is only marginal, indicating that the data cannot discriminate clearly between the two models.

4.4.4 Openness

In our analysis, we have followed the tradition of the development accounting literature assuming all economies to be closed. Free trade was only considered as a counterfactual. However, the absence of trade is a straightjacket, especially for more recent years. For this reason, in this section we re-estimate the model under the alternative assumption that there is free trade in year 2000, based on the results of Proposition 2.

Under free trade, the estimated barriers for OECD countries become very small, i.e., the estimated ξ is very high and also imprecisely estimated. The restriction that there are no technological barriers for OECD countries cannot be rejected at standard confidence levels.[14] Therefore, we impose the constraint that $\xi \to \infty$ for OECD countries. We report the result of the estimation using tertiary schooling from BL as the measure of skill. This results in $\xi = 10.06$ (s.e. 1.81) for the non-OECD non-sub-Saharan countries and $\xi = 3.88$ (s.e. 0.63) for the sub-Saharan countries. Therefore, estimating the model under free trade yields significantly lower barriers to technology. Interestingly, the open economy model fits better the data ($\Re^2 = 0.934$) than the closed-economy model. Figure 8 shows that there is a significant improvement in the fit of emerging economies such as China, India, Indonesia, Thailand, Mexico and Brazil. This is consistent with the observation that these economies are very open to international trade.

5 Conclusions

In this paper, we have built and estimated a model of the world income distribution based on the following ingredients: different types of labor (skilled and unskilled workers), cross-country differences in factor endowments and in the cost of capital, factor-biased (directed) technical progress and costly technology adoption. Our framework accounts for three sources of income differences: barriers to technology adoption, the inappropriateness (excessive skill-bias) of frontier technologies to local conditions and capital market imperfections. While each of these elements is not new, our contribution is to combine them into a unified empirical model which can be used to gauge the relative importance of different factors generating low productivity and to perform counterfactual experiments.

We summarize here the major findings. First, despite the parsimonious specification, the

[14] In practice, we test that $\xi_{2000} = 1'000'000$ cannot be rejected for the OECD countries.

model provides a good fit of the world income distribution. This suggests that the theory of directed technical change is broadly consistent with aggregate data once properly extended to consider technology adoption and international spillovers. Second, both barriers to adoption and the excessive skill-bias of frontier technologies appear to be quantitatively important. We find that barriers are higher in less developed countries and that they have fallen over time for OECD countries only. The complete removal of barriers would increase output per worker relative to the US (the effect is more pronounced for non-OECD countries) and would lead to higher skill premia. Third, we have used the model to study how the forces of globalization can shape the world income distribution. In the absence of global IPR protection, we find that integration of good markets is followed by SBTC, higher income disparities, and rising skill premia in the majority of countries. These results are however reverted if trade liberalization is coupled with international protection of IPR.

The analysis in this paper can be extended in a number of interesting directions. For instance, we have estimated our benchmark model under the assumption of no international trade and we have then studied globalization as a counterfactual experiment. While this is useful to understand the effects of economic integration, an alternative route would have been to estimate the model taking into account the degree of openness of each country. Finally, although our theory suggests that the removal of barriers to technology adoption has strong distributional consequences, we have not explored how these may generate a political support for the existence of barriers. We believe that including these consideration into the model may shed some light on the important question of which political institutions and reforms can be useful to speed up the much needed process of technological convergence.

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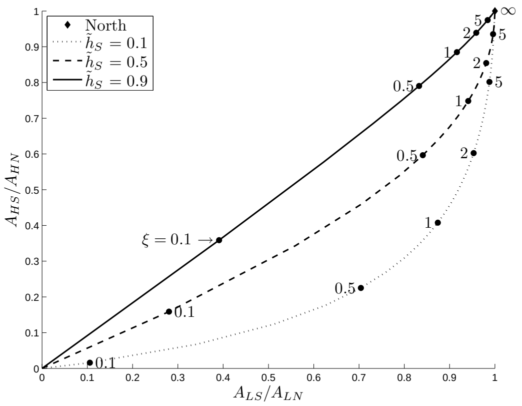
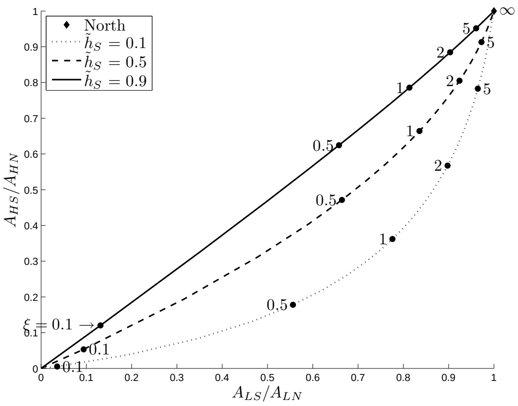
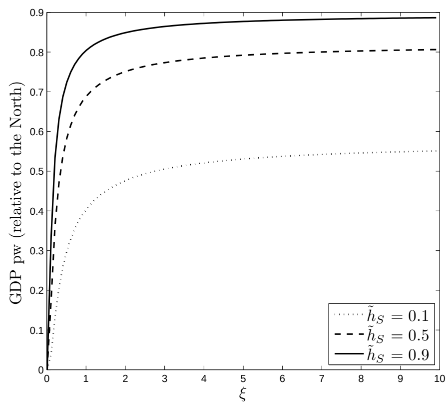
Figure 1: Steady state comparative statics



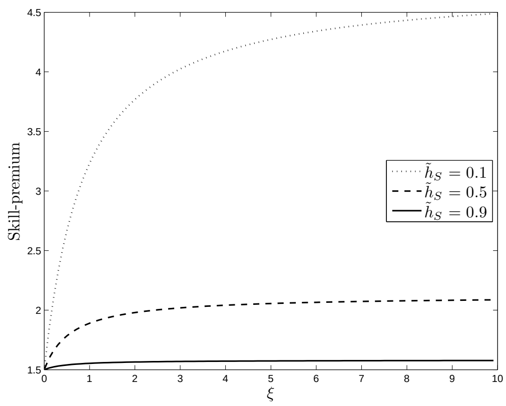
(a) $\chi_S/\chi_N = 1.2$



(b) $\chi_S/\chi_N = 1.5$

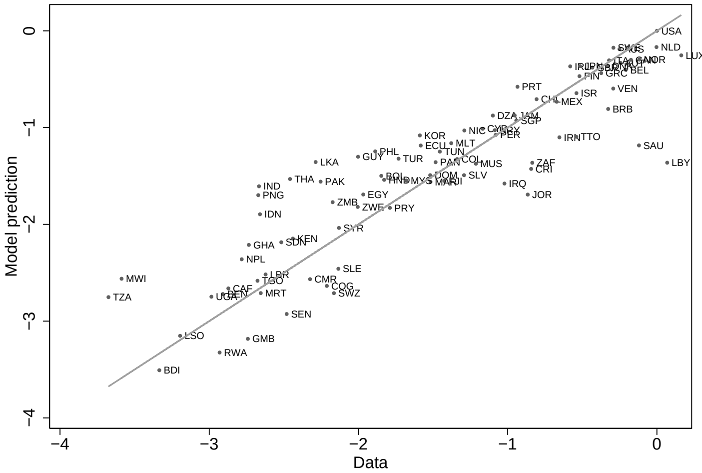


(c) $\chi_S/\chi_N = 1.2$

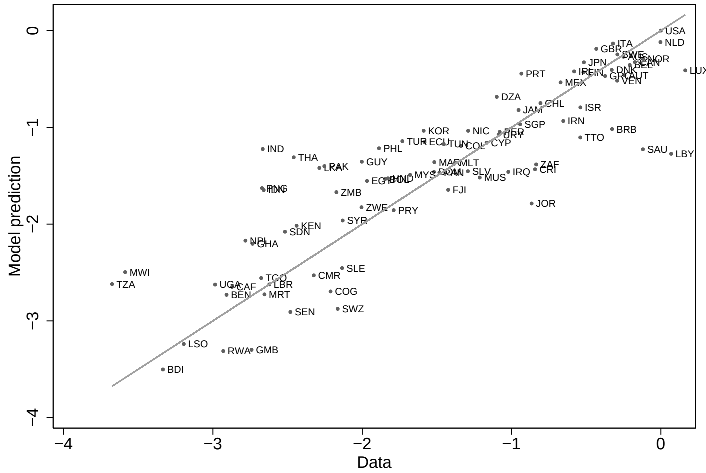


(d) $\chi_S/\chi_N = 1.2$

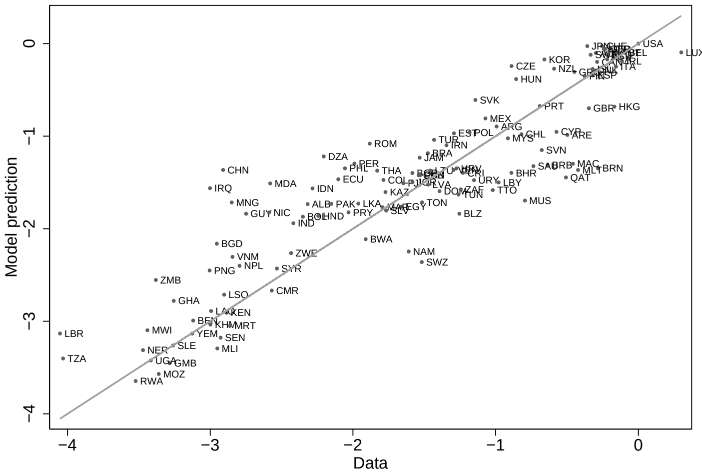
Figure 2: Baseline estimation: GDP pw (log-difference from the US)



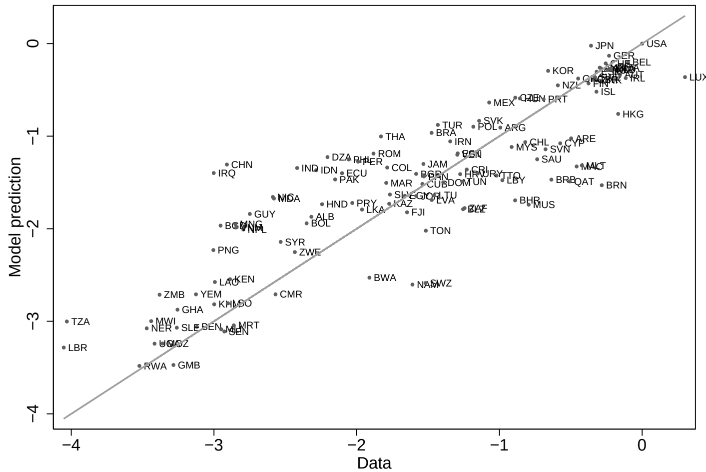
(a) 1970, secondary schooling



(b) 1970, tertiary schooling



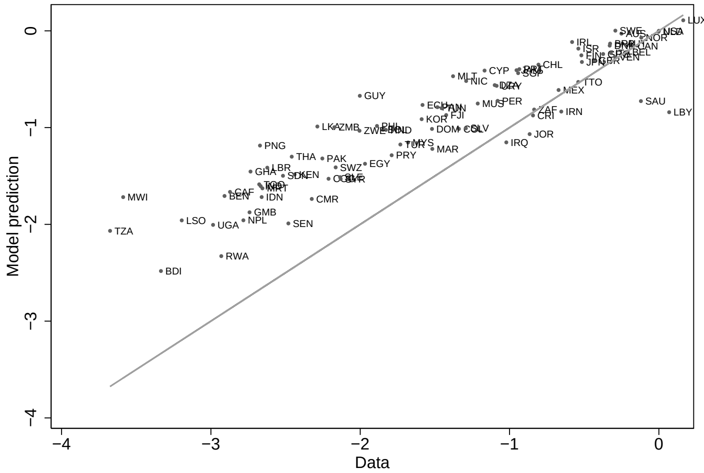
(c) 2000, secondary schooling



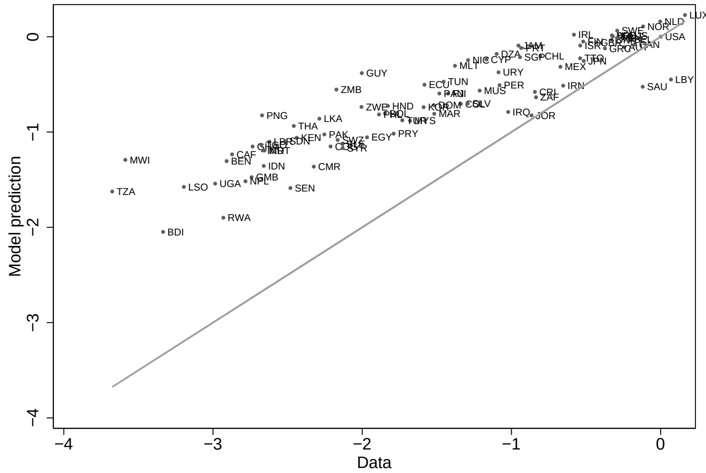
(d) 2000, tertiary schooling

Note: plots $\widehat{\log}(y_S/y_{US})$ against $\log(y_S/y_{US})$ across time and skill categories, ξ varies across OECD, sub-Saharan and other countries.

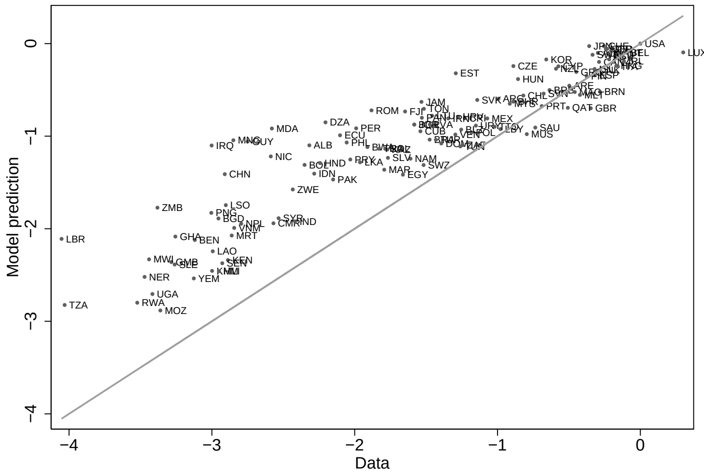
Figure 3: No barriers to technology adoption: GDP pw (log-difference from the US)



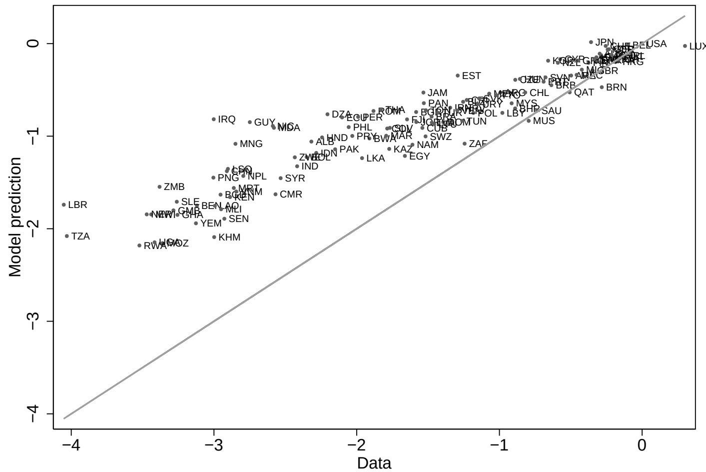
(a) 1970, secondary schooling



(b) 1970, tertiary schooling



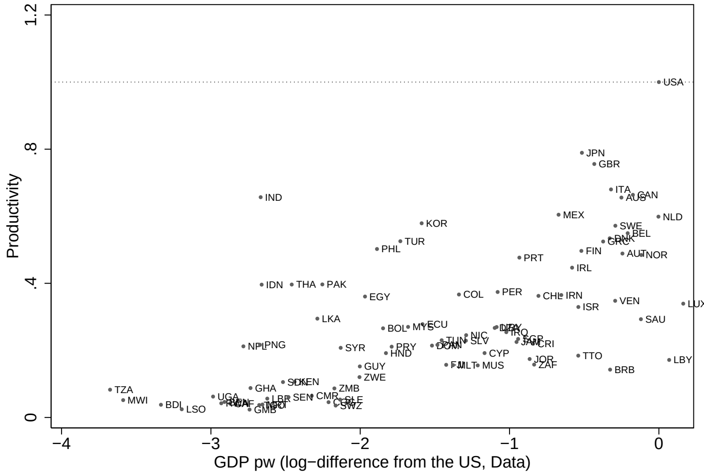
(c) 2000, secondary schooling



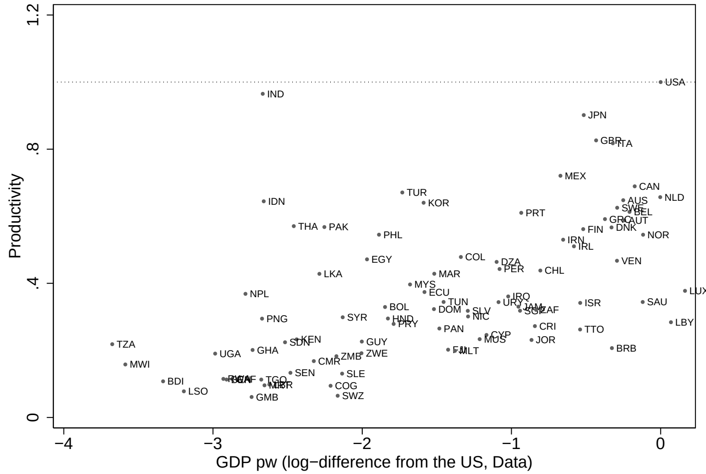
(d) 2000, tertiary schooling

Note: plots $\widehat{\log}(y_S/y_{US})$ against $\log(y_S/y_{US})$ across time and skill categories, $\xi \to \infty$ for all countries.

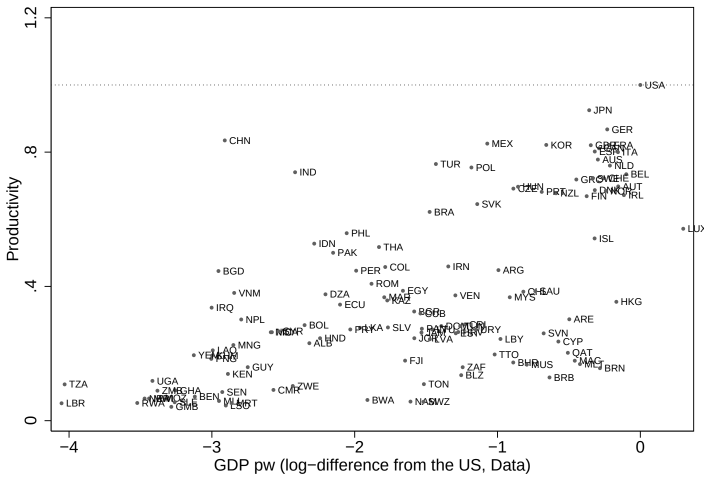
Figure 4: Sectoral productivities (relative to the US)



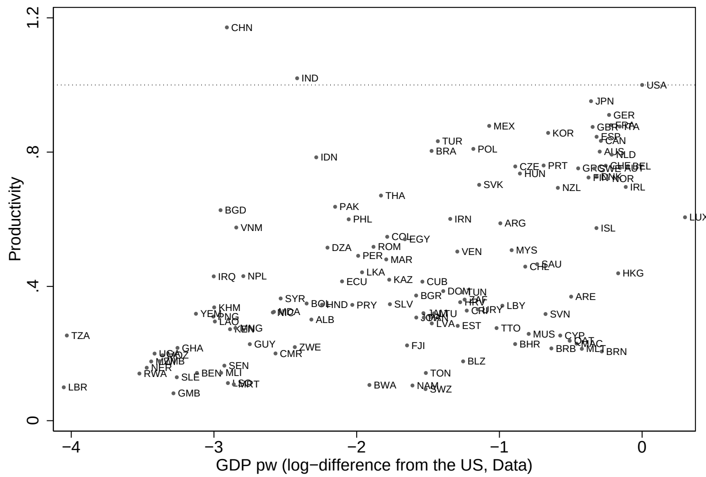
(a) 1970, high-skill sector



(b) 1970, low-skill sector



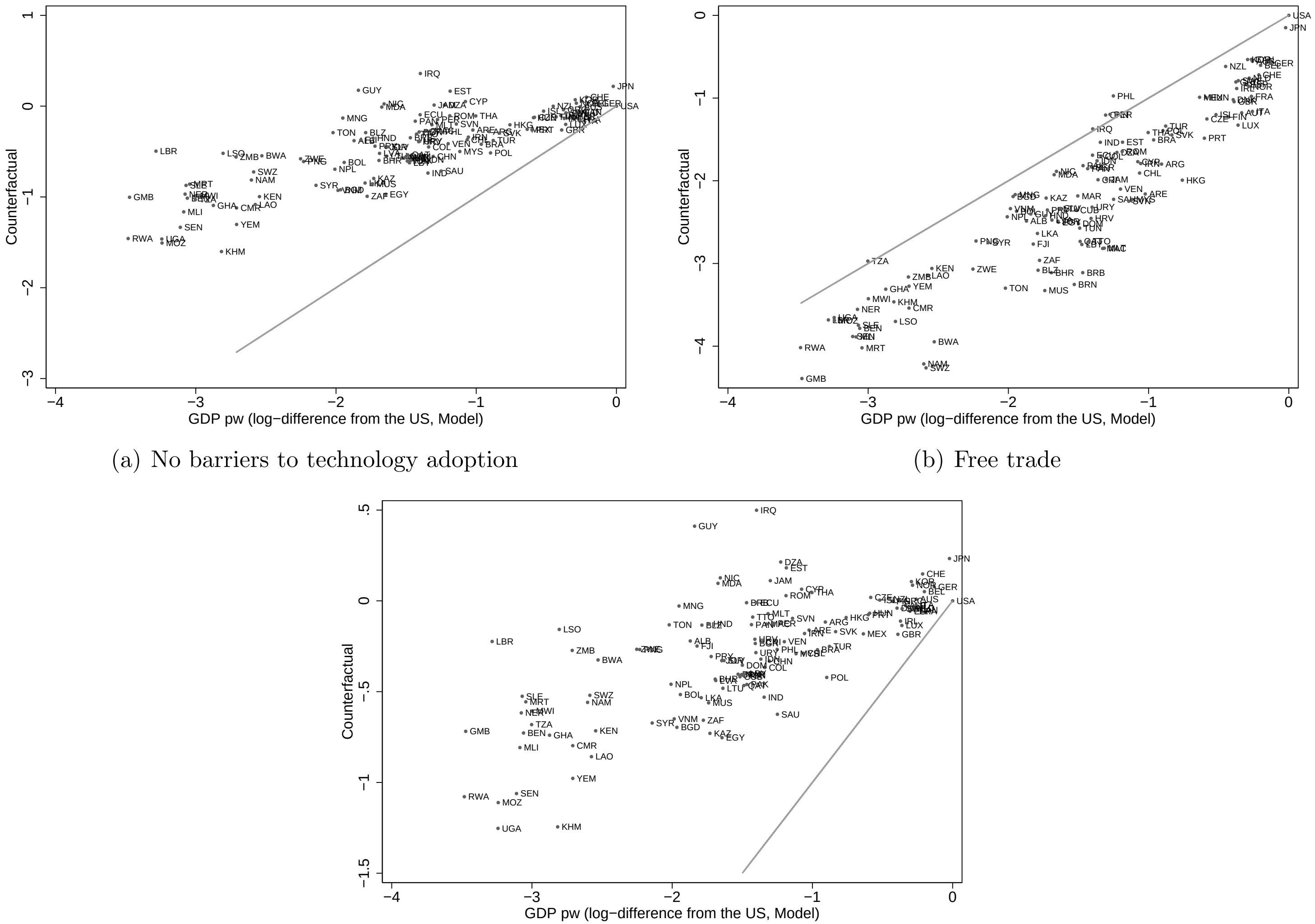
(c) 2000, high-skill sector



(d) 2000, low-skill sector

Note: plots $A_{HS}/A_{H,US}$ and $A_{LS}/A_{L,US}$ against $\log(y_S/y_{US})$ across time for the tertiary skill category. ξ varies across OECD, sub-Saharan and other countries.

Figure 5: Counterfactual GDP pw (log-difference from the US)



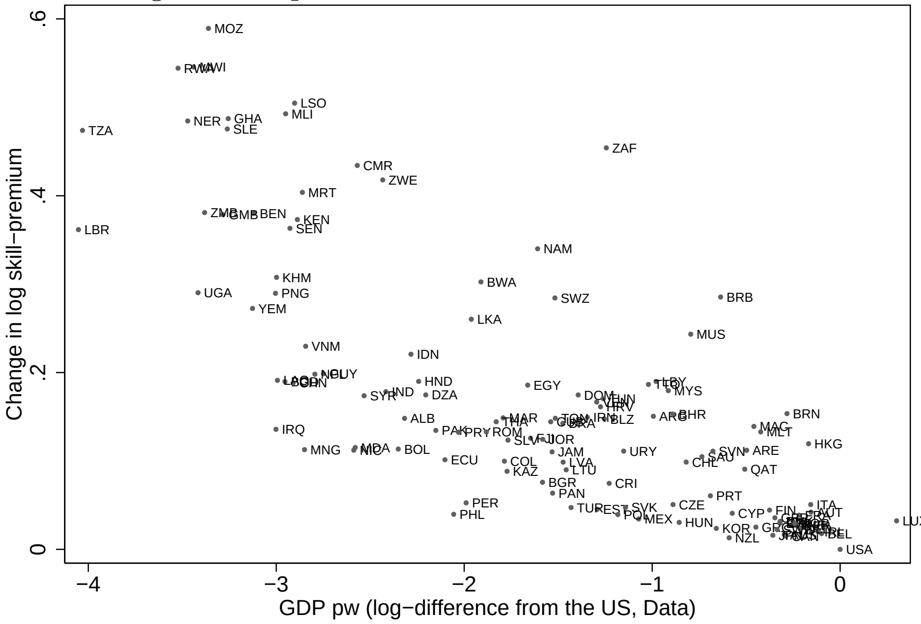
(a) No barriers to technology adoption

(b) Free trade

(c) Free trade and perfect IPR protection

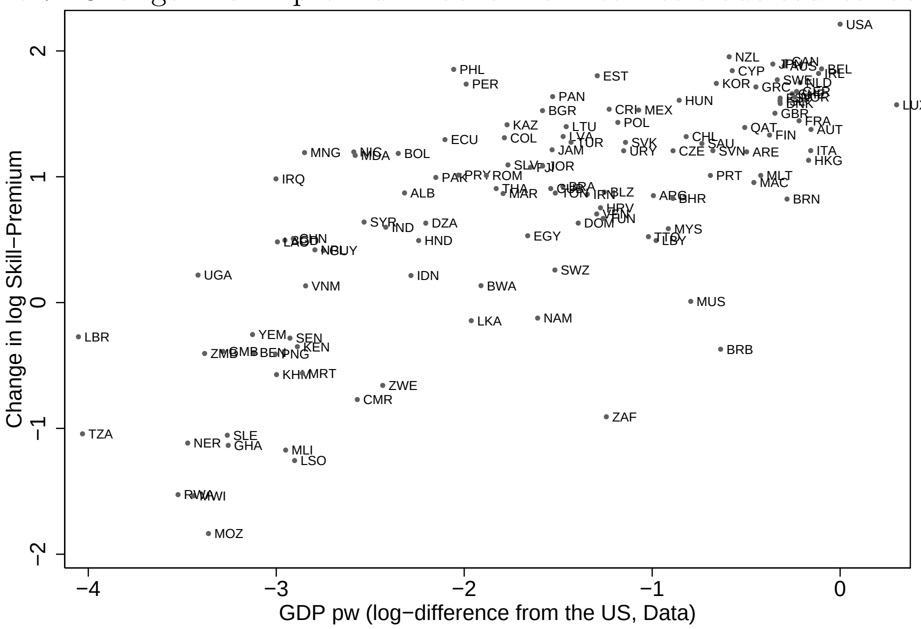
Note: plots $\widehat{\log}(y_S^{count}/y_{US}^{count})$ against $\widehat{\log}(y_S/y_{US})$ in 2000 for the tertiary schooling category. ξ varies across OECD, sub-Saharan and other countries.

Figure 6: Change in skill premium: benchmark to no barrier counterfactual



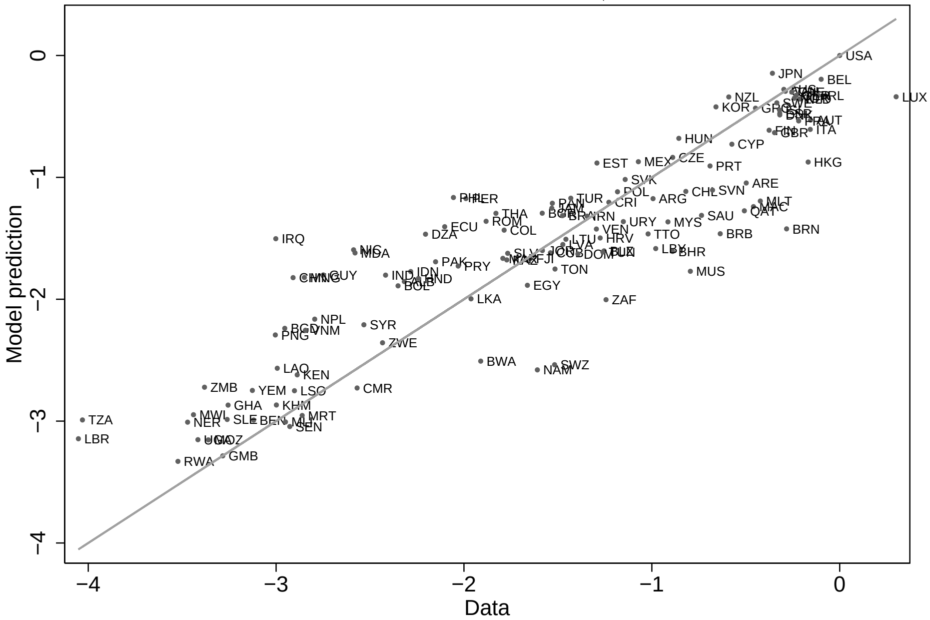
Note: plots $\widehat{\log} \tilde{w}_J^{nobarr} - \widehat{\log} \tilde{w}_J$ in 2000 for the tertiary schooling category. ξ varies across OECD, sub-Saharan and other countries.

Figure 7: Change in skill premium: benchmark to free trade counterfactual



Note: plots $\widehat{\log} \tilde{w}_J^{trade} - \widehat{\log} \tilde{w}_J$ in 2000 for the tertiary schooling category. ξ varies across OECD, sub-Saharan and other countries.

Figure 8: Open Economy Estimation: GDP pw (log-difference from the US)



Note: plots $\widehat{\log}(y_S/y_{US})$ against $\log(y_S/y_{US})$ for the open economy estimation in 2000, ξ varies across OECD, sub-Saharan and other countries.

A Appendix (not for publication)

In this appendix we provide the estimation results for a different sample selection than the one in Table 2 of section 4.2.2. We also provide the analog of Figure 2 when ξ is restricted to be the same across countries.

In Table 6 we repeat the analysis restricting the sample to countries for which information is available both in 1970 and 2000.

		All countries		OECD		Non-OECD					
						All		Sub-Sahara		Others	
		1970	2000	1970	2000	1970	2000	1970	2000	1970	2000
Data	Skill	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
BL	sec	5.00	4.89	10.72	54.97	4.64	4.20	3.15	3.44	6.10	4.78
		(0.58)	(0.59)	(3.60)	(76.11)	(0.55)	(0.48)	(0.38)	(0.47)	(1.11)	(0.79)
CS	sec	3.86	3.98	6.40	13.77	3.63	3.50	2.17	2.82	4.89	3.90
		(0.39)	(0.43)	(1.09)	(3.88)	(0.39)	(0.38)	(0.27)	(0.32)	(0.62)	(0.59)
BL	tert	3.28	3.28	5.91	17.48	3.08	2.87	2.24	2.17	3.84	3.47
		(0.29)	(0.34)	(1.48)	(9.34)	(0.28)	(0.28)	(0.23)	(0.22)	(0.49)	(0.49)
CS	tert	3.30	2.83	5.53	9.31	3.10	2.49	1.91	1.80	4.13	2.99
		(0.30)	(0.27)	(0.96)	(2.02)	(0.31)	(0.24)	(0.21)	(0.15)	(0.46)	(0.40)
Obs.	(BL/CS)	78/68		19/17		59/50		18/16		41/34	

Table 6: Baseline estimation with constant set of countries

In 1970, the point estimate for sub-Saharan countries is lower than the point estimate for the other non-OECD countries at the 1 percent level of significance across all specifications. In 2000, it is at least significantly lower at the 5 percent level for the *tert* skill category. For the *sec* skill category, the differences are very close to the 10 percent level of significance. OECD countries have significantly lower barriers than non-OECD countries at the 1 percent level in 2000 for CS (for the BL data we loose the significance), while they are lower at the 5 percent level of significance in 1970 across all specifications. The fit of this model is reported in Table 7 which is the analog of Table 3. The predictive power of the model is robust to the considered sample modification, in particular for the specifications in column 2 and 3 where we allow ξ to vary across country groups.

In Table 8 we present the results of the baseline estimation adding Kuwait to the sample. CS is missing education data for Kuwait, so we restrict the analysis to the BL data set. Kuwait is a strong outlier in terms of GDP pw in 1970, therefore, the point estimate for tertiary schooling in the other non-OECD countries increases from 3.88 (0.47) to 4.21 (0.63) compared to the sample where Kuwait is excluded. It is a general observation that the standard errors go up. However, our main results remain unchanged, only the difference of barriers between OECD and non-OECD countries in 1970 for the secondary schooling category falls short of the earlier significance level (10 percent instead of 5 percent). The $\Re^2$s stay high and are reported in

		Baseline estimation					
		(1)		(2)		(3)	
Data	Skill	1970	2000	1970	2000	1970	2000
BL	sec	0.918	0.938	0.921	0.948	0.930	0.950
CS	sec	0.928	0.945	0.931	0.953	0.948	0.954
BL	tert	0.896	0.910	0.901	0.927	0.913	0.934
CS	tert	0.917	0.922	0.921	0.936	0.942	0.944

Table 7: Goodness of fit constant set of countries

	All countries		OECD		Non-OECD					
					All		Sub-Sahara		Others	
	1970	2000	1970	2000	1970	2000	1970	2000	1970	2000
Skill	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
sec	5.11	5.45	10.72	18.66	4.79	4.88	3.17	3.80	6.90	5.46
	(0.61)	(0.56)	(3.60)	(8.27)	(0.59)	(0.50)	(0.31)	(0.47)	(1.53)	(0.74)
tert	3.32	3.82	5.91	11.71	3.15	3.43	2.25	2.35	4.21	4.12
	(0.30)	(0.34)	(1.48)	(3.37)	(0.29)	(0.31)	(0.19)	(0.24)	(0.63)	(0.48)
Obs.	86	122	19	29	67	93	23	23	44	70

Table 8: Baseline estimation for BL including Kuwait

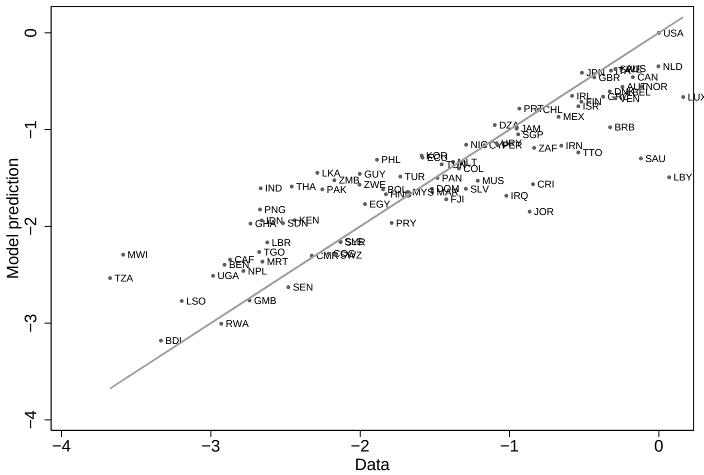
Table 9.

	Baseline estimation					
	(1)		(2)		(3)	
Skill	1970	2000	1970	2000	1970	2000
sec	0.914	0.930	0.917	0.935	0.928	0.937
tert	0.891	0.902	0.895	0.911	0.911	0.920

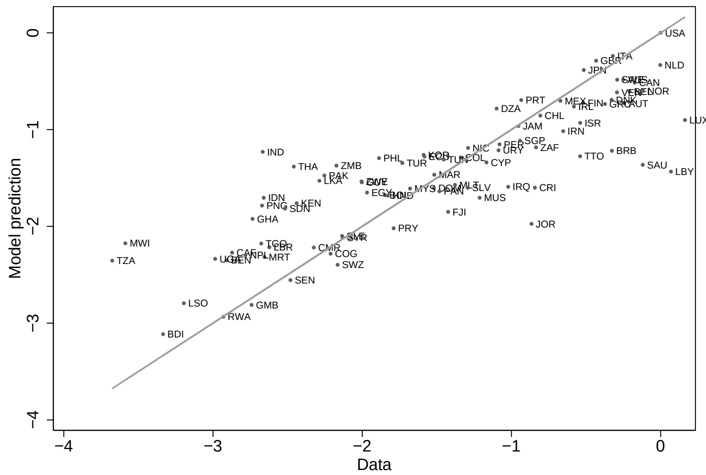
Table 9: Goodness of fit for BL including Kuwait

Finally, in Figure 9 we provide the relative GDP prediction of the baseline model from section 4.2.3 when we require the same ξ for all countries instead of letting it vary across OECD, sub-Saharan and other non-OECD countries as seen in Figure 2. Panels (a)-(d) clearly illustrate that we underpredict income differences for rich countries and underestimate them for poor when imposing a single ξ for all countries. This observation motivates the introduction of income groups in the baseline estimation.

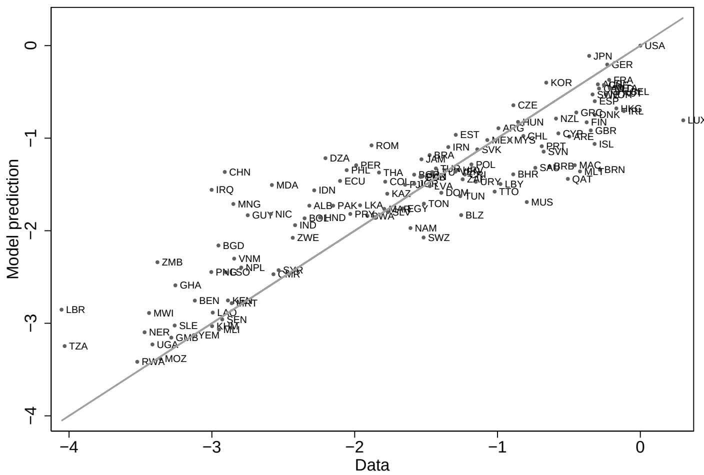
Figure 9: Baseline estimation: GDP pw (log-difference from the US)



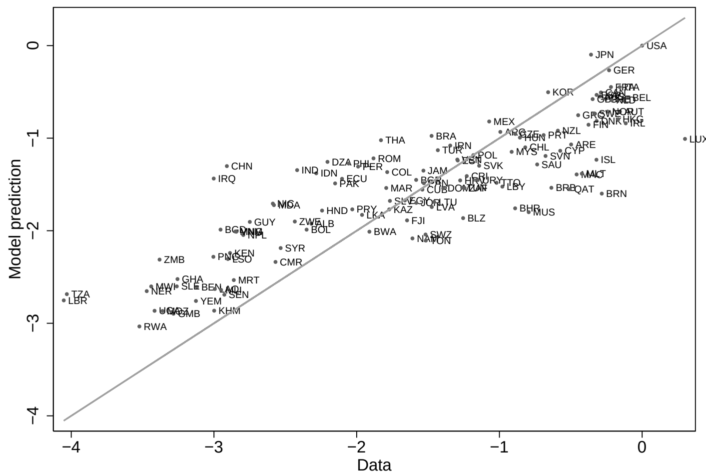
(a) 1970, secondary schooling



(b) 1970, tertiary schooling



(c) 2000, secondary schooling



(d) 2000, tertiary schooling

Note: plots $\widehat{\log}(y_S/y_{US})$ against $\log(y_S/y_{US})$ across time and skill categories, ξ is the same for all countries.