Structural Development Accounting

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Abstract

In this paper, 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 of our framework are different types of workers (skilled and unskilled labor), 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 90 countries in 1970 and 2000. We use the model to assess the relative importance of alternative factors affecting the world income distribution and to perform counterfactual experiments. Our results suggests that removing barriers to technology adoption would increase output of the average OECD economy relative to the US frontier from 68.3% to 92.5%. The average non-OECD country would instead increase from 17.4% to 53.8%. Slashing barriers would also lead to higher skill premia in all countries. We also study how globalization can shape income disparities. In the absence of global IPR protection, we find that 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 protection of IPR.

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1 INTRODUCTION

New technologies do not diffuse instantaneously across firms and nations, and adoption lags are often considered a major determinant of productivity differences. In a classic paper, Griliches (1957) documents that new seeds of hybrid corn diffused slowly across US agricultural regions, with a 15-year lag between adoption in Iowa and Alabama, and that diffusion was affected by local conditions, such as geography and market potential. The spread of more recent technologies shows similar patterns. Looking at ICT diffusion, Kiessling (2009) reports evidence of slow adoption 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 same time, there is overwhelming evidence that differences in technology are one of the most important determinants of cross-country income disparities. For instance, 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 first developed and then adopted (or fail to be 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 ϵ, instead, captures the elasticity of substitution between the two types of workers. Given data on factors and a value for υ, 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. Its contribution is not just

to propose an account of the world income distribution, but also to develop an empirical model that helps to shed some light on the determinants of technology diffusion and that can be used to study how phenomena like skill-biased technical change (SBTC) and globalization affect output and wages worldwide.[1]

Building on Acemoglu and Zilibotti (2001) and Gancia and Zilibotti (2009), we propose a theory of directed technical change and technology adoption that yields a micro-founded modified version of the aggregate production function (1). In the model, an advanced economy, identified with the US and possibly other significant contributors to the world stock of R&D 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., Acemoglu, 1998 and 2002), R&D effort can be devoted to develop H- or L-complement machines.[2] To capture the advantage of backwardness emphasized, among others, by Gerschenkron (1962), Nelson and Phelps (1966), and Acemoglu, Aghion and Zilibotti (2006) we assume that all other countries can *adopt* existing technology 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.

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 and depending on the value of ϵ, 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. Identifying which of these two mechanisms is main source of income differences is a major goal of this paper.

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 fact that both the relative skill supply and the skill premium have been growing steadily over the last quarter of the past century is consistent with

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[1] Banrejee-Duflo (2005) and Hsieh and Klenow (2009) argue that the technology gap is largely a within-country phenomenon, as there are considerable differences in the technologies used by different firms. Yet, in this paper we abstract from within-country technology differences.

[2] We also maintain the assumption that new technologies developed by the leader countries are sold in their markets only. I.e., there is no trade in technology or no international protection of intellectual property. We relax this assumption in an extension where we introduce international license contracts on the use of technology.

our model if the value of ϵ is larger than (and close to) two.[3] We therefore take this as the benchmark case, although we perform robustness checks using alternative values found in the literature (e.g., we also use $\epsilon = 1.5$, as in Ciccone and Peri (2005), and $\epsilon = 2$, as in Acemoglu and Zilibotti (2001)). The second parameter, barriers to technology adoption, is instead estimated from (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 deviations between predicted and observed output.

Despite the parsimonious parametrization, 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 significantly 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.

With this parametrization at hand, we use the model to perform a series of counter-factuals. First, we show that removing barriers to technology adoption would increase relative income from 17.4% to 53.8% for the average non-OECD country and from 68.3% to 92.5% 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 (for instance, Cyprus gains about six times more than the United Kingdom in relative income per worker). While these are large numbers, we also find that a large share of the cross-country income differences is explained by technology inappropriateness. Removing barriers also forces all countries to import the skill bias of the technology frontier, thereby inducing a generalized increase in the skill premium (on average, 4.0 percent among OECD countries and 29.1 percent among non-OECD countries).

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 Acemoglu (2003) and Acemoglu and Zilibotti (2001), trade liberalization may have triggered 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

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[3] A value of this elasticty close to two is within the bounds of most estimates reported in the literature. See, Freeman (1986) for a survy of earlier estimates and Behar (2009) for a more recent discussion.

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 3.5 for the average country), but also in the cross-country income gap (on average, the income per worker falls by 13 percentage points relative to the frontier).[4] 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 a strong income convergence worldwide.

The literature on international technology diffusion is vast. The idea that countries may benefit from technologies developed elsewhere was first put forward by Gerschenkron (1962) and Nelson and Phelps (1966) and then formalized by Barro and Sala-i-Martin (1997), Howitt (2000), Acemoglu, Aghion and Zilibotti (2006). 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. Empirical evidence in favor of international technology spillovers is provided, among others, by Benhabib and Spiegel (1994, 2005), Coe and Helpman (1995), Coe, Helpman and Hoffmaister (2009), Keller (2004), Caselli and Wilson (2004).

The point that barriers to technology adoption are key in explaining cross-county income disparities has been forcefully made by Parente and Prescott (1994, 2000, 2005). Comin and Hobijn (2010) document that major innovations diffuse slowly (on average, they are adopted 47 years after their invention) and that there is substantial variation across technologies and countries. Moreover, Comin, Easterly and Gong (2009) have found that differences in the speed of technology adoption are not only large, but also surprisingly persistent over long periods of time. Regarding the origin of such barriers to adoption, the idea that they may have politico-economic roots has been put forward, among others, by Parente and Prescott (1994, 2000), Krusell and Rios Rull (1997) and Acemoglu, Aghion and Zilibotti (2006). Comin and Hobijn (2009) provide evidence that lobbies may slow down technology diffusion. While our goal is mostly to estimate barriers to adoption abstracting from their political determinants, the model provides new insights on why some agents may benefit from their existence.

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), Diwan and Rodrik (1991), Basu and Weil (1998), Acemoglu and Zilibotti (2001). In this context, Acemoglu and Zilibotti (2001) is particularly related. 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 Acemoglu and Zilibotti (2001) and because of costly adoption.

The paper is also related to a long tradition, surveyed in Caselli (2005), of decompos-

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[4]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.

ing 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 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 structured as follows. Section 2 builds the benchmark model of a world economy where a technology leader engages in directed innovation, while n follower 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 (international intellectual property right – 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 that is related to Acemoglu (2002), Acemoglu, Gancia and Zilibotti (2010), Acemoglu and Zilibotti (2001) and Gancia and Zilibotti (2005 and 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. This is important for the quantitative analysis that is the main contribution of this paper. 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 bias, 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 factor. The optimal consumption plan satisfies the Euler equation:

$$\frac{\dot{c}_{Jt}}{c_{Jt}} = r_{Jt} - \rho, \tag{2}$$

where r_{Jt} is the interest rate, which may be different across countries, since capital markets are not integrated. We remove time indexes when this is no source of confusion. The set of assets comprises claims on physical capital, shares of intermediate firms and a bond in zero net supply.

2.2 Technology

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

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

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 *numeraire*, we have:

$$K_J = \frac{\alpha Y_J}{r_J \chi_J}, \tag{4}$$

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 neoclassical condition equating the interest rate to the marginal product of capital holds. Combining (3) and (4) yields:

$$Y_J = \left(\frac{\alpha}{r_J \chi_J} \right)^{\frac{\alpha}{1-\alpha}} \left[Y_{LJ}^{\frac{\epsilon-1}{\epsilon}} + Y_{HJ}^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon-1}}. \tag{5}$$

Profit maximization and then using (5) also imply the following inverse demand functions:

$$P_{HJ} = (1-\alpha) \left(\frac{\alpha}{r_J \chi_J} \right)^{\frac{(\epsilon-1)\alpha}{\epsilon(1-\alpha)}} \left(\frac{Y_J}{Y_{HJ}} \right)^{\frac{1}{\epsilon}} \quad \text{and} \quad P_{LJ} = (1-\alpha) \left(\frac{\alpha}{r_J \chi_J} \right)^{\frac{(\epsilon-1)\alpha}{\epsilon(1-\alpha)}} \left(\frac{Y_J}{Y_{LJ}} \right)^{\frac{1}{\epsilon}} \tag{6}$$

where P_L and P_H are the prices of Y_L and Y_H, respectively. Taking their ratio yields:

$$\frac{P_{HJ}}{P_{LJ}} = \left[\frac{Y_{LJ}}{Y_{HJ}}\right]^{\frac{1}{\epsilon}}. \tag{7}$$

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 and A_H are the measure of intermediate inputs produced with unskilled and skilled labor L, respectively. As in standard expanding-variety models *à la* Romer (1990), the range of available intermediates is a state variable capturing the state of technology. 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 this externality). Note that no externality is necessary if $\sigma = 2$.

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

$$\frac{y_{LJ}(i)}{y_{LJ}(j)} = \left[\frac{p_{LJ}(j)}{p_{LJ}(i)}\right]^{\sigma} \quad \text{and} \quad \frac{y_{HJ}(i)}{y_{HJ}(j)} = \left[\frac{p_{HJ}(j)}{p_{HJ}(i)}\right]^{\sigma}, \tag{8}$$

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 the parameter $Z > 1$ ensures that the equilibrium skill premium is positive. 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 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:

$$\pi_{LJ}(i) = \frac{p_{LJ}l_L(i)}{\sigma} \quad \text{and} \quad \pi_H(i) = \frac{p_{HJ}Zh_J(i)}{\sigma} \tag{9}$$

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:

$$Y_{LJ} = A_{LJ}L_J \quad \text{and} \quad Y_{HJ} = A_{HJ}ZH_J. \tag{10}$$

Note that output in each sector is a linear function of labor and of the state of technology. Plugging (10) into (7) yields the relative price:

$$\tilde{P}_J \equiv \frac{P_{HJ}}{P_{LJ}} = \left[\tilde{A}_J Z \tilde{h}_J\right]^{-\frac{1}{\epsilon}}. \tag{11}$$

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 (11), and noting that $p_{LJ}L_J = P_{LJ}Y_{LJ}$ and $p_{HJ}ZH_J = P_{HJ}Y_{HJ}$.

$$\tilde{w}_J \equiv \frac{w_{HJ}}{w_{LJ}} = Z\frac{P_{HJ}}{P_{LJ}}\frac{A_{HJ}}{A_{LJ}} = \left[Z\tilde{A}_J\right]^{1-\frac{1}{\epsilon}}\left[\tilde{h}_J\right]^{-\frac{1}{\epsilon}} \tag{12}$$

$$\tilde{\pi}_J \equiv \frac{\pi_{HJ}}{\pi_{LJ}} = \frac{P_{HJ}}{P_{LJ}}\frac{ZH_J}{L_J} = \tilde{A}^{-\frac{1}{\epsilon}}\left(Z\tilde{h}_J\right)^{1-\frac{1}{\epsilon}}, \tag{13}$$

Equation (13) 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 numeràire 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:

$$\tilde{A}_N = \left(Z\tilde{h}_N\right)^{\epsilon-1}. \tag{14}$$

Substituting $\tilde{A}_N$ into (12) yields the steady-state skill premium:

$$\tilde{w}_N = Z^{\epsilon-1}\left(\tilde{h}_N\right)^{\epsilon-2}. \tag{15}$$

To find the growth rate, we note that the interest rate is pinned down by either of the two free entry conditions, e.g.,

$$r_N = \frac{\pi_{HN}}{\mu} = \frac{P_{HN}ZH_N}{\mu\sigma} \tag{16}$$

Using (5), (6) and (10) to eliminate P_{HN}, and using the Euler equation yields the balanced growth rate of the economy,[5]

$$g_N = r_N - \rho = (1-\alpha)^{1-\alpha}\alpha^\alpha\left[\frac{L_N^{\epsilon-1} + (ZH_N)^{\epsilon-1}}{(\sigma\mu)^{\epsilon-1}}\right]^{\frac{1-\alpha}{\epsilon-1}} - \rho. \tag{17}$$

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.

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[5]Recall $\chi_N = 1$.

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. Thus, 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 (see Diwan and Rodrik (1991) for an empirical motivation of this assumption). In the absence of trade, the equilibrium conditions (2)–(17) 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 that is similar to innovation. Following Nelson and Phelps (1966), Barro and Sala-i-Martin (1997), and Acemoglu, Aghion and Zilibotti (2006) 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:

$$c_{LS} = \mu \left(\frac{A_{LS}}{A_{LN}} \right)^{\xi} \quad \text{and} \quad c_{HS} = \mu \left(\frac{A_{HS}}{A_{HN}} \right)^{\xi}, \quad \xi \geq 0 \tag{18}$$

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:

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

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

$$\frac{\pi_{HS}}{\pi_{LS}} = \frac{c_{HS}}{c_{LS}}, \tag{19}$$

where c_H and c_L are given by (18), and depend on the distance to the technology frontier in the respective sector. Then, using equations (13), (18) and (19), we can solve for the skill bias of the technology in the South:

$$\tilde{A}_S = \left(Z \tilde{h}_S \right)^{\frac{\epsilon - 1}{1 + \epsilon \xi}} \tilde{A}_N^{\frac{\epsilon \xi}{1 + \epsilon \xi}} = Z^{\epsilon - 1} \left[\tilde{h}_S \cdot \tilde{h}_N^{\epsilon \xi} \right]^{\frac{\epsilon - 1}{1 + \epsilon \xi}}. \tag{20}$$

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 Acemoglu and Zilibotti (2001).

2.5 Productivity Differences

As long as $\xi > 0$, a balanced growth path features $r_S = r_N = r^{ss}$, with the South and the North growing at the same rate, in spite of neither trade nor factor mobility. The model yields then predictions for steady-state output and productivity differences as function 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*

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

(21)

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

Proof. The production function, (3), yields

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

(22)

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

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

(23)

where the relative profits can be written as

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

(24)

using (9) and (10). Next, note that, since the price of Y_L equals its marginal product, then

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

(25)

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Next, (23), (24) and (25) imply that

$$\frac{A_{LS}}{A_{LN}} = \left(\frac{L_S}{L_N}\right)^{\frac{\epsilon-1}{\epsilon(\xi+\alpha)}} \left(\frac{K_S}{K_N}\right)^{\frac{\alpha}{\xi+\alpha}} \left[\frac{L_S^{\frac{\epsilon-1}{\epsilon}} + \tilde{A}_S^{\frac{\epsilon-1}{\epsilon}} (ZH_S)^{\frac{\epsilon-1}{\epsilon}}}{L_N^{\frac{\epsilon-1}{\epsilon}} + \tilde{A}_N^{\frac{\epsilon-1}{\epsilon}} (ZH_N)^{\frac{\epsilon-1}{\epsilon}}}\right]^{-\frac{\alpha\epsilon-1}{(\epsilon-1)(\xi+\alpha)}}. \qquad (26)$$

We can now use (26) to substitute away A_{LS}/A_{LN} into (22):

$$\frac{Y_S}{Y_N} = \left(\frac{L_S}{L_N}\right)^{\frac{(1-\alpha)(\epsilon-1)}{\epsilon(\xi+\alpha)}} \left(\frac{K_S}{K_N}\right)^{\alpha\frac{1+\xi}{\alpha+\xi}} \left[\frac{L_S^{\frac{\epsilon-1}{\epsilon}} + \tilde{A}_S^{\frac{\epsilon-1}{\epsilon}} (ZH_S)^{\frac{\epsilon-1}{\epsilon}}}{L_N^{\frac{\epsilon-1}{\epsilon}} + \tilde{A}_N^{\frac{\epsilon-1}{\epsilon}} (ZH_N)^{\frac{\epsilon-1}{\epsilon}}}\right]^{\frac{(1-\alpha)(1+\epsilon\xi)}{(\epsilon-1)(\alpha+\xi)}}. \qquad (27)$$

Finally, eliminating $\tilde{A}_N$ and $\tilde{A}_S$ from (27) using (14) and (20), respectively, and rearranging terms, yields (21). ∎

Note the formula of the output gap (21) resembles the ratio between two identical aggregate 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, parametrized 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).

Note that income differences depend on a scale effect, which is parametrized by the exponent $(1+\xi)/(\alpha+\xi)$. Namely, a larger total labor endowment (given the skill ratio) implies a closer proximity to the technology frontier. Thus, larger countries are predicted to be *ceteris paribus* more productive. This effect disappears as barriers to adoption vanish, since then all countries converge to the technology frontier. Indeed, as $\xi \to \infty$, we have that $\tilde{A}_S \to \tilde{A}_N$ and

$$\lim_{\xi\to\infty} \frac{Y_S}{Y_N} = \left(\frac{K_S}{K_N}\right)^{\alpha} \left[\frac{L_S^{\frac{\epsilon-1}{\epsilon}} + \left(Z\tilde{h}_N\right)^{\frac{(\epsilon-1)^2}{\epsilon}} \times (ZH_S)^{\frac{\epsilon-1}{\epsilon}}}{L_N^{\frac{\epsilon-1}{\epsilon}} + \left(Z\tilde{h}_N\right)^{\frac{(\epsilon-1)^2}{\epsilon}} \times (ZH_N)^{\frac{\epsilon-1}{\epsilon}}}\right]^{\frac{\epsilon(1-\alpha)}{\epsilon-1}}, \qquad (28)$$

which is the equation estimated by Acemoglu and Zilibotti (2001), who also set $\epsilon = 2$.

Figure 1 shows how the 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 frontier in the L and H sector,

respectively for different combinations of ξ and $\tilde{h}_S$, while holding constant $\chi_S = 1.2$. More precisely, 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 $\tilde{h}_S = 0.5$ (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 Acemoglu and Zilibotti (2001) 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 a 18 percent of the distance to the frontier. In contrast, a 74 percent of the productivity gap is due to technology mismatch, and the remaining 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 has the following expressions:

$$\tilde{w}_S = Z^{\epsilon-1}\tilde{h}_S^{\frac{\epsilon-\xi-2}{1+\epsilon\xi}}\tilde{h}_N^{\frac{(\epsilon-1)^2\xi}{1+\epsilon\xi}}. \tag{29}$$

This expressions is increasing in ξ, ranging between $\tilde{w}_{S|\xi=0} = Z^{(\epsilon-1)}\tilde{h}_S^{\epsilon-2}$ and $\tilde{w}_{S|\xi\to\infty} = Z^{(\epsilon-1)}\tilde{h}_S^{-\frac{1}{\epsilon}}h_N^{\frac{(\epsilon-1)^2}{\epsilon}}$. 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.
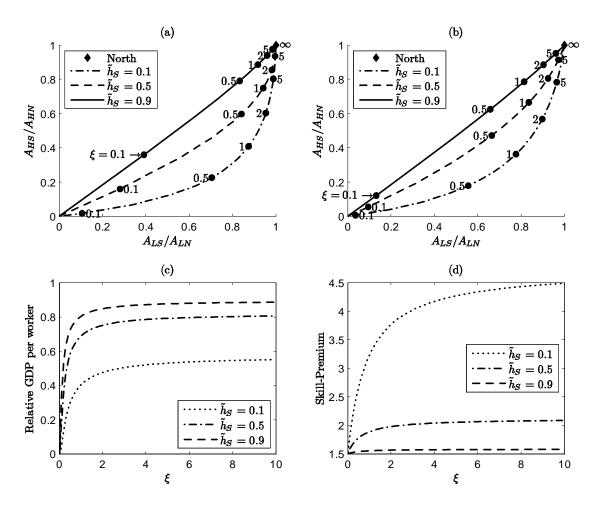
Figure 1: Productivity Differences

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 :

$$\tilde{P}^w \equiv \frac{P_H^w}{P_L^w} = \left[\frac{Y_L^w}{Y_H^w}\right]^{\frac{1}{\epsilon}} \tag{30}$$

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 $Y_H^w = A_{HN} Z H_N + \sum_{j=1}^n A_{HS_j} Z H_{S_j}$. 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 $\pi_{HN} = P_H^w Z H_N / \sigma$. 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 (30) 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:*

$$\tilde{A}_N = \tilde{A}_N^{trade} \equiv \frac{\left(Z \tilde{h}_N\right)^{\epsilon-1}}{\hat{h}} > \left(Z \tilde{h}_N\right)^{\epsilon-1}, \tag{31}$$

where

$$\hat{h} \equiv \frac{1 + \sum_{j=1}^n \left(\frac{H_{S_j}}{H_N}\right)^{\frac{1+\xi}{\xi}}}{1 + \sum_{j=1}^n \left(\frac{L_{S_j}}{L_N}\right)^{\frac{1+\xi}{\xi}}} < 1. \tag{32}$$

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

$$\tilde{A}_S = \tilde{A}_S^{trade} \equiv \frac{\left(Z \tilde{h}_N\right)^{\epsilon-1}}{\hat{h}} \left(\frac{\tilde{h}_S}{\tilde{h}_N}\right)^{\frac{1}{\xi}}. \tag{33}$$

Proof. Using (30) to substitute away $\tilde{P}^w$ from the equation $\tilde{P}^w = \left(Z \tilde{h}_N\right)^{-1}$ yields:

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

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

$$\tilde{A}_N = \left(Z\tilde{h}_N\right)^{\epsilon-1} \times \left(\frac{1 + \sum_{j=1}^n \frac{A_{LS_j}}{A_{LN}} \frac{L_{S_j}}{L_N}}{1 + \sum_{j=1}^n \frac{A_{HS_j}}{A_{HN}} \frac{H_{S_j}}{H_N}}\right) \equiv \tilde{A}_N^{trade}. \tag{34}$$

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 (18) to eliminate c_{HS} and c_{LS} yields:

$$\frac{A_{HS}}{A_{HN}} = \left(\frac{H_S}{H_N}\right)^{1/\xi}, \tag{35}$$

$$\frac{A_{LS}}{A_{LN}} = \left(\frac{L_S}{L_N}\right)^{1/\xi}. \tag{36}$$

Plugging (35)-(36) into (34) yields (31). Finally, (33) follows immediately from (31), (35) and (36). ∎

The numerator of (31) is identical to its no-trade counterpart, (14). 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 Acemoglu and Zilibotti (2001) to an environment in which technology adoption is costly. Equation (31) 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. This reflects a classical implication of the Heckscher-Ohlin model. Trade increases the price of the good that is intensive in the factor that is abundant in each country. Thus, from the standpoint of the North, the effect of integration with the South is larger the more different factor endowments are. Moreover, 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 (33)) is instead ambiguous. On the one hand, trade increases the relative price low-skill-intensive goods in the South, accelerating the adoption low-skill technologies. On the other, the higher skill-bias at the frontier makes it cheaper to adopt skilled technologies.[6]

The following Proposition provides an expression for output (productivity) differences – the analogue of equation (21) – under free trade.

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[6] 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).

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*

$$\frac{Y_S}{Y_N} = \left(\frac{K_S}{K_N}\right)^\alpha \left(\frac{L_S^{\frac{1+\xi}{\xi}} + \frac{(Z\tilde{h}_N)^{\epsilon-1}}{\hat{h}} \times H_S^{\frac{1+\xi}{\xi}}}{L_N^{\frac{1+\xi}{\xi}} + \frac{(Z\tilde{h}_N)^{\epsilon-1}}{\hat{h}} \times H_N^{\frac{1+\xi}{\xi}}}\right)^{1-\alpha} \equiv f_S^{TRADE} \tag{37}$$

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

$$P_{\hat{Y}}^w \hat{Y}_J = P_{HJ}^w \hat{Y}_{HJ} + P_{LJ}^w \hat{Y}_{LJ} = P_{HJ}^w A_{HJ} Z H_J + P_{LJ}^w A_{LJ} L_J, \tag{38}$$

where $P_{\hat{Y}}^w = \left[(P_L^w)^{1-\epsilon} + (P_H^w)^{1-\epsilon}\right]^{1/(1-\epsilon)}$ is the same for all countries. Thus, for any $S \in \hat{S}$, we can write

$$\frac{Y_S}{Y_N} = \left(\frac{K_S}{K_N}\right)^\alpha \left(\frac{\hat{Y}_S}{\hat{Y}_N}\right)^{1-\alpha} = \left(\frac{K_S}{K_N}\right)^\alpha \left(\frac{P_H^w A_{HS} Z H_S + P_L^w A_{LS} L_S}{P_H^w A_{HN} Z H_N + P_L^w A_{LN} L_N}\right)^{1-\alpha}, \tag{39}$$

where the second equality comes from (38) and from the fact that $\hat{Y}_S/\hat{Y}_N = P_{\hat{Y}}^w \hat{Y}_S / \left(P_{\hat{Y}}^w \hat{Y}_N\right)$. Rearranging terms yields

$$\frac{Y_S}{Y_N} = \left(\frac{K_S}{K_N}\right)^\alpha \left(\frac{A_{LS} L_S}{A_{LN} L_N} \cdot \frac{1 + \tilde{P}^w \tilde{A}_S Z \tilde{h}_S}{1 + \tilde{P}^w \tilde{A}_N Z \tilde{h}_N}\right)^{1-\alpha}. \tag{40}$$

Then, using (36) and (30) to eliminate A_{LS}/A_{HS} and $\tilde{P}^w$, respectively, and rearranging terms, yields (37). ∎

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} (equivalently, between $L_S^{(1+\xi)/\xi}$ and $H_S^{(1+\xi)/\xi}$) 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.[7] 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.

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.

In steady state, the PDV of the royalties in the two sectors equals, respectively,

$$\varphi_{LS} = \frac{\pi_{LS}}{r}, \;\; \varphi_{HS} = \frac{\pi_{HS}}{r}.$$

Licensing affects the incentive for frontier innovation. In particular, the zero-profit conditions yield

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

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

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

where $\tilde{h}^w \equiv \left(H + \sum_{j=1}^{n} H_{S_j} \right) / \left(L + \sum_{j=1}^{n} L_{S_j} \right)$. This yields $\tilde{P}^w = \left(Z \tilde{h}^w \right)^{-1}$. Then, using (30), 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, if the world economy is sufficiently skill-scarce, the skill premium may even turn negative.[8] Such an outcome does not seem realistic, as in that

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[7]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 firs to zero.

[8]In the empirical section, Z will be estimated under the benchmark case of autarky and trade opening (with and without licensing) will be studied as a counterfactual experiment. Thus, without any additional assumption, a negative skill premium may indeed arise.

case skilled workers would be willing to take unskilled jobs. In particular, assuming that a skilled worker produces Z times as much as an unskilled worker regardless of the sector of employment, implies that there is 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*

$$\frac{Y_S}{Y_N} = \left(\frac{K_S}{K_N}\right)^{\alpha} \left(\frac{L_S + \tilde{w}H_S}{L_N + \tilde{w}H_N}\right)^{1-\alpha} \equiv f_S^{IPR} \tag{41}$$

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 (40),

$$\frac{Y_S}{Y_N} = \left(\frac{K_S}{K_N}\right)^{\alpha} \left(\frac{L_S}{L_N} \frac{1 + \tilde{P}^w \tilde{A}_N Z\tilde{h}_S}{1 + \tilde{P}^w \tilde{A}_N Z\tilde{h}_N}\right)^{1-\alpha}, \tag{42}$$

where the only differences between (40) and (42) 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 (41). When $\tilde{w} = Z$, a similar argument applies after noticing that:

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

∎

Cross-country productivity differences are smaller under full IPR. However, it becomes important to draw a distinction between GDP and GNP: the GNP of the North now includes the royalties paid by Southern firms. In particular, since profits are proportional to labor income, which are in turn a share $1 - \alpha$ of GDP, we obtain $GNP_N = Y_N + (1 - \alpha) Y_S/\sigma$ and $GNP_S = Y_S (1 - (1 - \alpha)/\sigma)$. In general, it is ambiguous whether the GNP ratio increases with IPR. In particular, the ratio decreases in σ, i.e., it increases in the monopoly power of intermediate producers. 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:

$$\frac{y_S}{y_N} = \frac{\Omega_S}{\Omega_N} \times \frac{H_N + L_N}{H_S + L_S} \times f_S^{AUT}, \tag{43}$$

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where f_S^{AUT} is given by (21).[9] Equation (43) 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., Hall and Jones 1999, Klenow and Rodriguez-Clare 1997 and Caselli 2005), we will calibrate the key parameters, whenever this is possible. In particular,

– we set $\alpha = 0.35$ to match the non-labor share of GDP in industrialized countries;

– we set ϵ and Z so as to match the time evolution of the skill premium in the frontier economy using the predictions of our theory;

– we estimate ξ so as to obtain the best fit of cross-country productivity differences in a repeated cross-section of up to 90 countries.[10]

As it is customary in the literature, 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 cross-country 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 changes, and focus on the distribution of cross-country productivity differences in 1970 and 2000. We assume the US to be the frontier, and calibrate ϵ and Z using the change in the skill premium between 1970 and 2000 in the United States from the March Current Population Survey cleaned by Autor, Katz, and Kearney (2008).[11] 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 are dropped. 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. high school dropouts and college graduates vs. non-college graduates.

The data on gross domestic product (GDP), investments, 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 (2001) and Cohen and

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[9] 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.

[10] We discuss methodological issues related to this step of our procedure in section 4.4.2.

[11] 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.

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 derived by multiplying the labor force 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 interpolate the missing data points for 1970 and 2000 if necessary. We drop Kuwait since it is a strong outlier in terms of GDP per worker in 1970. We end up with a repeated cross-section of 78 (1970) to 91 (2000) countries when using the education data from Barro and Lee (2001), while we have 73 (1970) to 85 (2000) countries when using the data from Cohen and Soto (2007).

4.2 CALIBRATION

4.2.1 Elasticity of Substitution

We identify ϵ and Z using equation (15) given the evolution of the skill premium in the US. More formally, we set ϵ and Z so as to match exactly the equation

$$\log\left(\tilde{w}_{N,t}\right) = (\epsilon - 1)\log(Z) + (\epsilon - 2)\log\left(\tilde{h}_{N,t}\right) \tag{44}$$

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

$$\epsilon = 2 + \frac{\log\left(\tilde{w}_{N,2000}\right) - \log\left(\tilde{w}_{N,1970}\right)}{\log\left(\tilde{h}_{N,2000}\right) - \log\left(\tilde{h}_{N,1970}\right)}. \tag{45}$$

The skill premia are from the March Current Population Survey. As discussed above, we use two alternative measures of the skill premium: secondary and tertiary school. The wage premium for high-school graduates over high-school dropouts 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 high-school dropouts 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 many OECD economies a very large share of the population finishes secondary school, we regard tertiary education as the most appropriate measure of skill for our theory.

Equations (44)-(45) 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".

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. Note that

| | Calibration | |
Skill Measure	ϵ	Z
sec	2.29	1.05
tert	2.25	1.96

Table 1: Baseline Calibration

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 exogenous 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

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

where $f_{AUT,S}$ is given by (21), and $\log \varepsilon_S$ is an i.i.d. normally distributed disturbance.

Table 2 shows the estimation results with robust standard errors in parenthesis. The four raws refer to different skill categories (*sec* and *tert*) and data sets (Barro-Lee (BL) and Cohen-Soto (CS)). Columns 1-2 report the point estimate of ξ using the whole sample. Then, we allow ξ to vary between OECD (columns 3-4) and non-OECD countries (columns 5-6). The results show that ξ is significantly lower in non-OECD countries.[12] This finding 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 7-8) and other non-OECD countries (columns 9-10).[13] The differences between both the sub-Saharan and other non-OECD countries and OECD and non-OECD countries are in all but two cases highly significant.[14]

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[12] 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 estimates for OECD countries in the first row of Table 2 would be 5.35 (0.90) in 1970 and 13.45 (3.13) in 2000.

[13] We do not include Mauritius among the sub-Saharan countries. Mauritius is a clear outlier and has very special geographical and economic conditions (see Subramanian and Roy 2001). If Mauritius is included the point estimates are not very different. For instance, the first row in Table 2 would read 2.60 (0.25) in 1970 and 3.00 (0.39) for sub-Saharan countries and 3.78 (0.42) in 1970 and 3.62 (0.49) in 2000 for the other non-OECD countries.

[14] In 1970, the point estimate for sub-Saharan countries is lower than the point estimate for the other non-OECD countries at the 1% level of significance across all specifications. In 2000, it is significantly lower at the 5% level for the *tert* skill category. For the *sec* skill category, the differences are very close

		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	3.31	3.81	4.92	10.33	3.19	3.34	2.48	2.79	3.85	3.78
		(0.24)	(0.36)	(0.79)	(1.99)	(0.25)	(0.32)	(0.23)	(0.31)	(0.42)	(0.53)
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	ter	3.08	3.32	4.85	10.93	2.96	2.88	2.31	2.26	3.58	3.44
		(0.22)	(0.32)	(0.83)	(2.26)	(0.23)	(0.28)	(0.20)	(0.22)	(0.38)	(0.49)
CS	ter	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)		77/72	90/84	18/18	26/24	59/54	64/60	20/19	20/19	39/35	44/41

Table 2: Baseline Estimation

A sharp pattern emerges from the table: The estimated ξ doubles between 1970–2000 for OECD countries, while there is no significant change for non-OECD countries.[15] This suggests that technological integration increased mostly within the set of industrialized countries.

4.2.3   Results

Figure 2 plots the actual (horizontal axis) vs. predicted (vertical axis) relative GDP per worker for all countries, using educational variables from the Barro-Lee data set and allowing ξ to differ across OECD, non-OECD and sub-Saharan countries, as in Table 2. Panels *a-b* use the secondary school educational measure for years 1970 and 2000, respectively, whereas Panels *c-d* use the tertiary education measure for the same years. In the appendix 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 significant outliers. Among them, Malta, Cyprus and Hong-Kong 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. 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

to the 5% (BL) and 10% (CS) level of significance. OECD countries have significantly lower barriers than non-OECD countries at the 1% level in 2000, while they are at least lower at the 5% level of significance in 1970 across all specifications.

[15]In 2000, the estimates for OECD are significantly higher than in 1970 at the 1% and 5% level for the Barro-Lee and Cohen-Soto data set, respectively.
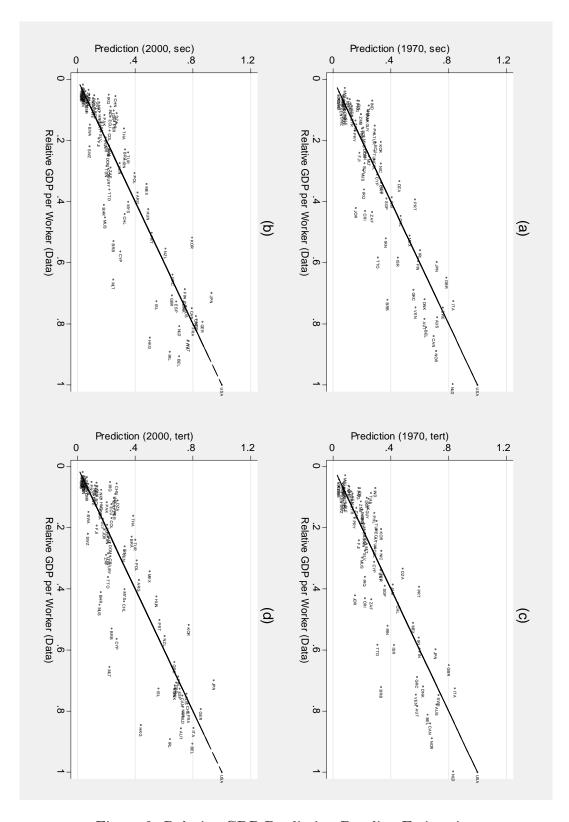
Figure 2: Relative GDP Prediction Baseline Estimation

the OECD, they cease to be outliers. Likewise, Bahrain, Barbados and Mauritius (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 Acemoglu and Zilibotti (2001). More formally, we let $\xi \to \infty$ – see equation (28) – while keeping all other parameters unchanged. Acemoglu and Zilibotti (2001) 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 statistics proposed by Acemoglu and Zilibotti (2001), $\Re^2 = 1 - \sum_J \left(y^J - \hat{y}^J\right)^2 / \sum_J \left(y^J\right)^2$, where y^J denotes output per worker from the data and $\hat{y}^J$ denote 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 in 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 countries and other non-OECD countries. In all cases, the model with barriers attains a much better the fit than the model with no barriers.[16] The model with no barriers is also strongly rejected in a formal Wald test.

| Data | Skill | Baseline Estimation | | | | | | No Barriers | |
| | | (1) | | (2) | | (3) | | (4) | |
		1970	2000	1970	2000	1970	2000	1970	2000
BL	sec	0.898	0.871	0.918	0.918	0.929	0.924	0.589	0.818
CS	sec	0.911	0.889	0.939	0.937	0.947	0.939	0.764	0.833
BL	tert	0.882	0.830	0.907	0.903	0.920	0.911	0.510	0.776
CS	tert	0.893	0.839	0.925	0.926	0.939	0.930	0.658	0.727

Table 3: Goodness of Fit

A concern is that our estimation may imply $A_L/A_{L,US}$ and/or $A_H/A_{H,US}$ larger than

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[16]The results are not directly comparable with those of Acemoglu and Zilibotti (2001). 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 year 2000. The $\Re^2$ of the model with no barriers is 0.829 and 0.585 using *sec* and *ter*, respectively. In contrast, the $\Re^2$ of column (3) in Table 3 would be 0.931 and 0.945, respectively.
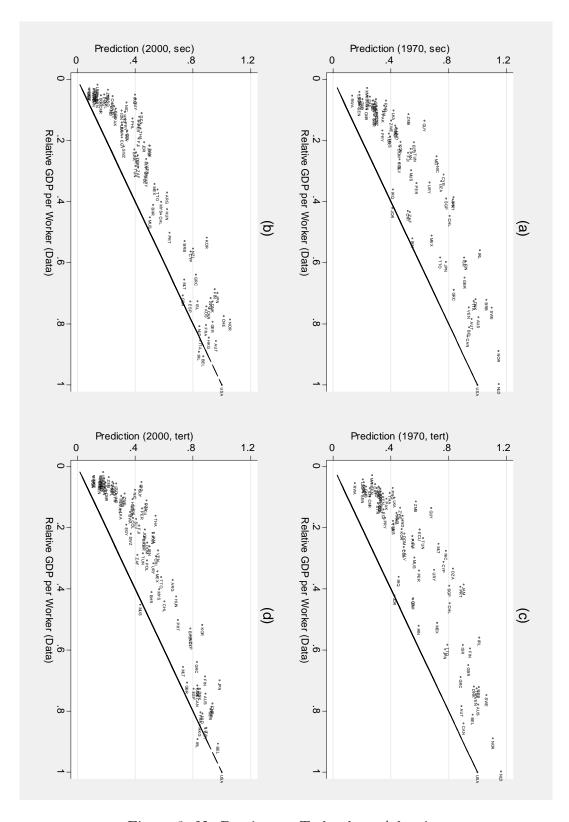
Figure 3: No Barriers to Technology Adoption

unity, violating the assumption that the US is the technology leader in both sectors. To address this concern, Figure 4 plots the implied cross-country distribution of the sectoral productivities, $A_L/A_{L,US}$ and $A_H/A_{H,US}$, using our 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. Or, perhaps, the assumption that large developing economies such as China and India have frictionless internal markets is 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.

For simplicity, we limit our discussion to the educational measures from the Barro-Lee data set and to the case in which ξ differs between OECD, sub-Saharan countries and other non-OECD (column 3–4 and 7–10 in Table 2). The parameter 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

$$\frac{\chi_S}{\chi_N} = \frac{Y_S/K_S}{Y_N/K_N},\tag{46}$$

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:

$$\frac{K_S^{count}}{K_N^{count}} = \frac{Y_S^{count}/\chi_S}{Y_N^{count}/\chi_N} = \frac{Y_S^{count}}{Y_N^{count}}\frac{K_S/Y_S}{K_N/Y_N}.\tag{47}$$
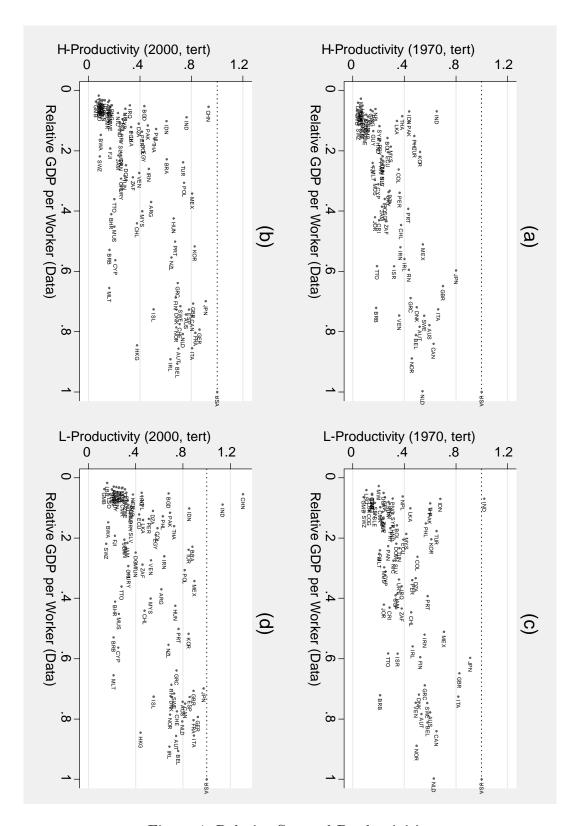
27

Figure 4: Relative Sectoral Productivities

Replacing K_S/K_N by $K_S^{nobarr}/K_N^{noabarr}$, K_S^{trade}/K_N^{trade} and K_S^{IPR}/K_N^{IPR}, respectively, into equations (28),(37) and (41), 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 make the thought experiment of slashing all technology barriers. The 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 (28) taking the capital ratio directly from the data. In contrast, here we infer the χ parameters 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:

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

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

where K_S/Y_S and K_N/Y_N are the observed capital output ratios.

Figure 5 plots counterfactual productivity ratios $y_S^{nobarr}/y_N^{nobarr}$ (vertical axis) against the productivity differences predicted level by the benchmark model (horizontal axis). 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 Norway, Korea, Finland, New Zealand and Switzerland.

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 (37), after replacing K_S/K_N by K_S^{trade}/K_N^{trade}, as given by equation (47). This yields

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

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.

Figure 6 plots y_S^{trade}/y_N^{trade} (vertical axis) against the predictions of the benchmark model (horizontal axis). Cross-country income inequality increases significantly, and so
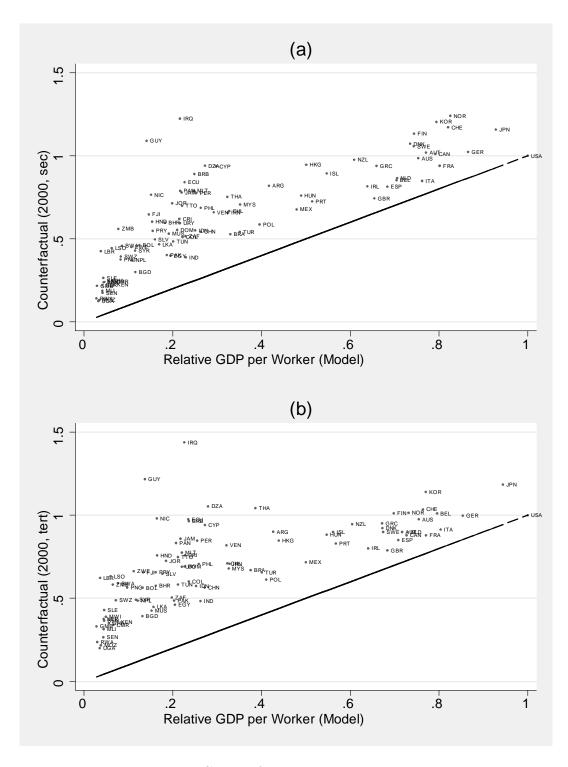
29

Figure 5: Counterfactual: Removing Barriers

does the distance of most countries from the US frontier, although the results are more mixed when skill is measured by tertiary schooling. 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 (41), after replacing K_S/K_N by K_S^{IPR}/K_N^{IPR} as given by (47). 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. Figure 7 plots y_S^{IPR}/y_N^{IPR} (vertical axis) against the productivity differences predicted level by the benchmark model (horizontal axis). The results are similar to those in Figure 5, 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 Acemoglu and Zilibotti (2001) 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 (11) and (20), 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 (32). 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 8 plots the log change in the steady-state skill premium for secondary and tertiary school (vertical axis) against GDP per worker relative to the US (horizontal axis) when barriers are removed starting from the benchmark steady state equilibrium.
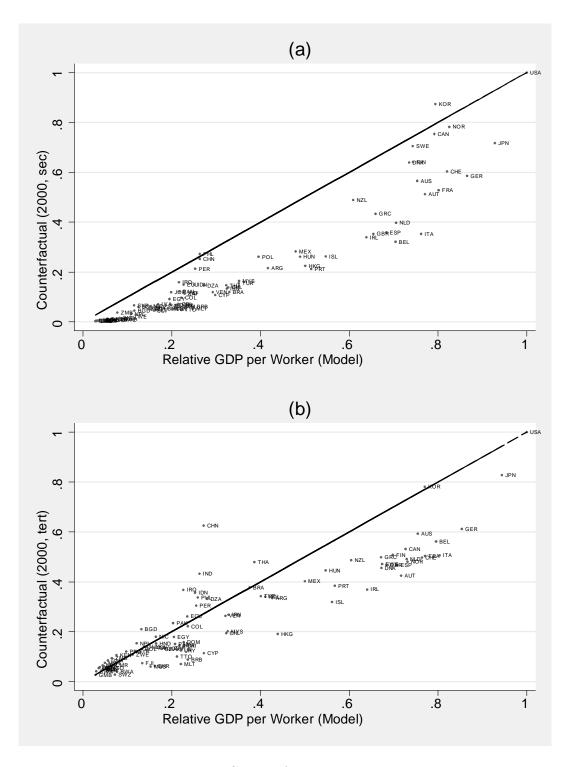
Figure 6: Counterfactual: Free Trade
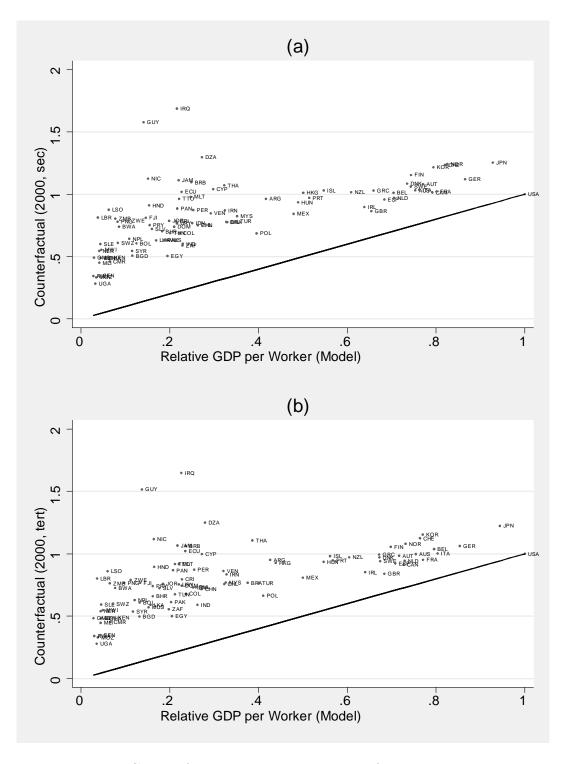
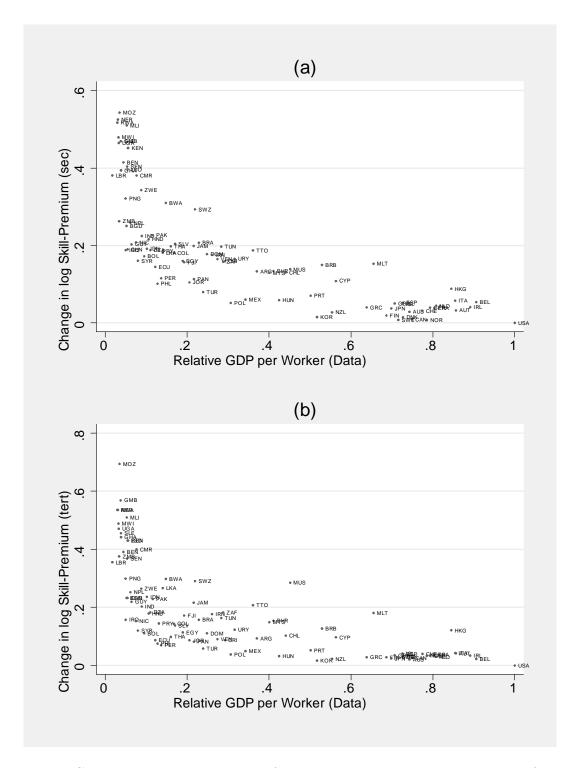Figure 7: Counterfactual: Free Trade and Perfect IPR Protection

(a)

(b)

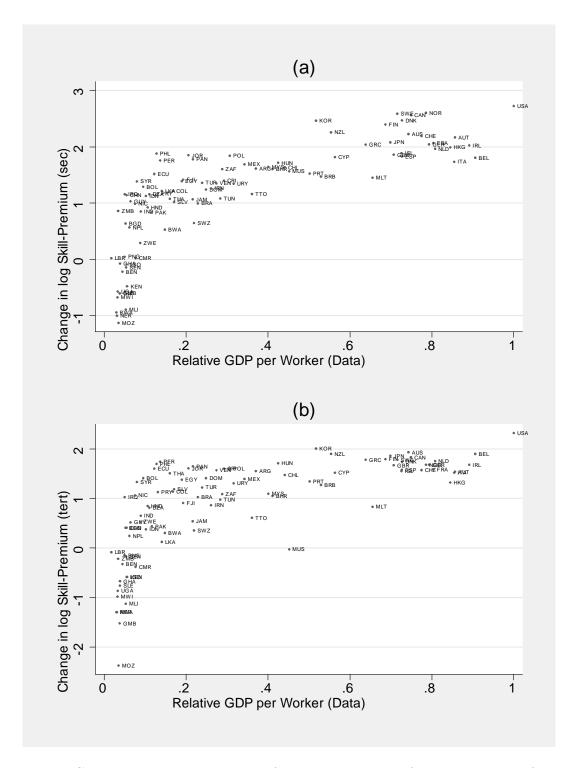Figure 8: Change in log skill premium from benchmark to no barrier counterfactual

Figure 9: Change in log skill-premium from benchmark to free trade counterfactual

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. Figure 9 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 (sub-Saharan countries), 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 abstract 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. Next, we compare our results with those that would obtain from an atheoretical development-accounting exercise.

4.4.1   Lower Short-Run Elasticity of Substitution

In this section, 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, for simplicity, to the BL dataset.

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 highly significant whenever they were significant in the baseline estimation of Table 2. In

	$\epsilon = 2$		$\epsilon = 1.5$	
Skill	Z_{1970}	Z_{2000}	Z_{1970}	Z_{2000}
sec	1.40	2.02	5.04	37.95
tert	1.57	1.88	0.51	1.52

Table 4: Robustness Calibration

summary, our analysis is not affected by setting $\epsilon = 2$. When $\epsilon = 1.5$, the results continue to be similar to the benchmark case when the skill measure is tertiary education. With secondary education, however, the estimate for OECD countries becomes very imprecise and the differences across groups and time become insignificant. In spite of this, the goodness of fit stays above 0.9.[17]

		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	sec	4.26	5.28	6.39	15.74	4.11	4.65	3.22	4.40	4.95	4.83
		(0.34)	(0.55)	(1.11)	(4.20)	(0.35)	(0.49)	(0.31)	(0.60)	(0.61)	(0.72)
BL	tert	3.19	3.43	5.07	11.31	3.07	2.97	2.39	2.37	3.71	3.52
		(0.23)	(0.33)	(0.88)	(2.38)	(0.24)	(0.51)	(0.21)	(0.23)	(0.40)	(0.50)
		$\epsilon = 1.5$									
BL	sec	10.68	11.63	14.81	47.65	10.38	10.27	8.98	18.79	11.63	7.54
		(1.45)	(2.12)	(5.14)	(37.36)	(1.49)	(1.91)	(1.47)	(8.96)	(2.62)	(1.39)
BL	tert	3.59	3.83	5.76	12.67	3.45	3.34	2.71	2.81	4.16	3.81
		(0.27)	(0.37)	(1.06)	(2.86)	(0.27)	(0.32)	(0.24)	(0.27)	(0.46)	(0.56)
Obs. (BL/CS)		77/72	90/84	18/18	26/24	59/54	64/60	20/19	20/19	39/35	44/41

Table 5: Robustness Estimation

Figure 10 shows the fit of the model for the case of $\epsilon = 1.5$.

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

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[17]The mixed results in the case of secondary school are not surprising. In 2000, the vast majority of the labor force has completed secondary school in the US. In order for this to be consistent with a positive (and large) skill premium, given a low ϵ, it is necessary to have a very large coefficient Z. However, this is hard to reconcile with the evidence for other countries.
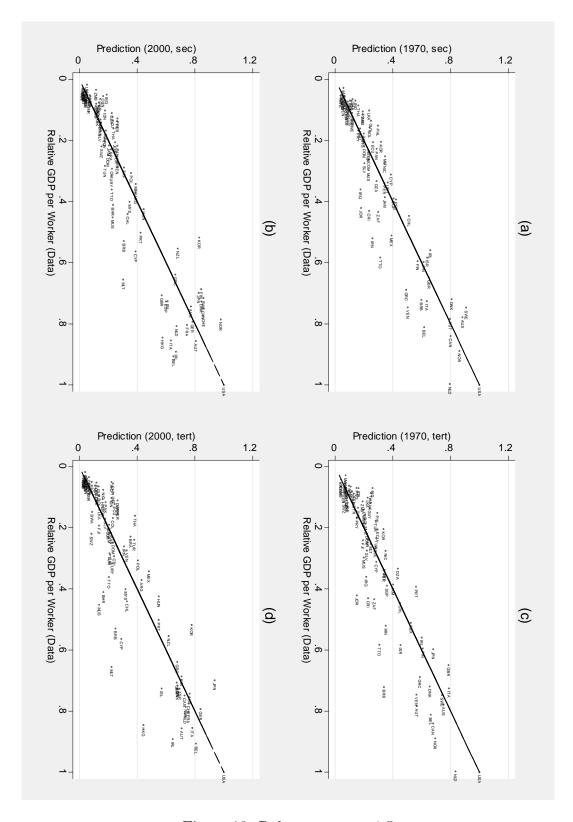
Figure 10: Robustness: $\epsilon = 1.5$

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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 *apriori* 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.[18] For the sake of such comparison, we estimate the following alternative (reduced-form) model:

$$
\frac{Y_S}{Y_N} = \left(\frac{K_S}{K_N}\right)^{\alpha} \left(\frac{L_S^{\frac{\upsilon-1}{\upsilon}} + \left(\frac{\bar{A}_H}{\bar{A}_L}H_S\right)^{\frac{\upsilon-1}{\upsilon}}}{L^{\frac{\upsilon-1}{\upsilon}} + \left(\frac{\bar{A}_H}{\bar{A}_L}H_N\right)^{\frac{\upsilon-1}{\upsilon}}} \right)^{\frac{\upsilon(1-\alpha)}{\upsilon-1}} , \qquad (48)
$$

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 (BL data) the best estimates yield $\upsilon_{1970} = 1.06$ and $\upsilon_{2000} = 0.36$ (with secondary school, $\upsilon_{1970} = 0.84$ and $\upsilon_{2000} = 0$). With such low elasticities, the model fits quite well the data. In particular, we obtain $\Re^2_{1970} = 0.699$ and $\Re^2_{2000} = 0.916$ (with secondary school, $\Re^2_{1970} = 0.902$ and $\Re^2_{2000} = 0.938$). 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 $\Re^2_{1970} = 0.599$ and $\Re^2_{2000} = 0.817$ with BL data and $\Re^2_{1970} = 0.721$ and $\Re^2_{2000} = 0.763$ with CS data. For comparison, the corresponding $\Re^2$s of Table 3 range between 0.83 and 0.94. In addition, the reduced-form model systematically underpredicts the cross-country productivity differences. On both ground, the reduced-form model performs significantly worse than our structural model with tertiary education. With secondary school, the results are less clear-cut. In particular, the reduced-form model

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[18]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 (21).

yields $\Re^2_{1970} = 0.817$ and $\Re^2_{2000} = 0.905$ (BL), and $\Re^2_{1970} = 0.901$ and $\Re^2_{2000} = 0.874$ (SC). The fit continues to be inferior to that of our model, but the differences are smaller.

In summary, a reduced-form model without market-size effect does not outperform our structural model. Yet, our model appears to exaggerate the scale effect when it comes to very large countries. As Figure 4 shows, the model's prediction are overly optimistic for China and India, especially in year 2000. In spite of their successes since the 1980's, the predictions of our theory for these two large economies lie significantly above the 45-degree line, i.e., they appear to underperform relative to the predictions of the theory.

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 model provides a good fit of the world income distribution. This suggests that the theory of directed technical change, with its emphasis on the role of prices and market size, 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. More precisely, 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 relative output per worker by 36.4 percentage points in the average non-OECD country, by 24.2 percentage points in the average OECD country, 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 amplifies income disparities. Interestingly, trade opening is followed by skill-biased technology adoption 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, in line with the literature on development accounting, we have estimated our benchmark model under the assumption of no international trade. 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 distrib-

utional 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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In this appendix we provide the results of some sensitivity analysis about the estimates of Table 2 in 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	3.38	3.55	4.92	10.22	3.25	3.22	2.52	2.66	3.80	3.60
		(0.27)	(0.35)	(0.79)	(2.35)	(0.28)	(0.33)	(0.28)	(0.33)	(0.43)	(0.50)
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	ter	3.14	3.11	4.85	11.28	3.01	2.80	2.34	2.19	3.53	3.26
		(0.25)	(0.31)	(0.83)	(2.89)	(0.25)	(0.28)	(0.25)	(0.24)	(0.39)	(0.46)
CS	ter	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)		72/69	72/69	18/18	18/18	53/50	53/50	16/16	16/16	37/34	37/34

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% level of significance across all specifications. In 2000, it is at least significantly lower at the 5% level for the *tert* skill category. For the *sec* skill category, the differences are very close to the 5% (BL) and 10% (CS) level of significance. OECD countries have significantly lower barriers than non-OECD countries at the 1% level in 2000, while they are at least lower at the 5% level of significance in 1970 across all specifications. The fit of this model is reported in Table 7 which is the

| | | Baseline Estimation | | | | | |
| | | (1) | | (2) | | (3) | |
Data	Skill	1970	2000	1970	2000	1970	2000
BL	sec	0.900	0.852	0.919	0.911	0.927	0.916
CS	sec	0.913	0.875	0.937	0.934	0.947	0.937
BL	tert	0.885	0.812	0.909	0.899	0.918	0.906
CS	tert	0.896	0.818	0.926	0.915	0.938	0.921

Table 7: Goodness of Fit

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 reclassify Cyprus, Malta and Hong Kong as OECD countries although this economies were not formally OECD members (see discussion in the text).

Data	Skill	All countries		OECD		Non-OECD					
						All		Sub-Sahara		Others	
		1970	2000	1970	2000	1970	2000	1970	2000	1970	2000
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
BL	sec	3.31	3.81	4.52	11.89	3.15	3.12	2.48	2.79	3.84	3.38
		(0.24)	(0.36)	(0.48)	(2.12)	(0.26)	(0.28)	(0.23)	(0.31)	(0.42)	(0.44)
CS	sec	3.78	3.98	5.94	12.00	3.54	3.37	2.25	3.00	4.92	3.60
		(0.35)	(0.38)	(0.85)	(2.45)	(0.36)	(0.32)	(0.24)	(0.32)	(0.63)	(0.48)
BL	ter	3.08	3.32	4.48	12.68	2.92	2.68	2.31	2.26	3.55	3.06
		(0.22)	(0.32)	(0.50)	(2.44)	(0.23)	(0.24)	(0.20)	(0.22)	(0.41)	(0.41)
CS	ter	3.23	2.83	5.36	9.15	3.01	2.37	1.97	1.86	4.12	2.78
		(0.28)	(0.24)	(0.75)	(1.53)	(0.28)	(0.19)	(0.19)	(0.13)	(0.47)	(0.32)
Obs. (BL/CS)		77/72	90/84	18/18	26/24	59/54	64/60	20/19	20/19	39/35	44/41

Table 8: Baseline estimation with Malta, Cyprus and Hong Kong as OECD

In 1970, the point estimate for sub-Saharan countries is lower than the point estimate for the other non-OECD countries at the 1% level of significance across all specifications. In 2000, it is at least significantly lower at the 5% level for the *tert* skill category. For the *sec* skill category, the differences are very close to the 5% (BL) and 10% (CS) level of significance. OECD countries have significantly lower barriers than non-OECD countries at the 1% level in 2000 and in 1970 across all specifications. The fit of the model is reported in Table 9. Column Column (1) is unchanged by construction. For

Data	Skill	Baseline Estimation					
		(1)		(2)		(3)	
		1970	2000	1970	2000	1970	2000
BL	sec	0.898	0.871	0.915	0.940	0.926	0.941
CS	sec	0.911	0.889	0.934	0.943	0.945	0.944
BL	tert	0.882	0.830	0.904	0.932	0.916	0.935
CS	tert	0.893	0.839	0.924	0.936	0.938	0.938

Table 9: Goodness of Fit

the other specifications, there is a small improvement of the fit in 2000.

Finally, we plot 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 countries as in Figure 2.
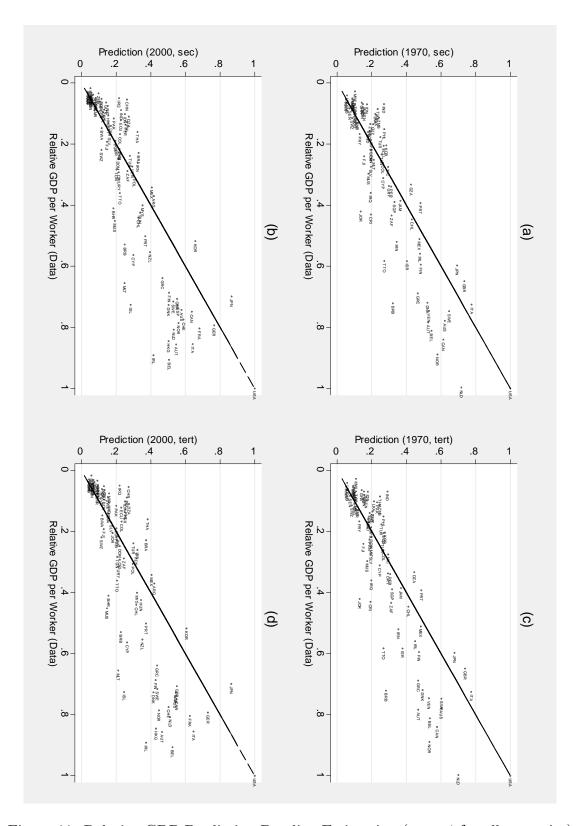
Figure 11: Relative GDP Prediction Baseline Estimation (same ξ for all countries)