Year: 2001

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First Version: August, 1998.
This Version: April, 2000.

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JEL Classification: F43, O14, O34, O47.

Keywords: Development, Directed Technical Change, Human Capital, Intellectual Property Rights, Labor Productivity, Sectoral TFP Differences, Technology-Skill Mismatch, Total Factor Productivity.

*We thank Thomas Eisensee, Christina Lönnblad, Chris Mazingo and Marcus Salomonsson for assistance, and Alberto Alesina, Joshua Angrist, Abhijit Banerjee, Chad Jones, Ellan McGrattan, Jonathan Temple, Jaume Ventura, and seminar participants at Boston University, Brown, Columbia, Harvard, IIES, Jerusalem, Johns Hopkins, LSE, MIT, NBER Economic Fluctuations and Growth meetings for useful comments. Special thanks go to Sandy Wolfson for general help with the U.N. data. An anonymous referee provided very useful suggestions and comments. Acemoglu acknowledges financial support from NSF Grant SBR-9602116 and Zilibotti from Carl Mannerfelt's fund.

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I. Introduction

What accounts for the large disparities in per capita income across countries? Many economists believe that differences in technological knowledge are the main source of these income differences (e.g., Romer [1993] or Prescott [1998]). This view receives support from a number of recent studies that find significant "total factor productivity" (TFP) differences across countries (e.g., Klenow and Rodriguez [1997], Caselli et al. [1997], and Hall and Jones [1999]). Large cross-country differences in technology are difficult to understand, however. Ideas, perhaps the most important ingredient of technologies, can rapidly flow across countries, and machines that embed better technologies can be imported by less developed countries (LDCs).

In this paper, we argue that even when all countries have access to the same set of technologies, there will be large cross-country productivity differences. Many technologies used by the LDCs (the South) are imported from more advanced countries (the North).[1] These technologies are designed to make optimal use of the prevailing factors and conditions in these richer countries because lack of intellectual property rights and other barriers to technology transfer induce R&D firms to target their innovations towards the needs of the North. The center-piece of our argument is that because of differences in economic conditions and factor prices, these technologies will often be inappropriate for LDCs. Although there are many dimensions in which technological needs of the South differ from those of the North, including climate, geography, and culture, we focus on differences in skill scarcity, which we believe to be important in practice. The North is more abundant in skills and tends to develop relatively skill-complementary (*skill-biased*) technologies. For example, in the United States, over 13 percent of all company funded R&D in 1987 was for office computing, the prototypical example of skill-complementary technology (NSF R&D Industry Detailed Statistical Tables). More generally, in the richest countries, new technologies in most industries appear to be substituting skilled workers for tasks previously performed by the unskilled (e.g. Katz and Murphy [1992]; Berman, Bound and Machin [1998]), and are therefore of only limited use to the skill-scarce LDCs.

The main result of our paper is that this technology-skill mismatch will lead to productivity differences and to large output gaps between the North and the LDCs even in the absence of any barriers to technology transfer. LDCs must use unskilled workers in tasks performed by skilled workers in the North. But technologies in these tasks have been designed to be operated by skilled workers, and their productivity will be low when operated by unskilled workers.

[1] Over 90 percent of the R&D expenditure in the world is carried on in the OECD, and over 35 percent is in the U.S. (Authors' calculation from UNESCO [1997]).

The contrast in the experiences of Japan and India in the production of diesel engines illustrates some of the salient issues faced by skill-scarce LDCs in using imported technologies. During the early 1960s, Cummins Engine Co., a U.S. technological leader, formed a joint venture with a Japanese company, Komatsu, and also, a partnership with an Indian company, Kirloskar, to produce the same truck engine. While the Japanese plant quickly reached the U.S. quality and cost levels, in the Indian plant productivity and quality were low, and costs were 3.5 to 4.1 times higher than U.S. costs. The reason appears to be that, in contrast to the Japanese, the Indian workers did not possess the "high degree of technical skill...required to convert techniques and produce the new technical drawings and manufacturing specifications." (Baranson [1972], pp. 58-59, and [1967], pp. 80-81). This case illustrates how technology-skill mismatch can lead to significant productivity differences even when LDCs have access to all the technologies used in the North. Companies that invest in LDCs are often aware of these problems. After interviewing managers of multinational corporations investing in LDCs in textiles, garments, plastics, and electronics, (Chen [1983], pp. 118-119) argues that multinationals very often decide not to introduce advanced technologies in their overseas subsidiaries because of skill shortages in these markets.[2]

Whether technology-skill mismatch can account for a substantial fraction of the cross-country productivity differences is an empirical question. We perform two exercises to evaluate the empirical importance of technology-skill mismatch. First, we test the implications of our model regarding cross-country differences in sectoral productivity. We construct measures of industry TFPs for 27 three-digit manufacturing industries in 22 countries using United Nations (U.N.) data. A naive intuition based on the notion of technology differences would suggest that TFP gaps between the United States and LDCs should be largest in the skill-intensive sectors which tend to be the more high technology sectors. In contrast, our model predicts that these gaps should be largest in the least skill-intensive sectors. This is because LDCs have access to the same set of technologies and are relatively scarce in skilled workers, so their prices and value of production

[2]Baranson [1969] reports that problems associated with mismatch between skills and technologies are especially severe in the auto industry. According to Volkswagen managers, "engineers from developing countries often lack the necessary practical experience to take over plant responsibilities... Typically, there was an inadequate supply of the 20 to 30 middle managers, technical supervisors, and master mechanics necessary to set up initial procedures..." (p. 27).

Other examples of technology-skill mismatch include the choice of maize grinding technique in Kenya and choice of techniques for can making in Kenya, Tanzania and Thailand. Stewart [1977], chapter 9, reports that despite its greater efficiency, the roller mill was rarely adopted in Kenya, and most producers used the less productive hammer mill. Cooper et al [1975] point out that in many instances manual production was used in can making despite the presence of continuous automatic machines. Part of the reason in both cases was the skill demands of the more advanced technologies, in both operation and repair.

in the skill-intensive sectors will be relatively high.[3] This is the pattern we find in the data. For example, average TFP in LDCs is 22 percent of the U.S. level in the 9 least skill-intensive sectors, whereas the same number is 30 percent in the 9 most skill-intensive sectors. Interestingly, we do not find the same pattern when comparing industry TFPs between the United States and other rich economies, which is consistent with our theory.

As a second exercise to evaluate the importance of technology-skill mismatch, we undertake a simple calibration of our model using measures of cross-country differences in skill supplies. This exercise suggests that the differences predicted by our model are sizeable, and significantly larger than those predicted by a simple "neoclassical" model. For example, using cross-country variation in physical capital and secondary school attainment, the neoclassical model predicts that average output per worker in the LDCs should be approximately 41 percent of the United States while our model predicts the same number to be 27 percent, substantially closer to the 21 percent number we observe in the data. Moreover, our calculations suggest that if technologies were not biased towards the needs of the rich economies, output per worker differences would be much smaller.

A number of other papers have emphasized the difficulties in adapting advanced technologies to the needs of LDCs. Evanson and Westphal [1995] suggest that new technologies require a large amount of tacit knowledge, which slows down the process of technological convergence. The importance of "appropriateness" of technology has also received some attention, for example from Salter [1969], Atkinson and Stiglitz [1969], David [1974], and Stewart [1978]. An important recent contribution is Basu and Weil [1998]. They adopt the formulation of Atkinson and Stiglitz where technological change takes the form of learning-by-doing and influences productivity at the capital labor ratio currently in use. Our paper differs from Basu and Weil and the rest of the appropriate technology literature in a number of ways. First, what matters in our theory is not capital-labor ratios (as in Atkinson and Stiglitz and Basu and Weil) or size of plants (as in Stewart), but relative supplies of skills, which we believe to be more important in practice. Second, our results do not follow because productivity depends on the exact capital-labor or skilled-unskilled labor ratios in use, but because unskilled workers in the South perform some of the tasks performed by skilled worker in the North. Third, and perhaps most important, technological change is not an unintentional by-product of production, but a purposeful activity. In particular, R&D firms in the North direct their innovations towards different technologies depending on relative profitability. All our results originate from the fact that the relative abundance of skills in the North induces "skill-biased" innovations. In this respect, our model is closely related to Acemoglu [1998] who models directed techni-

[3] This prediction would follow from other multisector-multiskill models in which different countries have access to the same set of technologies. We are not aware of any other papers that derive this prediction.

cal change, but focuses on its implications for wage inequality. A number of other papers, including Mankiw, Romer and Weil [1992], Chari, Kehoe and McGrattan [1997] and Parente, Rogerson and Wright [1998], try to explain cross-country income differences without technology differences, but do not feature the technology skill-mismatch emphasized in this paper. Finally, our paper is also related to the literature on innovation, imitation, trade and technology transfer, for example, Vernon [1966], Krugman [1979], Grossman and Helpman [1991], Rivera-Batiz and Romer [1991], Barro and Sala-i-Martin [1997], Eaton and Kortum [1999] and Zeira [1999].

The plan of the paper is as follows. Section II introduces our basic model. It shows that productivity is higher in the North than in the South, and derives implications regarding cross-industry productivity differences between rich and poor economies. Section III shows that cross-country industry TFP patterns conform with the predictions of our model. In this section, we also perform a simple calibration to evaluate the potential contribution of technology-skill mismatch to differences in output per worker. Section IV discusses a number of extensions. We first analyze technical change and productivity differences in a world with commodity trade. We show that international trade reduces productivity differences, but at the same time causes divergence in output per worker. We also discuss the predictions of the model when intellectual property rights are enforced in the South and when Southern firms have access to less-skill intensive local technologies. Section V concludes.

II. The Basic Model

A. The Environment

We consider a world economy consisting of a large advanced country, which we call the North, and a set of small less developed countries which we refer to as the South. To simplify the analysis, we assume all Southern countries to be identical. What distinguishes the North and the South, other than their relative sizes, is the abundance of skills. The North has H^n skilled and L^n unskilled workers, while the South has H^s skilled and L^s unskilled workers. We assume that $H^n/L^n > H^s/L^s$, so the North is more abundant in skills. As we will see shortly, all technological progress will originate in the North. But the South can also adopt these technologies.

All countries admit a representative consumer with Constant Relative Risk Aversion preferences

$$\int_t^\infty \frac{C(\tau)^{1-\sigma}-1}{1-\sigma}\cdot\exp(-\rho(\tau-t))\cdot d\tau,$$

at time t, where $C(\tau)$ is consumption at time τ and ρ is the discount rate. We suppress time and country indexes when this causes no confusion.

The production technology is common across countries. Consumption and investment come out of a Cobb-Douglas output aggregate,

$$C + I + X \leq Y \equiv \exp\left[\int_0^1 \ln y(i) di\right], \tag{1}$$

where I is investment in machines, X is expenditure on R&D, and $y(i)$ denotes output in sector i. We normalize the price of the consumption aggregate in each period to 1.

Each final good can be produced by two technologies. The first uses unskilled labor (l) and a set of differentiated intermediate goods ("machines"), whereas the second uses skilled labor (h) and a different a set of machines. The key assumption is that some machines can only be used by unskilled workers, while some other machines can only be used by skilled workers. This assumption captures the fact that the relative productivity of technologies differ by worker skill. More formally, good i is produced as;

$$y(i) = \left[\int_0^{N_L} k_L(i,v)^{1-\beta} dv\right] \cdot [(1-i) \cdot l(i)]^\beta + \left[\int_0^{N_H} k_H(i,v)^{1-\beta} dv\right] \cdot [i \cdot Z \cdot h(i)]^\beta, \tag{2}$$

where $k_z(i,v)$ is the quantity of machines of variety v used in sector i together with workers of skill level z. The terms $(1-i)$ and $Z \cdot i$ denote exogenous sector- and technology-specific productivity levels. This implies that the skilled technology is relatively more productive in producing goods with higher indexes. The parameter $Z \geq 1$ measures the relative productivity of skilled workers. N_L and N_H are the number (measure) of machines that can be used with unskilled and skilled workers.

Producers of the final good $i \in [0,1]$ are price takers. They maximize profits,

$$p(i) y(i) - w_L l(i) - w_H h(i) - \int_0^{N_L} \chi_L(v) k_L(i,v) dv - \int_0^{N_H} \chi_H(v) k_H(i,v) dv,$$

taking the prices of their products, $p(i)$, wages, w_L and w_H, and the rental prices of all machines, $\chi_L(v)$ and $\chi_H(v)$, as given. This maximization gives the following sectoral demands for machines;

$$\begin{aligned} k_L(i,v) &= \left[(1-\beta) \cdot p(i) \cdot ((1-i) \cdot l(i))^\beta / \chi_L(v)\right]^{1/\beta}, \\ k_H(i,v) &= \left[(1-\beta) \cdot p(i) \cdot (i \cdot Z \cdot h(i))^\beta / \chi_H(v)\right]^{1/\beta}. \end{aligned} \tag{3}$$

Intuitively, firms demand more machines when their product prices, $p(i)$, are higher, when machine prices, $\chi_L(v)$ and $\chi_H(v)$, are lower, and when their employment, $l(i)$ or $h(i)$, are greater. This latter feature leads to a market size effect; there will be a greater demand for technologies complementing the factor that is more abundant.

Each type of machine is produced by the monopolist who owns the patent for that variety. For simplicity, we assume that machines depreciate instantaneously (see Acemoglu and Zilibotti [1999] for the case of slow depreciation). We also assume the marginal cost for the production of any machine is constant and equal to θ units of the final good. So a monopolist producing a machine for sector z will set the machine price so as to maximize its profits,

$$\pi_z(\nu) = (\chi(\nu) - \theta) \int_0^1 k_z(i, \nu) di, \tag{4}$$

subject to the demand equations given in (3). Since (3) define isoelastic demands with elasticity β, the profit maximizing price is $\chi_z(\nu) = \theta/(1-\beta) = \chi$. Without loss of generality, we normalize the marginal cost of machine production to $\theta \equiv \delta^{\beta/(1-\beta)}(1-\beta)^2$, so that $\chi = \delta^{\beta/(1-\beta)}(1-\beta)$. The parameter δ differs across countries and captures cross-country differences in the price of capital. We normalize $\delta = 1$ in the North, and presume that typically $\delta \geq 1$ in the South (see, e.g., Jones [1995]). Although all our qualitative conclusions hold if machine prices are identical in the South and the North, i.e., $\delta = 1$ in all countries, we allow machine prices to be greater in the South to facilitate the analysis in the quantitative section.

Substituting machine prices into (3), and then using the resulting expressions with (2), we obtain output in sector i as

$$y(i) = \delta^{-1} \cdot p(i)^{(1-\beta)/\beta} \cdot [N_L \cdot (1-i) \cdot l(i) + N_H \cdot i \cdot Z \cdot h(i)].$$

Increases in N_H improve the productivity of skilled workers in all sectors, while increases in N_L improve the productivity of unskilled workers. The ratio N_H/N_L determines the relative productivity of skilled and unskilled technologies, and will be the measure of skill-bias in the economy.

Technical progress takes the form of increases over time in N_L and N_H. This is similar to the expanding variety model of Romer [1990] and Grossman and Helpman [1991], but allows for technical change to be skill-or labor-complementary as in Acemoglu [1998]. In particular, new labor-complementary (complementary to unskilled workers) or skill–complementary machines are invented as a result of R&D. Most important, technical change is *directed*; the degree to which new technologies are skill-complementary is endogenous (see Acemoglu [1998]). New technologies are developed using final output. In particular, the R&D to invent a new variety of either type of machine costs μ. A firm that invents a machine obtains an indefinite patent to produce it. This specification implies that with a total expenditure of X, there will be X/μ new varieties invented. Therefore, the law of motion of N_z is given by

$$\dot{N}_z = \frac{X_z}{\mu},$$

where X_z denotes total output devoted to improving the technology of group $z = L$ or H.

B. Analysis

We now characterize the equilibrium in the North and the South for a given state of technology, N_L and N_H. Both the North and the South have access to this technology. We assume for now that there is no international trade, and continue to omit country indices.

The pattern of comparative advantage embedded in the production function (2) makes skilled workers relatively more productive in high indexed goods. Using this fact, it is straightforward to prove that there will exist a threshold sector $J \in [0,1]$ such that only unskilled workers will be used to produce goods with $i \leq J$ (i.e., $h(i) = 0$ for all $i \leq J$), and only skilled workers will be used to produce goods with $i \geq J$ (i.e., $l(i) = 0$ for all $i \geq J$) (see Acemoglu and Zilibotti [1999] for a formal proof).

We can then write the production of good i as

$$y(i) = \begin{cases} \delta^{-1} \cdot p(i)^{(1-\beta)/\beta} \cdot (1-i) \cdot N_L \cdot l(i) & \text{if} \quad 0 \leq i \leq J \\ \delta^{-1} \cdot p(i)^{(1-\beta)/\beta} \cdot i \cdot N_H \cdot Z \cdot h(i) & \text{if} \quad J < i \leq 1 \end{cases} . \tag{5}$$

In equilibrium, the marginal value product of unskilled workers, $\delta^{-1} \cdot p(i)^{1/\beta} \cdot (1-i) \cdot N_L$, has to be equalized across all sectors $i \leq J$. Similarly, the marginal value product of skilled workers, $\delta^{-1} \cdot p(i)^{1/\beta} \cdot i \cdot N_H \cdot Z$, also has to be equalized across all sectors $i \geq J$. Moreover, the Cobb-Douglas structure in (1) implies that expenditures across goods are equalized, i.e., $p(i)\, y(i)$ is constant for all i. Combining these two observations with market clearing, $\int_0^J l(i)di = L$ and $\int_J^1 h(i)di = H$, we obtain[4]

$$\text{for any } i \leq J,\ p(i) = P_L \cdot (1-i)^{-\beta} \text{and} \ \ l(i) = L/J, \text{ and} \tag{6}$$

$$\text{for any } i \geq J,\ p(i) = P_H \cdot i^{-\beta} \text{and } h(i) = H/(1-J), \tag{7}$$

where $P_L = p(0)$ and $P_H = p(1)$ are two price indices to be determined. Notice that goods with higher indexes produced with unskilled labor have a less productive technology and command higher prices. The converse is true for skilled goods.

To fully characterize the equilibrium, we need to find the threshold sector J. This can be done by noting that in sector J both a firm that uses unskilled workers and a firm that uses skilled workers should breakeven. In other words, both equations (6) and (7)

[4] For the marginal value product to be the same for all $i \in [0, J]$, $p(i)^{1/\beta} \cdot (1-i)$ has to be constant. Define this constant as P_L. Then, $p(i) = P_L \cdot (1-i)^{-\beta}$. Substituting this into (5) and using $p(i)y(i) = cst$, we find that $l(i)$ has to be constant, hence $l(i) = L/J$. The argument for the skill-intensive sectors is identical.

should hold for $i = J$, implying that

$$\frac{P_H}{P_L} = \left(\frac{J}{1-J}\right)^{\beta}. \tag{8}$$

Moreover, since $p(i)\,y(i)$ is constant for all i, $P_H\,y(1) = P_L\,y(0)$. Therefore, using (5) and (8), we obtain

$$J = \left(1 + \left(\frac{N_H}{N_L}\frac{ZH}{L}\right)^{\frac{1}{2}}\right)^{-1}. \tag{9}$$

This equation shows that either if the technology is highly skill-biased (high N_H/N_L) or if there is a large relative supply of skilled workers (high H/L), the fraction of sectors employing skilled workers and using the skilled technology will be large—i.e., J will be small). In this case, equation (8) implies that the relative price of skill intensive goods will also be low.

Also, using the fact that $\exp\left[\int_0^1 \ln p(i)di\right] = 1$, we find the price indices to be

$$P_L = \exp(-\beta)\cdot\left(1 + \left(\frac{N_H}{N_L}\frac{ZH}{L}\right)^{\frac{1}{2}}\right)^{\beta} \text{ and } P_H = \exp(-\beta)\cdot\left(1 + \left(\frac{N_H}{N_L}\frac{ZH}{L}\right)^{-\frac{1}{2}}\right)^{\beta}. \tag{10}$$

So the prices of labor-intensive goods are higher (and the prices of skill-intensive goods are lower) when the relative supply of skill-intensive goods is larger—i.e., when technology is more skill-biased and when there is a large relative supply of skilled workers.

Next, since factor markets are competitive, the relative wage of skilled workers is

$$\frac{w_H}{w_L} = Z\left(\frac{N_H}{N_L}\right)^{1/2}\left(\frac{ZH}{L}\right)^{-1/2}. \tag{11}$$

Therefore, the skill premium is greater when technologies are more skill-biased and when skilled workers are relatively more scarce. Finally, combining the definition $Y = \int_0^1 p(i)y(i)di$ with (5), (8), (9), and (10) gives

$$Y = \exp(-1)\cdot\delta^{-1}\cdot\left[(N_L L)^{1/2} + (N_H ZH)^{1/2}\right]^2. \tag{12}$$

This simple representation of the aggregate technology, which features constant elasticity of substitution between two types of labor, will be useful in the analysis of productivity differences between the North and the South.

As we will see in more detail below, the state of technology, N_H/N_L, is the same in both the North and the South, but the relative supply of skills is lower in the South, i.e., $H^s/L^s < H^n/L^n$. This leads to a number of immediate implications. First, there will be more sectors using unskilled workers and unskilled technologies in the South ($J^s > J^n$). Second, the relative prices of skill intensive goods will be higher in the South, i.e., $P_H^s/P_L^s > P_H^n/P_L^n$. In fact, from (10), we have $P_H^s > P_H^n$ and $P_L^s < P_L^n$. Finally, the skill premium, w_H/w_L, will be higher in the South.

C. Technological Progress

We now characterize the evolution of the state of technology, and the degree of skill-bias, N_H/N_L. We will show that in equilibrium there will only be innovations in the North, while producers in the South will copy the technologies developed in the North.

Suppose that intellectual property rights are not enforced internationally. Recall also that there is no international trade. In the absence of international property rights intermediate producers located in one country cannot sell their machines (or copyrights) to firms located in the other countries, so the relevant market for technologies is the local market. Since the R&D technology specified above entails a market size effect, this implies that the share of GDP spent by each economy on R&D will be an increasing function of the local market size, $L^c + ZH^c$ (see below). Because the South consists of a set of "small" economies, intermediate firms will have an infinitesimal market, and the South, collectively, will not invest in R&D. Southern producers will instead copy all their technologies from the North. Although the market size effect in our model conveniently rules out R&D in the South, we believe that lack of property rights and other distortions are more important in practice in limiting R&D in LDCs. Furthermore, if R&D is skill-intensive, then the scarcity of skills will also reduce R&D in LDCs. Our assumption that each Southern country is small captures these considerations in a simple way.

We assume that new technologies developed in the North can be copied and adapted in each Southern economy at some small cost ε. The fact that $\varepsilon > 0$ implies that once a firm adapts a new technology, it is not profitable for any others to do so because this would lead to Bertrand competition and negative net profits. Hence, all machines invented in the North will immediately be copied in the South, and supplied to producers by a (local) monopolist. This monopolist also faces isoelastic demands given by (3) and will therefore set the profit maximizing price, $\chi = \delta^{\beta/(1-\beta)}(1-\beta)$.[5] Therefore, firms in the South will have access to exactly the same set of technologies, N_L and N_H, as in the North.

Since the South performs no R&D, the evolution of N_L and N_H only depends on the returns to innovation in the North. We denote the value of a monopolist producing machine v complementary to workers of skill type z at time t by $V_z^n(v,t)$, where the superscript n denotes "the North". Symmetry across machines implies that $V_z^n(v,t) = V_z^n(t)$ for all v, so all machines produced for skill type z are equally profitable. In particular;

$$V_z^n(t) = \int_t^\infty \exp\left[-\int_t^\tau r(\omega)d\omega\right]\pi_z^n(\tau)d\tau \tag{13}$$

[5] The implicit assumption is that a local firm will be the first one to adapt the new technology to the local market. If the original inventor were to be the first, it could make additional profits from sales in the South.

where $r(\tau)$ is the interest rate at date τ, and

$$\begin{aligned}\pi^n_L(\tau) &= (\chi^n - \theta)\int_0^{J^n} k^n_L(i)di = \beta(1-\beta)\left(P^n_L(\tau)\right)^{1/\beta} L^n, \text{ and} \\ \pi^n_H(\tau) &= (\chi^n - \theta)\int_{J^n}^{1} k^n_H(i)di = \beta(1-\beta)\left(P^n_H(\tau)\right)^{1/\beta} ZH^n\end{aligned} \tag{14}$$

are the flow profits. The expressions in (14) are obtained using (3), (6), (7), and the fact that $\chi^n \equiv (1-\beta)$ (as $\delta = 1$ in the North). Since monopolists can only sell machines to Northern producers employing Northern workers, L^n and H^n are the markets for new technologies (machines).

Free-entry implies that the value of a monopolist cannot exceed the cost of innovation, μ. Thus, $V^n_z(t) \leq \mu$ for all t. Whenever $V^n_z(t) < \mu$, there will be no R&D activity to create new z-complementary machines.[6]

Along the Balanced Growth Path (BGP), N_L and N_H must grow at the same rate. Since there is only research in the North, this implies that Northern firms must devote the same relative research expenditure to skill- and labor-complementary innovations, i.e., $X^n_L/N_L = X^n_H/N_H$. This is only possible if $V^n_L = V^n_H = \mu$ which, in turn, implies that the flow profits from selling labor-and skill-complementary machines should be equal, i.e., $\pi^n_L = \pi^n_H$. Hence, in the BGP, we need

$$\frac{P^n_H}{P^n_L} = \left(\frac{ZH^n}{L^n}\right)^{-\beta}. \tag{15}$$

Intuitively, when there are more skilled workers, the market for skill-complementary machines is larger, and so the relative price of skill-intensive goods has to be lower to ensure $\pi^n_L = \pi^n_H$. Using (6), (7), and (9), we obtain:

$$\frac{N_H}{N_L} = \frac{1-J^n}{J^n} = \frac{ZH^n}{L^n}. \tag{16}$$

This equation defines the relative productivity of skilled and unskilled workers along the BGP as a function of the relative supply of skilled workers in the North. It also determines the threshold sector J^n along the BGP. The reason why N_H/N_L is increasing in H/L is the market size effect: it is more profitable to invent technologies that have greater clienteles, and when there are more skilled workers, skill-complementary technologies have a greater market.

The next proposition summarizes this result and the dynamics of the economy outside the BGP both in the North and in the South (proof in Appendix A).

[6]Notice at this point that in the South there will be no R&D; since L^s and H^s are small, π^s_z is small, so $V^s_z < \mu$.

Proposition 1 There exists a unique and globally (saddle path) stable BGP, given by equations (6), (7), (8), (9), and (16). Along this growth path, GDP, consumption, N_L and N_H grow at the rate

$$g = \frac{1}{\sigma} \cdot \left[\exp(-1) \cdot \beta \cdot (1-\beta) \cdot \mu^{-1} \cdot (L^n + ZH^n) - \rho \right]. \tag{17}$$

There is a unique BGP, and starting from any N_L and N_H, the economy converges to this BGP. Since both N_L and N_H grow at the common rate g, the relative productivities of skilled and unskilled workers are constant. Relative productivities can change along the transition path, however. As in Acemoglu [1998], an increase in H^n/L^n leads to skill-biased technical change, that is an increase in H^n/L^n raises N_H/N_L. Interestingly, the skill premium in the North is always $w_H^n/w_L^n = Z$. Skill-biased technical change induced by an increase in H^n/L^n therefore exactly cancels the negative direct impact of this variable on relative wages (see equations (11) and (16)).

Finally, both net output, NY, and consumption, C, are maximized in the BGP, because the equilibrium skill-bias, N_H/N_L, is chosen "appropriately" for the North's skill composition (proof omitted):

Corollary 1 Let $NY \equiv Y - X$ and $C = Y - I - X$. Then, the BGP value of N_H/N_L, given by equation (16), maximizes NY and C in the North.

In contrast, since factor abundance in the South does not affect the direction of technical change, new technologies developed by the North are inappropriate for the needs of the South. In particular, net output and consumption in the world economy, $NY^w \equiv Y^n + Y^s - X^n$ and $C^w \equiv Y^n + Y^s - I^n - I^s - X^n$, are not maximized by the technology choices in the North (i.e., by N_H/N_L as given by (16)).

D. Productivity Differences Between the North and the South

In this subsection, we describe the main theoretical results that will be tested in the next section. We derive two sets of predictions. The first concerns the pattern of cross-industry TFP differences between rich and poor economies. Our model predicts that sectoral TFPs should be larger in the North relative to the South in the labor-intensive rather than in skill-intensive sectors. The second concerns aggregate productivity. We will show that even though the South has access to the same technological opportunities as the North, aggregate productivity (as measured by either output per worker or TFP) should be higher in the North than in the South.

To analyze cross-industry TFP differences, we decompose the value added of each industry, obtained by multiplying (5) with prices, into three components; capital input, labor input and TFP. More formally;

$$
\begin{aligned}
p^c(i) \cdot y_L^c(i) &= a_L^c(i) \cdot K_L^c(i)^{1-\beta} \cdot l^c(i)^\beta, \\
p^c(i) \cdot y_H^c(i) &= a_H^c(i) \cdot K_H^c(i)^{1-\beta} \cdot [Z \cdot h^c(i)]^\beta,
\end{aligned}
\tag{18}
$$

where $c \in \{n, s\}$ is the country index, $K_z^c(i) \equiv \int_0^{N_z} k_z^c(i, v)\, dv$ is the capital input of industry i, and $a_L^c(i) \equiv p^c(i) \cdot [(1-i) \cdot N_L]^\beta$ and $a_H^c(i) \equiv p^c(i) \cdot [i \cdot N_H]^\beta$ are sectoral (industry) TFPs. Using equations (6) and (7), we obtain;

$$
\begin{aligned}
a_L^c(i) &= a_L^c = P_L^c N_L^\beta, \\
a_H^c(i) &= a_H^c = P_H^c N_H^\beta.
\end{aligned}
\tag{19}
$$

Next, recall that, in a BGP, $P_H^n / P_L^n = (N_H/N_L)^{-\beta}$ (see equations (15) and (16)). So, along the BGP, all sectors in the North have the same TFP, i.e., $a_L^n = a_H^n \equiv a^n$.[7] Also from equation (10), $P_H^s > P_H^n$ and $P_L^s < P_L^n$, which reflects the relative scarcity of skills in the South. Therefore, (19) implies that TFP will be larger in the North in the sectors that use unskilled technologies in the South, and will be larger in the South in the sectors that use skilled technologies in the South. This result is represented in Figure 1 diagrammatically and summarized in the following Proposition (proof omitted).

Proposition 2 $H^s/L^s < H^n/L^n$ implies that $a_H^s(i \geq J^s) > a^n > a_L^s(i \leq J^s)$.

This prediction is driven by the pattern of relative prices in the two countries. In the South, skilled labor is scarce, so skill-intensive goods are more expensive, leading to greater TFPs in these sectors.

We next turn to the analysis of aggregate productivity differences. First, define "physical productivity" in sector i as $a_z^c(i)/p^c(i)$. From our previous analysis;

$$
\frac{a_z^c(i)}{p^c(i)} = \begin{cases} ((1-i) N_L)^\beta & \text{if } i \leq J^c \\ (i N_H)^\beta & \text{if } i \geq J^c \end{cases} .
$$

This expression shows that physical productivities are the same in the North and the South in all sectors where firms in the two countries adopt the same technology. In particular, in sectors $i \leq J^n$ as well as $i \geq J^s$. However, physical productivity is higher in the North in sectors $i \in [J^n, J^s]$, where the South uses unskilled workers and the labor-intensive technology, while the North uses skilled workers and the skill-intensive technology. Figure 2 plots the physical productivities, $a_z(i)/p(i)$, in each of the two technologies. Note that the two schedules cross at $J^n \equiv N_L/(N_L + N_H)$ (as given by the BGP condition (16)). This implies that physical productivity is higher in the skilled technology in all sectors

[7] Specifically, using equations (9), (10), (16) and (19), we obtain $a^n = \exp(-\beta) \cdot (N_L + N_H)^\beta$.

$j > J^n$, exactly as in the North. This is because R&D is *directed* at the North's needs. Since $H^s/L^s < H^n/L^n$, however, we have $J^s > J^n$, and physical productivity is lower in the South than in the North in some sectors.

This result can be translated into a measure of aggregate TFP. Write total output as:

$$Y^c = \exp\left(\int_0^{J^c} \ln y_L^c(i)\, di + \int_{J^c}^1 \ln y_H^c(i)\, di\right) = A(J^c, N_L, N_H) \cdot \left(K_L^{1-\beta} l^\beta\right)^J \left(K_H^{1-\beta} (Zh)^\beta\right)^{1-J}, \tag{20}$$

where $A(J, N_L, N_H) \equiv \exp\left(\int_0^J \ln\left(a_L(i)/p(i)\right)\, di + \int_J^1 \ln\left(a_H(i)/p(i)\right)\, di\right)$ is aggregate TFP, obtained from separating the terms with factor content from the technology terms.[8] Since, in a BGP, physical productivities are the same in all sectors, except in $i \in [J^n, J^s]$ where the North has higher productivity than the South, aggregate TFP is higher in the North than in the South.

It is important to note that in this economy all countries have access to the same aggregate production possibilities frontier. So one might conjecture that there should be no aggregate TFP differences across countries (though cross-sectoral TFP differences should continue to exist). However, since countries with different factor endowments will choose different points along the aggregate production possibilities frontier, the measures employed in practice and even our theoretical measure, $A(J, N_L, N_H)$, will lead to aggregate TFP differences. Given these issues, it is perhaps more transparent to look at simpler measures of aggregate productivity; output per worker, y^c, and output per efficiency unit of labor, $y^{eff,c}$,

$$y^c(H^c, L^c, N_L, N_H \mid \delta) \equiv \frac{Y^c}{L^c + H^c} = \exp(-1) \cdot \delta^{-1} \cdot \frac{\left[(N_L L^c)^{1/2} + (N_H Z H^c)^{1/2}\right]^2}{L^c + H^c}.$$

$$y^{eff,c}(H^c, L^c, N_L, N_H \mid \delta) \equiv \frac{Y^c}{L^c + ZH^c} = \exp(-1) \cdot \delta^{-1} \cdot \frac{\left[(N_L L^c)^{1/2} + (N_H Z H^c)^{1/2}\right]^2}{L^c + ZH^c}.$$

In writing these expressions, we condition on δ because this variable determines the equilibrium capital labor ratio. Differentiation establishes that given N_H/N_L, $y^{eff}(H, L, N_L, N_H \mid \delta)$ is an inverse U-shaped function of H/L with a maximum at $H/L = N_H/N_L$, whereas $y(H, L, N_L, N_H \mid \delta)$ is an inverse U-shaped function of H/L with a maximum at $H/L = ZN_H/N_L$. These observations immediately establish (proof omitted):

Proposition 3 Assume that N_H/N_L is given as in (16), then:

1. *For any* $H/L \neq H^n/L^n$, *we have* $y^{eff}(H^n, L^n, N_L, N_H \mid \delta) > y^{eff}(H, L, N_L, N_H \mid \delta)$.

[8] To obtain the expression for $A(J, N_L, N_H)$, use $\int_0^1 \ln p(i)\, di = 0$.

2. For any $H/L < H^n/L^n$, we have $y(H^n, L^n, N_L, N_H \mid \delta) > y(H, L, N_L, N_H \mid \delta)$.

When N_H/N_L is chosen according to the North's needs, both output per efficiency unit of labor and output per worker are higher in the North than in the South. Output per efficiency unit is in fact maximized in the North, whereas output per worker would be maximized by a skill endowment larger than the relative skill endowment in the North (recall that $Z > 1$). Furthermore, both $y^{eff,n}/y^{eff,s}$ and y^n/y^s, productivity and output per worker in the North relative to the South, are strictly increasing in N_H/N_L. Therefore, as technologies become more skill-biased, the output gap (per worker or per efficiency unit of labor) between the North and the South widens. These exercises compare two economies with the same cost of capital δ. Since $\delta = 1$ in the North and $\delta \geq 1$ in the South, we have $y^{eff}(H^n, L^n, N_L, N_H \mid \delta = 1) > y^{eff}(H^s, L^s, N_L, N_H \mid \delta^s)$ and $y(H^n, L^n, N_L, N_H \mid \delta = 1) > y(H^s, L^s, N_L, N_H \mid \delta^s)$ a fortiori when $\delta^s > 1$.

The reason for the aggregate productivity differences between the North and the South, measured in terms of TFP or output per worker, is technology-skill mismatch. The North develops technologies that are most appropriate to its needs. In particular, the North invests more in skill-biased technologies, N_H, because there are relatively more skilled workers using these technologies in the North. However, these Northern technologies are mismatched to the skills of the LDCs' workforces. In our model, this is because in sectors $j \in [J^n, J^s]$, production in the LDCs is carried out using unskilled workers, and these workers use the unskilled technology, N_L, rather than the skilled technology, and are less productive as a result.

It is also important to note that if R&D firms could sell to Southern producers, they would invest more in unskilled technologies (i.e., develop less skill-biased technologies), and productivity in the South would not be as low. Similarly, if the South could perform R&D, it would direct it to unskilled machines, and the productivity gap would be smaller. It is therefore the combination of the South importing technologies from the North and directed technical change in the North that leads to the productivity differences between the North and the South.

III. Empirical Evidence and Quantitative Assessment

In this section, we test the prediction regarding sectoral TFPs, and investigate whether the theoretical mechanism we developed could be quantitatively significant.

A. Cross-country Patterns in Industry TFPs

We start by investigating some of the implications of Proposition 2. To do this, we calculate sectoral TFPs using data from the U.N. General Industrial Statistics on the number of production workers, number of nonproduction workers, employment, value added and investment (converted into U.S. dollars) in 27 three digit manufacturing sectors in 22 countries.[9] From these data, we construct sectoral capital stocks and TFP for each country. The construction of these variables is described in Appendix B. We use the number of nonproduction workers as a proxy for high skill workers as in previous work in this area (e.g. Berman, Bound and Griliches [1994]; Berman, Bound and Machin [1998]). The data for employment and value added are for 1990, but since data on the number of nonproduction workers is often missing for 1990, we use the average between 1986 and 1990 for all countries and sectors.

The first three rows of Table 1 report selected averages for these measures. With a view to testing the predictions of our model, we rank sectors according to "skill-intensity" in the United States defined as the ratio of nonproduction workers to total employment in that industry. We then create three groups, low-skill, medium-skill, and high-skill, each consisting of 9 industries (see Table 1). We report (weighted) average values of value added per worker, capital per worker, and ratio of nonproduction workers in total workforce for each group, separately for the LDCs and the "rich" economies (those with GDP per capita greater than $6,500, see Table 1). Not surprisingly, value added and capital per worker, and the ratio of nonproduction workers in the workforce are lower in the LDCs than in the rich economies.[10]

Proposition 2 implies a *strong* and a *weak* hypothesis. The strong hypothesis is that TFP in the South should be higher than in the North in the less skill intensive industries and lower than in the North in the more skill intensive industries. The weak hypothesis is that TFPs in the LDCs relative to the United States should be higher in the skill intensive sectors. In the empirical work, we focus mainly on the weak hypothesis.

[9] Berman, Bound and Machin [1998] use this data set to analyze skill upgrading in advanced countries, Berman and Machin [1999] use it to analyze inequality trends and skill upgrading in developing countries, and Wolfson [1999] uses the related UNIDO dataset to analyze the factor content of trade between less and more developed countries.

[10] The statistics reported in the first and second row of Table 1 imply somewhat lower capital-output ratios than is commonly estimated in developed countries. This ratio is sensitive to the choice of the depreciation rate for capital. Our choice of a depreciation rate of 8% implies an average lifetime of capital of 12.5 years which is rather short. This choice is motivated by the constraint on the number of observations for investment (see Appendix B), since a relatively high depreciation rate mitigates the problems associated with the short sample. The capital-output ratio is the only measure which is sensitive to this choice. We checked the robustness of our analysis by using a depreciation rate of 5% and also no depreciation over the sample. In these cases, the capital output ratios were higher, but relative TFPs and regression results were very similar to those reported here.

First, the strong hypothesis requires technology-skill mismatch to be the only source of productivity differences between the United States and the LDCs, which is clearly unrealistic. Second, production-nonproduction distinction understates skill differences across countries, leading to exaggerated TFP differences between the United States and the LDCs in all sectors. For example, the ratio of workers with high school or more in the labor force is 70 percent in the United States, whereas 15 percent in the set of LDCs considered in this section (see next subsection for data details). In contrast, the ratio of nonproduction workers in manufacturing is 33 percent in the United States vs. 23 percent in this set of LDCs. This implies that both production and nonproduction workers in the United States will be more educated, and hence more productive even when using the same technologies, than production and nonproduction workers in LDCs. These differences in productivity will be reflected in our TFP estimates, exaggerating the TFP differences between the United States and the LDCs. So TFP will tend to be higher in the United States than the LDCs in all sectors.[11] In any case, we believe that the weak hypothesis is a challenging test for our theory; this hypothesis contrasts with a naive intuition that TFP differences should be largest in the most skill-intensive sectors, which are often the most high-technology sectors.

It is important to note that in our database value added observations are computed using local prices. Therefore, our sectoral TFP calculations will correspond to the theoretical TFP measure we discussed in the previous section, a_z^c.[12]

We assume that output in sector i in country c is given by

$$y_{ic} = TFP_{ic} \cdot F_i(k_{ic}, e_{ic}),$$

where e is efficiency units of labor and the production function F_i is constant returns the scale. So all countries share the same technology in each industry, except for a multiplicative TFP term. We calculate the efficiency units of labor as

$$e_{ic} = prod_{ic} + \zeta \cdot nonprod_{ic},$$

where $prod_{ic}$ is the number of production workers in country c and industry i, $nonprod_{ic}$ is the number of nonproduction workers in country c and industry i, and ζ is the efficiency

[11] We can get a sense of how large this measurement problem is by comparing aggregate manufacturing TFP differences that are implied by our calculations in this subsection to the aggregate TFP differences as calculated by Hall and Jones [1999]. The numbers here suggest that the LDCs in our sample have on average TFP levels that are approximately 23 percent of the U.S. level. In contrast, the data reported in Hall and Jones [1999] imply that the same set of countries should have TFP levels equivalent to 57 percent of the U.S. level, or approximately 2.5 larger than the LDC TFP levels implied by the U.N. data. This substantiates the claim that the use of production-nonproduction classification will exaggerate TFP differences between rich and poor countries.

[12] As discussed in the previous section, our theory also has implications on the cross-sectoral pattern of differences in physical productivities, $a_z^c(i)/p(i)$. To test these implications, one would need sectoral price indices that are comparable across countries in levels, which we do not have.

units that a nonproduction worker possesses relative to a production worker. This corresponds to Z in terms of our model, though in the equilibrium of our model skilled and unskilled workers never work in the same industry. Berman, Bound and Machin [1998] report the relative wage of nonproduction to production workers is approximately 1.5 in the OECD economies, so we take this as our baseline case.[13]

We use three different methods to calculate TFP. The first is a direct analog of the TFP calculation over time applied across countries within an industry. We rank countries in each industry according to capital labor ratios, and apply the standard TFP calculation method (see Appendix B). We denote the output of this exercise by TFP_{ic}^{CW} where i and c refer to industry and country, CW refers to chain-weighted. The second method simply assumes the production function, F_i, to be Cobb-Douglas, and uses average labor share within each industry to calculate TFP. We refer to this measure as TFP_{ic}^{CD}. Finally, the third method constructs a TFP measure calculated as the residual from the regression;

$$\ln y_{ic}^{l} = \upsilon_i^k \ln k_{ic}^{l} + \upsilon_i^e \ln e_{ic}^{l} + \widehat{\varepsilon}_{ic}$$

where y^l denotes value added per worker, k^l capital per worker and e^l efficiency units of labor per worker, and the coefficients $\{\upsilon_i^k, \upsilon_i^e\}_{i=1}^{27}$ are estimated by OLS. We define $\ln TFP_{ic}^{R} = \widehat{\varepsilon}_{ic}$ and refer to this measure as "regression adjusted TFP". This third method may be biased as variations in capital and skill across industries are likely to be correlated with the residuals. Nevertheless, this measure provides a check on whether our results are driven by the functional form assumptions used in the construction of TFP_{ic}^{CW} and TFP_{ic}^{CD}. In all cases, we normalize $TFP_{iUS} = 1$, so all TFPs are relative to the United States TFP in that sector.

Descriptive statistics for sectoral TFPs are given in the last three rows of Table 1 for the three industry groups and the three measures of TFP. In each case, we report average TFPs relative to the United States. We weight observations using value added, which amounts to giving more weight to larger sectors and larger countries.

We can already see the relevant patterns of industry TFPs from Table 1. First, TFP is significantly higher in the North in all sectors. This might be because of differences in the access to the most advanced technologies across countries, or because of the measurement problems mentioned above. In any case, there is no support for the strong hypothesis predicted by our theory. More important for our purposes, the data appear consistent with our weak hypothesis. For example, using either TFP^{CW} or TFP^{CD}, TFP in the LDCs is 22 percent of the United States in the low skill industries, 26-27 percent of the United States in the medium skill industries, and 30 percent of the United States in the

[13]We also calculated TFP measures using $\zeta = 1.3$ and 1.7. The results were very similar in all cases, so we do not report those. Details are available upon request.

high skill industries. Using regression adjusted TFP, the same numbers are 34 percent, 49 percent, and 64 percent. Therefore, with all three measures, TFP gaps are smaller between the LDCs and the United States (and other rich economies) in the highest skill sectors.[14]

We now use regression analysis to document the relationship between relative TFPs and skill intensity more formally. Our baseline regressions relating TFP_{ic}^{CW} to skill-intensity in the United States are reported in Table 2 and support the basic conclusion from Table 1 that TFP gaps are smaller between the LDCs and the United States in the highest skill sectors. The estimates in Table 2 are obtained by regressing $tfp_{ic}^{CW} \equiv \ln TFP_{ic}^{CW}$ on the (log) ratio of nonproduction workers to total employment in that industry in the North, pn_North. We take the North to be either the United States or the average of the United States, the United Kingdom and Canada (the "G3"). All regressions are weighted by value added and include country effects, and the standard errors are corrected for clustering of pn_North, which varies only at the industry level. The corrected standard errors are typically about 70 percent larger than the regular standard errors. The results show that the coefficient on pn_North is positive when the sample is limited to poor countries, but not when limited to rich countries, which is the prediction of our model. For example, the estimate in column 1, which is from a regression that uses the United States as the North, suggests that an industry with a 10 percent higher ratio of nonproduction workers in total employment will have about 2.4 percent higher TFP in the LDCs compared to the United States (relative to the average TFP in that country). This effect is statistically significant at the 5 percent level and also of a plausible magnitude: pn_North (for the United States) varies between 0.13 and 0.51 in the sample, so the result in column 1 implies that relative TFP in the LDCs is higher by about 10 percent in the most skilled intensive industry than in the least skilled intensive industry. India, one of our LDCs, is an outlier in the regression of column 1. There is reason to believe in that data quality is lower for India as investment data for this country were missing for a large number of years. We therefore repeat the regression without including India in column 2. This leads to a greater parameter estimate, 0.36, indicating that a 10 percent higher ratio of nonproduction workers in total employment is associated with a 3.6 percent higher TFP in the LDCs compared to the United States.

[14] The 70 percent gap between the United States and LDC TFPs in the most skill-intensive industries may suggest that technology-skill mismatch can explain only a small fraction of the productivity differences across countries. However, recall that this 70 percent gap is in part due to the measurement problems noted above. If we apply the 2.5 correction suggested by footnote **??**, we would obtain that TFP levels in the LDCs are 75 percent of the United States in the most skill-intensive industries and 55 percent in the least skill-intensive industries. This suggests that although there are other factors at work, technology-skill match could be responsible for over one-third of TFP differences between the LDCs and the U.S..

This estimate is now significant at the 1 percent level. In column 3, we use the ratio of nonproduction workers to total employment in the United States, the United Kingdom and Canada instead. This leads to a parameter estimate of 0.31, which is again highly significant. In contrast to these results for LDCs, we do not find a statistically significant relationship between pn_North and industry TFPs among rich countries (columns 3 and 4).[15]

Figure 3 plots TFP (relative to the United States) for a number of the LDCs in our sample against the rank of that industry in terms of skill intensity in the United States (where rank=1 stands for the least skill-intensive industry). The curves represent fitted log-regressions. Colombia, Malaysia, the Philippines and Turkey illustrate the positive relationship shown in Table 2 (also found in Venezuela). India is one of the three countries in which no significant relationship is found (the others are Indonesia and Ecuador). Overall, as the last figure shows, there is a well-defined relationship when we look at the average across all the LDCs. In a number of countries, miscellaneous petroleum products (MISCPET) and beverages (BEV) appear as outliers.[16] Excluding these industries does not alter the main results reported in Table 2, but reduces the point estimates; without these industries, the regression coefficients in column 1, 2 and 3 decrease to 0.14 (s.e.=0.08), 0.23 (s.e.=0.09) and 0.22 (s.e.=0.11).

The regressions in columns 6, 7 and 8 use the sample of 21 countries (the entire sample minus the United States since all numbers are relative to the United States), but add an interaction term between the right hand side variable and the relative GDP of the country in question. According to our theory, the relationship between TFP and skill intensity should be stronger for poorer countries because P_H/P_L and a_H/a_L are increasing in the skill-intensity gap between the country in question and the United States. The interaction term in these regressions is parameterized so that the main effects are evaluated at the mean. Hence we expect both the interaction term and the main effect to be positive, so that TFP in the high skill industries (relative to the rest of the industries) in the average country should be higher than in the United States, and the gap should become larger as we consider poorer countries. The results in columns 6, 7 and 8 support this prediction. The interaction term is always positive, and statistically significant at the 5 percent level.

Variations using different measures of TFP or different estimation methods are re-

[15] The results are robust to different splits of the sample into rich countries and LDCs. For example, if the threshold were set at \$7,000 rather than \$6,500, Greece, Portugal and Korea would also be classified as LDCs. In this case, the estimates in columns 1, 2 and 3 of Table 1 are, respectively, 0.14 (s.e.=0.07), 0.17 (s.e.=0.07) and 0.20 (s.e.=0.09), while the effect remains negative and statistically insignificant for rich countries.

[16] Scientific Equipment is also an outlier in the opposite direction. The large TFP gap between the U.S. and the LDCs in this sector suggests that technological differences may be quite important in this industry.

ported in Table 3, and confirm the basic findings. We report estimates from regressions that use the alternative measures, TFP_{ic}^{CD} and TFP_{ic}^{R}, and from regressions weighted by value added relative to the country average (value added relative to country average) or weighted by employment. We also report specifications that use the rank of the industry in terms of the corresponding skill-intensity measure, *rank*. All regressions in Table 3 include country effects. In almost all cases, TFP gaps are larger in the sectors that are less skill-intensive in the North (the United States or G3). Moreover in most cases, this effect is statistically significant, except when we weight observations by employment, the relationship is typically statistically insignificant. Once again, when we remove India from the sample, which plays a disproportionate role when observations are weighted by employment, the effects are statistically significant at the 5 percent level. Overall, we take this as evidence that there is a relatively robust relationship between sectoral TFPs in LDCs and skill intensity of the sector, consistent with the predictions of our theory.

B. Aggregate Productivity Differences

We now turn to an investigation of how important our mechanism may be in accounting for cross-country differences in output per worker. Although we do not think that our mechanism accounts for all the variation in output per worker across countries, to perform this exercise we abstract from all other sources of productivity differences. We therefore view this exercise as providing an upper bound on how much of the cross-country productivity differences technology-skill mismatch could explain. More specifically, we compare the predictive power of our model with that of a comparable neoclassical model, where all countries have access to the same technology and output is Cobb-Douglas in human and physical capital. According to the neoclassical formulation, country c's output is;

$$Y_{NC}^{c} = Q \cdot (K^{c})^{\alpha} \cdot (L^{c} + ZH^{c})^{1-\alpha}, \tag{21}$$

where the technological parameter Q is the same across countries. This is effectively the model used, among many others, by Hall and Jones [1999], adapted to our environment with two types of workers. We use K^c, L^c and H^c from the data, and set $\alpha = 0.33$ (which is equivalent to $1 - \beta$ in our model), since this is the share of capital in the model. Z is chosen to match the relevant wage premium observed in the United States. Given K^c, L^c, H^c, Z and α, we can calculate GDP per worker as predicted by the neoclassical benchmark model, $\hat{y}_{NC}^{c} = \frac{Y_{NC}^{c}}{L^c + H^c}$, and we choose Q to normalize $\hat{y}_{NC}^{US} = 1$.

In contrast, in our model output per worker, $\hat{y}_{AZ}^{c}$, is:

$$\hat{y}_{AZ}^{c} = \frac{Y_{AZ}^{c}}{L^c + H^c} = \qquad \exp(-1) \cdot \frac{(\delta^c)^{-1} \cdot \left[(N_L L^c)^{1/2} + (N_H Z H^c)^{1/2}\right]^2}{L^c + H^c}$$

$$= \frac{(K^c)^{1-\beta} \cdot \left[(N_L L^c)^{1/2} + (N_H Z H^c)^{1/2}\right]^{2\beta}}{L^c + H^c}, \tag{22}$$

where the level of N_L is set to normalize $\hat{y}_{AZ}^{US} = 1$.[17] In our baseline parameterization, we treat the United States as the North, and set $N_H/N_L = ZH_{US}/L_{US}$ (see equation (16)).

We use differences in schooling in 1985 from the Barro-Lee data set to capture differences in the supply of skilled workers across countries.[18] To reduce the sensitivity of our results to measurement error and arbitrary choice involved in breaking the population into two skill groups, we construct four different measures for H/L from this data set. The first is the ratio of the population over 25 with at least primary school attainment to those over 25 with no primary school attainment. The second is the ratio of those with secondary school attainment to those without. The third uses secondary completion instead, and the fourth uses college attendance. Secondary schooling or college attendance better approximate differences between skilled and unskilled workers emphasized in our model. Nevertheless, to obtain a highly conservative estimate of the differences in the supply of skilled workers between the North and the South, we also look at primary school attainment, which minimizes the cross-country variability in skills.

We use output per worker and capital per worker for 1988 calculated from the Summers-Heston data set.[19] Finally, we need to determine the parameter, Z, relative productivity of skilled workers. In our model this is the skill premium in the North (see Section II.C). In the United States, the mean earnings of workers with high school attainment (10th grade) or more divided by the mean earnings of workers with no high school attainment (9th grade or less) is over 2, while the mean earnings of full time workers with some college or more divided by the mean earnings of full time workers with no college is approximately 1.75 (all numbers calculated from Current Population Survey of the United States [1996]). We use $Z = 1.8$ as an upper bound of the relative productivity of skilled

[17] To obtain the second line of (22), use *(i)* the equilibrium condition that the price of capital is equal to its marginal product, i.e.,

$$\frac{\delta^c}{\delta^{US}} = \left(\frac{\left[(N_L L^c)^{1/2} + (N_H Z H^c)^{1/2}\right]^2}{\left[(N_L L^{US})^{1/2} + (N_H Z H^{US})^{1/2}\right]^2} \frac{K^{US}}{K^c} \right)^{1-\beta},$$

(ii) the fact that $\delta^{US} = 1$, and *(iii)* the normalization of N_L that $K^{US} / \left[(N_L L^{US})^{1/2} + (N_H Z H^{US})^{1/2}\right]^2 = 1$.

[18] Web address for Barro-Lee data http://www.worldbank.org/html/prdmg/grthweb/ddbarle2.htm, see also Barro and Lee [1993]. We also repeated the same exercise using schooling data for 1990, which may be less appropriate since output and capital data are for 1988. The results were very similar. We have also experimented with other measures of skills that use average years of schooling rather than the fraction of the population with various degrees. The results were once again very similar.

[19] These are as constructed by Hall and Jones [1999], with a correction for the contribution of the mining sector. Descriptive statistics for this sample were given in Table A1 of our working paper version, Acemoglu and Zilibotti [1999], and to save space, we do not report those here.

workers. We also use $Z = 1.5$, which we view as a more reasonable estimate of the relative productivity of "skilled" workers, especially when we use secondary school attainment. In fact, the average earnings of those with high school attainment and completion to those with no high school (less than 9th grade) in the United States is approximately 1.5.[20]

Our main results are reported in Table 4. The first three columns refer to the neoclassical model, while columns 4-6 refer to our model using the United States as the North. Rows refer to different measures of skill supply and to different values of the parameter Z. We report three statistics for each experiment, $\hat{y}^{LDC}$, $\hat{y}^{5th-}$ and $\Re^2_s$. $\hat{y}^{LDC}$ denotes the average GDP per worker relative to the United States among the "LDCs" (the 79 poorest countries in the sample), and $\hat{y}^{5th-}$ denotes output per worker relative to the United States in the 5th poorest country in the sample. $\Re^2_s$, "constrained R^2", is a more general measure of goodness of fit. In particular, let y^c denote output per worker from the data and $s \in \{NC, AZ\}$, then we define $\Re^2_s = 1 - \sum_c (y^c - y^c_s)^2 / \sum (y^c)^2$. This is the "$R^2$" from a regression of output per worker in the data on predicted values when we constrain the slope to be equal to 1 and the constant to be 0. $\Re^2$ would be equal to 1, if there were a perfect fit between the model and the data, though this measure could also be negative if the fit were particularly bad.

The average output per worker among the LDCs in the sample is about 19 percent of the United States, and output per worker in the fifth poorest country is about 1/30th of the U.S. level. The neoclassical model predicts average output among the LDCs to be between 40 percent and 50 percent, and output per worker in the fifth poorest country to be between 1/5th and 1/7th of the U.S. level. Like the neoclassical model, our model underestimates the productivity gap between rich and poor countries, but much less so. When the skill endowment is measured by secondary school attainment or completion, our model predicts output per worker differences quite similar to those which we observe in the data. For example, with secondary school attainment and $Z = 1.5$, we obtain $\hat{y}^{LDC}_{AZ} = 0.28$ and $\hat{y}^{5th-}_{AZ} = 0.05$. In contrast, with the same parameter values, the neoclassical model implies $\hat{y}^{LDC}_{NC} = 0.41$ and $\hat{y}^{5th-}_{NC} = 0.16$.[21] Using other measures of relative skill supply and other values of Z yield similar results, consistently better with directed technical change than with the neoclassical model.

[20] Results with values of Z less than 1.5 give also very similar results.

[21] Expressed alternatively, to explain the cross-country variations with $Z = 1.5$ and secondary school attainment as the measure of skills, the neoclassical model needs TFP, Q in equation (21), to be 54 percent lower in the LDCs than in the U.S. (recall that output in the LDC is on average 19 percent of that in the U.S., and the neoclassical model predicts it to be 41 percent of the U.S.; $0.54 = 1 - (0.19/0.41)$). In contrast, for our model to explain the data, we would need the LDCs to have 30 percent lower TFP than the U.S. for other reasons ($0.30 = 1 - (0.19/0.27)$). Roughly speaking, therefore, this exercise suggests that our mechanism can account for one-third to a half of the TFP gap between the U.S. and the LDCs (see also footnote 15).

The neoclassical model also appears to perform reasonably well when we look at the constrained R^2 measure. This is because differences in physical and human capital are important determinants of output per worker. For example, using secondary school attainment and $Z = 1.5$, we obtain $\Re^2_{NC} = 0.74$, though the fit is lower with the alternative measures. Incorporating the fact that technologies are not appropriate to the LDCs' needs improves the fit substantially; with secondary school measure, $Z = 1.5$ and the United States as the North, the constrained R^2 rises to $\Re^2_{AZ} = 0.93$.[22]

Figures 4 and 5 plot output per worker, y^c, and the predicted values from the two models, $\hat{y}^c_{NC}$ and $\hat{y}^c_{AZ}$. They show, once again, that our mechanism contributes significantly to differences in output per worker (recall that $y^{US} = \hat{y}^{US}_{NC} = \hat{y}^c_{AZ} = 1$). The neoclassical model systematically underpredicts the differences in output per worker between the United States and the LDCs; in Figure 4 almost all points are above the 45^0 line. In contrast, our model predicts differences in line with those in the data, and in Figure 5, the cloud of points shifts towards the 45^0 line. We therefore conclude that the mismatch between the technologies developed in the North and the skills of the LDCs could be an important factor in explaining the large differences in output per worker and income per capita across countries.

Although we believe that new technologies being directed at the U.S. market is a good approximation, it may exaggerate inappropriateness of new technologies to the LDCs' needs. For this reason, we also report results using countries with a GDP per worker higher than \$20,000 in 1988 as the target of new technologies (see Table 5, columns 1-3). More precisely, we set $N_H/N_L = Z\left(\overline{H}/\overline{L}\right)_{rich}$, where $\left(\overline{H}/\overline{L}\right)_{rich}$ is a weighted average of the number of skilled and unskilled workers in the rich countries using capital stocks as weights (as implied by our model). In this case too, our model performs substantially better than the neoclassical model. For example, with technical change directed at an average rich economy's needs, $Z = 1.5$ and secondary school attainment, we obtain $\hat{y}^{LDC}_{AZ} = 0.31$ and $\hat{y}^{5th-}_{AZ} = 0.07$ as compared to $\hat{y}^{LDC}_{NC} = 0.41$, $\hat{y}^{5th-}_{NC} = 0.16$ for the neoclassical model. These results are only slightly worse than the results when technical change was directed at the United States alone.

Finally, to assess the importance of directed technical change in these results, we calculate the predictions of the model in the case where technologies are directed at the average LDC (GDP per worker below \$20,000 in 1990 U.S. Dollars) rather than for the United States or the rich economies. For this purpose, we choose $N_H/N_L = Z\left(\overline{H}/\overline{L}\right)_{LDC}$,

[22] The quantitative results are clearly sensitive to some of the assumptions embedded in in our model. For example, our model implies that the elasticity of substitution between skilled and unskilled workers is equal to 2. Modifying the production function, equation (2), and the preferences, equation (1), changes this elasticity of substitution, and affects the fit of the model. In all cases, however, our model performs better than the neoclassical alternative.

where $\left(\overline{H}/\overline{L}\right)_{LDC}$ is the average skill endowment of the 79 poorest countries in the sample. The results are reported in columns 4-6 of Table 5. With skills measured by secondary school attainment and $Z = 1.5$, for instance, we obtain that the average output per worker in the LDCs would be 46 percent of the U.S. level instead of 28 percent predicted by our model when the North is taken to be the United States. Furthermore, $\Re^2 = 0.57$, instead of $\Re^2 = 0.93$ as was the case when technical change is directed to the United States. Directed technical change is also very important when we use the higher education attainment measure, though substantially less so when skills are measured by primary education attainment.[23] Interestingly, not only does the model with technical change directed towards the LDCs performs worse than our benchmark, but it performs typically worse than the neoclassical model (see columns 1-3 of Table 4). These results therefore demonstrate that directed technical change, towards North's needs, is central for our results.

IV. Extensions

In this section, we briefly discuss a number of extensions to our basic framework. The working paper version of the paper, Acemoglu and Zilibotti [1999], provides a more detailed analysis of these issues.

First, it is straightforward to generalize the model to include international trade. The main result of this exercise is that international trade leads to *productivity convergence,* but causes *divergence in output per worker.*

To see this, briefly consider a world where all commodities $i \in [0,1]$ are traded internationally, and assume $\delta^s = 1$ for simplicity. Because patents are not enforced internationally, the balanced growth equilibrium condition, (15), is unchanged; Northern R&D firms continue to consider H^n and L^n as their markets. Thus, (world) prices, P_H^T and P_L^T, have to adjust to satisfy (15). This implies that in the BGP, world relative prices will only depend on the factor endowment of the North: $P_H^T/P_L^T = (ZH^n/L^n)^{-\beta}$. Next, notice that with international trade, commodity prices are equalized in all countries. Since different commodities can be produced by skilled or unskilled workers only, factor price equalization is always guaranteed. As a result, countries will now adopt the same technology (same threshold J^T). More specifically,

$$\frac{P_H^T}{P_L^T} = \left(\frac{J^T}{1-J^T}\right)^{\beta} = \left(\frac{N_H^T}{N_L^T}\frac{ZH^w}{L^w}\right)^{-\beta/2}, \tag{23}$$

[23] This is because even in the LDC sample average primary school attainment is quite high, while there are a number of countries with very low attainment. If, instead of looking at technical change directed at the average LDC, we consider technical change directed at the median LDC, the results are very different from the case where innovations are directed at the rich economies.

where $L^w = L^s + L^n$ and $H^w = H^s + H^n$ are the world supplies. Combining (23) with (15), we obtain the equilibrium relative skill-bias of world technology as

$$\frac{N_H^T}{N_L^T} = \left(\frac{ZH^n}{L^n}\right)^{1/2} \left[\frac{H^n}{L^n}\left(\frac{H^w}{L^w}\right)^{-1}\right]^{1/2}. \tag{24}$$

N_H^T/N_L^T is larger than the closed economy ratio, since $(H^n/L^n) > (H^w/L^w)$. Intuitively, this is because the integrated world economy is more skill-scarce than the North alone. This result implies that *trade induces skill-biased technical change.*[24] More specifically, the direction of technical change depends on the relative market sizes, H/L, and relative prices, P_H/P_L (recall π_L and π_H above). Market sizes for technologies do not change, because inventors continue to sell their machines in the North only. But trade, at first, increases the relative price of skill intensive goods (see equation (23) at a given N_H/N_L). This makes skill-complementary innovations more profitable and accelerates the creation of skill-complementary machines. Since technologies are now more skill-biased, skilled workers have higher relative productivities and wages compared to their Southern counterparts. Trade therefore unambiguously *amplifies income differences* between the South and the North. As we saw above, trade induces new technologies to be further biased towards skilled workers. This reduces the productivity of unskilled workers both in the South and the North, and because the South is more abundant in unskilled workers, its relative income with respect to the North deteriorates after this change.

Despite causing divergence in output per worker, trade also leads to convergence in output per efficiency unit of labor and in TFP. The difference between these two sets of results is due to changes in factor prices caused by trade. In fact, not only do TFP differences decrease, but they actually *disappear*. The reason for TFP equalization is *factor price equalization*. TFP is low in the South when unskilled workers perform tasks for which they have little comparative advantage. Commodity trade, however, ensures factor price equalization and induces firms in the South to employ unskilled workers only in the tasks performed by unskilled workers in the North. Since the productivity of unskilled workers in these sectors is the same in the North and the South, and likewise for skilled workers, TFP differences disappear. Naturally, in the absence of full factor price equalization, there will continue to be TFP differences between the North and the South (see Acemoglu and Zilibotti, [1999])

Second, our assumption of no property rights in the South is clearly unrealistic. Although the intellectual property rights of Northern companies may be less vigorously protected in the South than in North, they still receive royalties and enter into joint

[24] This possibility was first raised by Wood [1994], though without providing a mechanism for it. Acemoglu [1998] and [1999] demonstrate that trade can induce skill-biased technical change in a related model.

partnerships with local firms. It is therefore instructive to investigate how our results change when property rights are enforced in the South.

A number of important conclusions follow from this analysis. The presence of property rights in the South induces the North to develop technologies that are more appropriate to the South's needs (as also pointed out by Diwan and Rodrik [1991]). There is no guarantee, however, that even with full enforcement of intellectual property rights, equilibrium technologies will be equally appropriate to the South's needs as the North's needs. This will depend on whether the South or the North is a more important market for new technologies. Although, in practice, the South is more populous, what matters is how much producers are willing to pay for new technologies, which in our model is determined by the relative price of capital, δ. For example, if δ is high in the South due to distortions, the relative price of capital goods in the South will be substantially higher than in the North and selling machines to the Northern market will be more profitable. In this case, our qualitative results continue to hold. In practice, there are also a number of other reasons for why the market for new technologies may be larger in the North, including smaller markets for new goods in the LDCs, credit market problems, or general delays in the adaptation of new technologies to the conditions in the South.

Why would Southern countries not enforce intellectual property rights? First of all, even though Southern countries benefit from more appropriate technologies, when property rights are enforced, they will also have to pay higher prices. So it is not clear whether they would benefit on the whole. More interestingly, even if the South would benefit overall from the enforcement of intellectual property rights, there is a prisoner's dilemma among Southern countries. Each country prefers others to enforce property rights to encourage Northern producers to develop technologies appropriate to the South's needs overall, but it will not have an incentive to enforce these property rights itself. This suggests that there may be a role for international organizations in coordinating the enforcement of intellectual property rights or in encouraging the production of technologies appropriate to the conditions in the South.

Finally, we have assumed throughout that all industries always use the frontier technology. Many of our examples suggest, however, that producers in the LDCs often prefer to use backward technologies when frontier technologies are not appropriate to their skill base. It is straightforward to incorporate this possibility into our set up by allowing less skill intensive local technologies to be used simultaneously. In the previous version of the paper, we showed that as long as these local technologies improve less rapidly than the frontier technology, which seems reasonable, skill-scarce countries may use local technologies at first, but eventually, all local technologies will be abandoned. During this process of switching from local to frontier technologies, there will be faster convergence between the South and the North.

V. Conclusion

Existing explanations for productivity differences across countries emphasize barriers to technology transfer (e.g., Parente and Prescott [1994]). In contrast, we have proposed a model where productivity differences between the less developed and advanced economies arise even in the absence of such barriers. The North has more skilled workers, and employs them in tasks performed by unskilled workers in the South. Furthermore, we made two crucial, but plausible, assumptions: most new technologies are developed in the North, and technical change is directed, in the sense that more profitable technologies get developed and upgraded faster. The larger supply of skills in the North implies that new technologies are relatively skill-complementary, whereas the South, which employs unskilled workers in most tasks and sectors, needs more labor-complementary technologies. This mismatch between the skills of the South and technologies imported from the North is the source of the productivity differences, and amplifies the differences in output per worker.

Our calculations indicate that this technology-skill mismatch may be an important factor in explaining the cross-country income differences. Encouraging the development of technologies more appropriate to the LDCs could therefore reduce the output gap. In fact, a number of international organizations are already active in developing technologies useful to the LDCs. An investigation of the empirical importance of this mechanism and the benefits of investing further in technologies appropriate for the LDCs, either by international organizations or by private R&D firms, may be a fruitful area for further study.

Our model also suggests that if the tendency towards more skill-bias technologies in the United States and other OECD economies, documented among others by Berman, Bound and Machin [1998], continues, income differences across countries may increase. This is because richer countries will benefit more from the more skill-biased technologies than the relatively skills-scarce LDCs. Raising the supply of skilled workers in the LDCs would be a natural remedy to counterbalance this tendency.

Finally, technologies developed in the North may be inappropriate not only to the skills, but to a range of other conditions prevailing in the South. Climate, tastes, cultures and institutions affect the relative productivities of different technologies. Whether "appropriateness" in these dimensions is equally important as the mismatch between technologies and skills is mostly an empirical question, and one which we believe deserves study.

Appendix A: Proof of Proposition 1

The Euler equation for individual utility maximization gives $\dot{C}(t)/C(t) = \sigma^{-1} \cdot (r(t) - \rho)$ where $r(t)$ is the interest rate at time t. In a BGP, consumption, output and all varieties of machines grow at the same rate, $g = \sigma^{-1} \cdot (r - \rho)$. As discussed in the text, in order for N_H and N_L to grow at the same rate, we must have that $r = \pi_H/\mu = \pi_L/\mu$. The unique BGP growth rate (17) immediately follows using the expressions for π_L and π_H in (14) .

Consider now an economy starting out of the BGP. Assume that $(N_H/N_L)_{t_0} < ZH/L$. We will prove that, in this case, over an interval of time $t \in [t_0, t_0 + s]$, $X_H(t) > 0$ and $X_L(t) = 0$, or, equivalently, $\dot{N}_H(t) > 0$ and $\dot{N}_L(t) = 0$.

First, notice that free entry implies $\mu \geq \max[V_H, V_L]$. Moreover, $\mu > V_z$ if and only if $X_z = 0$ (and, consequently, $\dot{N}_z = 0$). In order for the variety of machines to expand in both sectors, we would then need to have $\mu = V_H(t) = V_L(t)$ for an interval of time. Now rewrite (13) as

$$r(t)V_z(t) = \pi_z(t) + \dot{V}_z(t).$$

This immediately implies that $\mu = V_H(t) = V_L(t)$ is only possible if $\dot{V}_H(t) = \dot{V}_L(t) = 0$. This, in turn, would require $\pi_H(t) = \pi_L(t)$ over the same interval of time. However, $(N_H/N_L)_{t_0} < ZH/L$ immediately implies that $(P_H^n/P_L^n)_{t_0} > (ZH^n/L^n)^{-\beta}$, and, $\pi_H(t_0) > \pi_L(t_0)$. So $\mu = V_H(t) = V_L(t)$ for $t \in [t_0, t_0 + s]$ is impossible given $(N_H/N_L)_t < ZH^n/L^n$.

Therefore, as long as $(N_H/N_L)_t < ZH^n/L^n$, we have $\mu = V_H(t) = \pi_H(t)/r(t)$ and $\mu > V_L(t)$. So $\dot{N}_H(t) > 0$ and $\dot{N}_L(t) = 0$. Thus, the economy monotonically approaches the BGP, and arrives there in finite time. The argument to show that an economy starting from $(N_H/N_L)_t > ZH^n/L^n$ converges to the BGP is identical. QED

VI. Appendix B: Data

A. Nonproduction Workers, Output and Capital Stock Data

The U.N. General Industrial Statistics dataset contains information on the employment of production (operative) and nonproduction workers. We construct the nonproduction workers' employment share as the number of nonproduction workers divided by total employment.

The data on value added and investment are in local prices. Value added data are converted to 1990 U.S. dollars using the purchasing power parity (PPP) for GDP, and investment data are converted to the U.S. dollars using the PPP for investment.

We construct the capital stock data from the investment data using standard depreciation formulae. Our sample is limited to countries with information on nonproduction workers and investment, but we dropped Hungry and Poland to focus on non-communist countries (the inclusion of these two countries does not change the results), Germany and Hong Kong because of differences in industry classification, and finally Bolivia because problems with investment data.[25] This left us with a sample of 22 counties, consisting of Australia, Austria, Canada, Cyprus, Denmark, Finland, Greece, Ireland, Japan, Korea, Portugal, Spain, United Kingdom, USA, Columbia, Ecuador, India, Indonesia, Malaysia, Philippines, Turkey and Venezuela.

A potential problem with the investment data is that there are missing values, and observations start in different years for different industries and countries. We deal with this problem by interpolating the investment series for the missing years after the starting year of that industry-country pair. This gives us an investment series $\{I_{c,i,t}\}$ for each country, c, and industry, i, starting at some date $t = T_{c,i}$. From the series, we construct the capital stock for 1990 as follows.

We start with the standard capital accumulation equation

$$K_{c,i,t} = \sum_{s=-\infty}^{t} (1-d)^{t-s} I_{c,i,s}, \tag{25}$$

where d is the depreciation rate and, here, $t = 1990$ (or, if this is missing, the most recent observation available). Equation (25) can be rewritten as

$$K_{c,i,t} = \frac{\widehat{I}_{c,i,t}}{d}$$

where

$$\widehat{I}_{c,i,t} \equiv \frac{\sum_{s=-\infty}^{t}(1-d)^{t-s} I_{c,i,s}}{\sum_{s=-\infty}^{t}(1-d)^{t-s}} \tag{26}$$

[25] Investment output ratio is extremely high for Bolivia, so the implied capital output ratios are greater than 1,000, indicating that the data for this country are not reliable.

is a weighted average investment flow, calculated using depreciation rates as weights.

Now suppose that we do not have investment data before time $T_{c,i}$ for this particular country-industry pair. Then, we calculate a weighted average investment flow analogous to (26) as

$$\widehat{I}^T_{c,i,t} = \frac{\sum_{s=T_{c,i}}^{t} (1-d)^{t-s} I_{c,i,s}}{\sum_{s=T_{c,i}}^{t} (1-d)^{t-s}},$$

We can finally construct an estimated capital stock as K_t^e where

$$K_t^e = \frac{\widehat{I}^T_{c,i,t}}{d}.$$

We calculated our capital stock data using this procedure with a depreciation rate of $d = 0.08$. We checked the robustness of the results to other depreciation rates, including depreciation rates of 0.10, 0.05 and also no depreciation over the sample period; the results were very similar.

B. Construction of the TFP Series

Chain-weighted TFP, TFP^{CW}, is calculated as follows. Let $n \in \{1, 2, ..., 24\}$ denote country ranks in terms of industry i's capital-labor ratio. Let also $x[n_i]$ denote the value of variable x for the country ranked as n-th in industry i. We calculate the "cross-country growth rate" of value added per worker (y^l), capital per worker (k^l) and efficiency units of labor per worker (e^l) as

$$d\log(x[n_i]) = \log x[n_i] - \log x[n_i - 1]$$

for $n_i > 1$. We then calculate chain weighted labor share as

$$\tilde{s}[n_i] = \frac{\bar{s}[n_i]}{2} - \frac{\bar{s}[n_i - 1]}{2}$$

for $n_i > 1$, where $\bar{s}$ is the share of labor (in value added) calculated as total wage bill divided by value added. Then,

$$d\log(TFP[n_i]) = d\log\left(y^l[n_i]\right) - (1 - \tilde{s}[n_i]) \cdot d\log\left(k^l[n_i]\right) - \tilde{s}[n_i] \cdot d\log\left(e^l[n_i]\right).$$

We obtain TFP^{CW}_{ic} by setting the United States as the numeraire in each industry. See also Hall and Jones [1999] for the use of this methodology to calculate cross-country aggregate TFPs.

Cobb-Douglas TFP, TFP^{CW}, is calculated using a similar formula

$$d\log(TFP[n_i]) = d\log\left(y^l[n_i]\right) - (1 - s_i) \cdot d\log\left(k^l[n_i]\right) - s_i \cdot d\log\left(e^l[n_i]\right),$$

where s_i is the average share labor income across all countries in industry i.

Overall, we have data on the following sectors: furniture, clothes, rubber, wood, leather, pottery, shoes, textile, glass, iron, tobacco, metal, plastic, other mineral, paper, other manufacturing, food, fabricated metals, beverages, printing, machinery, electrical machines, scientific equipment, chemical, other chemical, miscellaneous petroleum products, and petroleum. Productivity in the petroleum industry is unlikely to be related to the factors discussed in this paper. When included, this industry is a massive outlier, but actually strengthens our results. To err on the conservative side, we dropped this industry from the analysis.

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Table 1: Descriptive statistics

	low skill		medium skill		high skill	
	rich	poor	rich	poor	rich	poor
value added	36,951	4,563	66,272	6,722	78,374	9,530
per worker	(15,152)	(4,813)	(36,778)	(7,489)	(33,984)	(10,376)
capital	25,027	14,227	56,687	24,561	55,814	27,694
per worker	(17,450)	(13,012)	(54,901)	(31,814)	(39,599)	(23,439)
nonprod	0.26	0.14	0.33	0.21	0.41	0 .29
per worker	(0.18)	(0.04)	(0.15)	(0.07)	(0.10)	(0.10)
TFP^{CW}	1.01	0.22	1.02	0.27	1.04	0.30
	(0.28)	(0.11)	(0.25)	(0.20)	(0.21)	(0.20)
TFP^{CD}	1.01	0.22	1.02	0.26	1.03	0.30
	(0.26)	(0.11)	(0.23)	(0.19)	(0.19)	(0.20)
TFP^{R}	1.32	0.34	1.25	0.49	1.21	0.64
	(0.75)	(0.24)	(0.37)	(0.35)	(0.41)	(0.52)

Notes: Low-skill industries are furniture, clothes, rubber, wood, leather, pottery, shoes, textile and glass. Medium-skill industries are iron, tobacco, metal, plastic, other mineral, paper, other manufacturing, food and fabricated metals. High-skill industries are beverages, printing, machinery, electrical machines, scientific equipment, chemical, other chemical and miscellaneous petroleum products. The rich countries are those with GDP per capita greater than \$6,500 in 1988. These are Australia, Austria, Canada, Cyprus, Denmark, Finland, Greece, Ireland, Japan, Korea, Portugal, Spain, United Kingdom and USA. The LDCs are Columbia, Ecuador, India, Indonesia, Malaysia, Philippines, Turkey and Venezuela. nonprod is nonproduction workers divided by total employment. Value added and capital data are in 1990 U.S. dollars. The first three rows give averages weighted by employment. TFP^{CW}, TFP^{CD}, and TFP^{R} are the three alternative measures of sectoral total factor productivity (relative to the U.S.), and the averages are weighted by value added. Standard deviations are given in parentheses.

Table 2: Basic results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
pn_North	0.24	0.36	0.32	-0.03	-0.04	0.11	0.21	0.15
	(0.11)	(0.13)	(0.14)	(0.08)	(0.09)	(0.08)	(0.09)	(0.10)
interaction						0.13	0.23	0.17
						(0.06)	(0.09)	(0.08)
sample	LDCs	LDCs	LDCs	rich	rich	all	all	all
North	US	US	G3	US	G3	US	US	G3
incl. India	yes	no	yes	-	-	yes	no	yes
# obs.	213	186	213	344	344	557	530	557

Notes: The dependent variable in all regressions is log(TFP^{CW}) relative to the U.S. All regressions include fixed country effects. pn_North is the log proportion of nonproduction workers in total employment in either the U.S. or the G3, that is the U.S., the United Kingdom and Canada. In this latter case, it is the unweighted average proportion of nonproduction workers in these three countries. Whether we use the U.S. or the G3 is indicated on the fourth row. The fifth row indicates whether India, and outliers, is included in the regression or not. The interaction term included in columns 6, 7 and 8 is defined as $\log(\text{GDP90}^{avg}/\text{GDP90}^{c})*\log(\text{pn}^{i}_{-North}/\text{pn}^{avg}_{-North})$, so the main effect of pn_North is evaluated at the mean. The number of observations is less than the corresponding number of countries times 27 because data for some industries are missing. All regressions are weighted by value added and standard errors corrected for clustering of pn_North are reported in parentheses.

Table 3: Variations

Dep. var.→	TFP^{CW}	TFP^{CD}	TFP^{R}	weight by	North	incl. India
Indep. var.↓						
pn_North	0.24	0.28	0.63	val. added	US	yes
	(0.11)	(0.11)	(0.16)			
pn_North	0.36	0.38	0.75	val. added	US	no
	(0.13)	(0.13)	(0.21)			
pn_North	0.32	0.36	0.54	val. added	G3	yes
	(0.14)	(0.14)	(0.23)			
pn_North	0.23	0.26	0.60	val. added	US	yes
	(0.12)	(0.12)	(0.17)	rel to co avg		
pn_North	0.27	0.30	0.65	val. added	US	no
	(0.12)	(0.13)	(0.19)	rel to co avg		
pn_North	0.30	0.34	0.52	val. added	G3	yes
	(0.14)	(0.14)	(0.24)	rel to co avg		
pn_North	0.07	0.11	0.34	empl.	US	yes
	(0.10)	(0.10)	(0.16)			
pn_North	0.29	0.31	0.53	empl.	US	no
	(0.12)	(0.12)	(0.26)			
pn_North	0.13	0.19	0.18	empl.	G3	yes
	(0.13)	(0.13)	(0.24)			
rank_North	0.12	0.13	0.26	val. added	US	yes
	(0.04)	(0.04)	(0.09)			
rank_North	0.18	0.19	0.33	val. added	US	no
	(0.05)	(0.05)	(0.11)			
rank	0.15	0.17	0.24	val. added	G3	yes
	(0.05)	(0.05)	(0.11)			

Notes: Dependent variable is log of TFP relative to the U.S. calculated in various ways (TFP_{ic}^{CW}, TFP_{ic}^{CD} and TFP_{ic}^{R}). The regressors are pn_North, log proportion of non-production workers in the U.S. or the G3 (the U.S., the United Kingdom and Canada), or rank, (log) rank of the industries according to pn_North. All regressions include country effects, and standard errors corrected for clustering are in parenthes.

Table 4: The neoclassical model vs. directed technical change

		Neoclassical model			Our model(North=US)		
H/L	Z	$\hat{y}_{NC}^{LDC}$	$\hat{y}_{NC}^{5th-}$	$\Re_{NC}^2$	$\hat{y}_{AZ}^{LDC}$	$\hat{y}_{AZ}^{5th-}$	$\Re_{AZ}^2$
Primary	1.5	0.46	0.19	0.44	0.40	0.10	0.57
Sec. att.	1.5	0.41	0.16	0.76	0.27	0.05	0.93
Sec. compl.	1.5	0.41	0.17	0.74	0.30	0.08	0.92
Higher	1.5	0.45	0.19	0.67	0.38	0.14	0.80
Primary	1.8	0.48	0.18	0.48	0.42	0.10	0.58
Sec. att.	1.8	0.38	0.15	0.82	0.25	0.05	0.94
Sec. compl.	1.8	0.39	0.15	0.81	0.28	0.07	0.93
Higher	1.8	0.43	0.18	0.72	0.36	0.13	0.84

Notes: $\hat{y}^{LDC}$ is the predicted (unweighted) average GDP per worker in 1988 in LDCs. LDCs are all countries with a Summers-Heston GDP per worker in 1988 below \$20,000. $\hat{y}^{5th-}$ is the predicted GDP per worker of the 5th poorest country in the sample. In the data, $y^{LDC} = 0.19$ and $y^{5th-} = 0.03$. H/L is the relevant ratio of skilled to unskilled workers, and Z is the skill-premium.

Table 5. Importance of directed technical change

		TC directed to avg. "DC"			TC directed to avg. "LDC"		
H/L	Z	$\hat{y}_{AZ}^{LDC}$	$\hat{y}_{AZ}^{5th-}$	$\Re_{AZ}^{2}$	$\hat{y}_{AZ}^{LDC}$	$\hat{y}_{AZ}^{5th-}$	$\Re_{AZ}^{2}$
Primary	1.5	0.43	0.10	0.58	0.45	0.11	0.54
Sec. att.	1.5	0.31	0.07	0.90	0.46	0.15	0.58
Sec. compl.	1.5	0.36	0.11	0.85	0.49	0.18	0.50
Higher	1.5	0.43	0.16	0.72	0.49	0.20	0.52
Primary	1.8	0.43	0.10	0.58	0.44	0.10	0.55
Sec. att.	1.8	0.29	0.06	0.92	0.42	0.13	0.69
Sec. compl.	1.8	0.33	0.10	0.89	0.46	0.16	0.62
Higher	1.8	0.41	0.15	0.77	0.48	0.19	0.58

Notes: Calculations are as in columns 4-6 of Table 4, but with different N_H/N_L's. In columns 1-3, we use $N_H/N_L = Z\bar{H}/\bar{L}$, where $\bar{H}/\bar{L} = (\Sigma_{c=1}^{24} K^c/\bar{K}^{rich}) * (H^c/L^c)$ is the weighted average skill endowment (weighted by total capital) of the 24 richest countries (GDP per worker in 1988 higher than $20,000). These are the U.S., Canada, Switzerland, Australia, Kuwait, Belgium, Italy, Netherlands, Norway, West Germany, France, Sweden, United Kingdom, Finland, New Zealand, Iceland, Austria , Denmark, Spain, Israel, Hong Kong, Singapore, Trinidad, Japan and Ireland. In columns 4-6, we use $N_H/N_L = Z\bar{H}/\bar{L}$, where $\bar{H}/\bar{L} = (\Sigma_{c=1}^{24} K^c/\bar{K}^{rich}) * (H^c/L^c)$ is the weighted average skill endowment (weighted by total capital) of the 79 poorest countries (GDP per worker in 1988 smaller than $20,000).

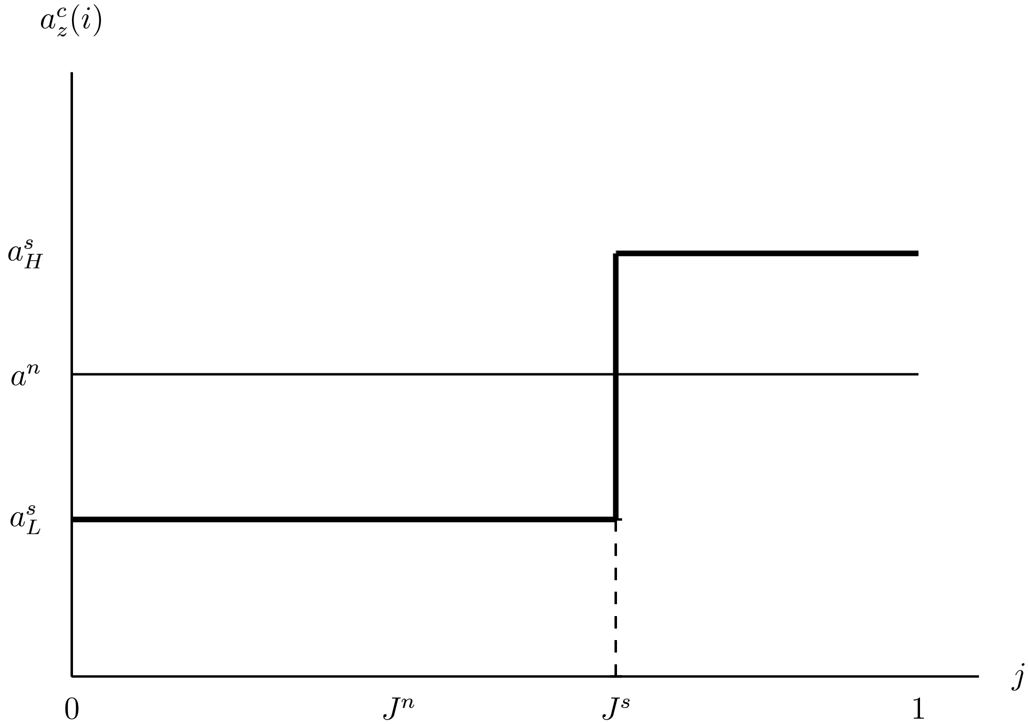


Figure 1: Sectoral TFP Patterns in the North (a^n) and the South (a_L^s, a_H^s).

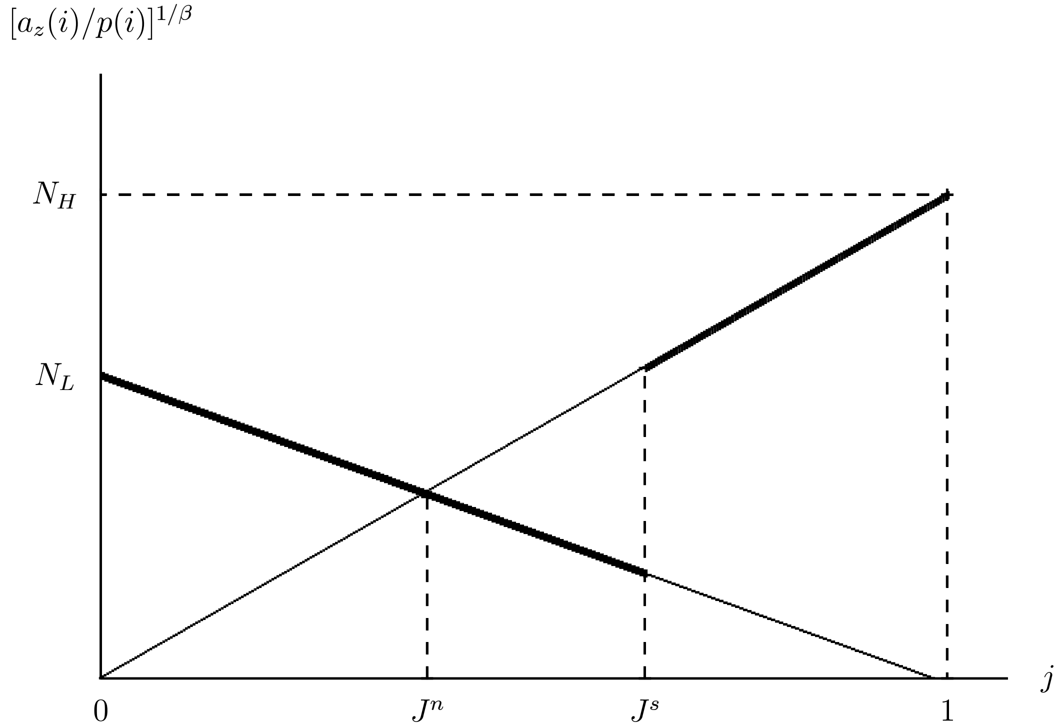
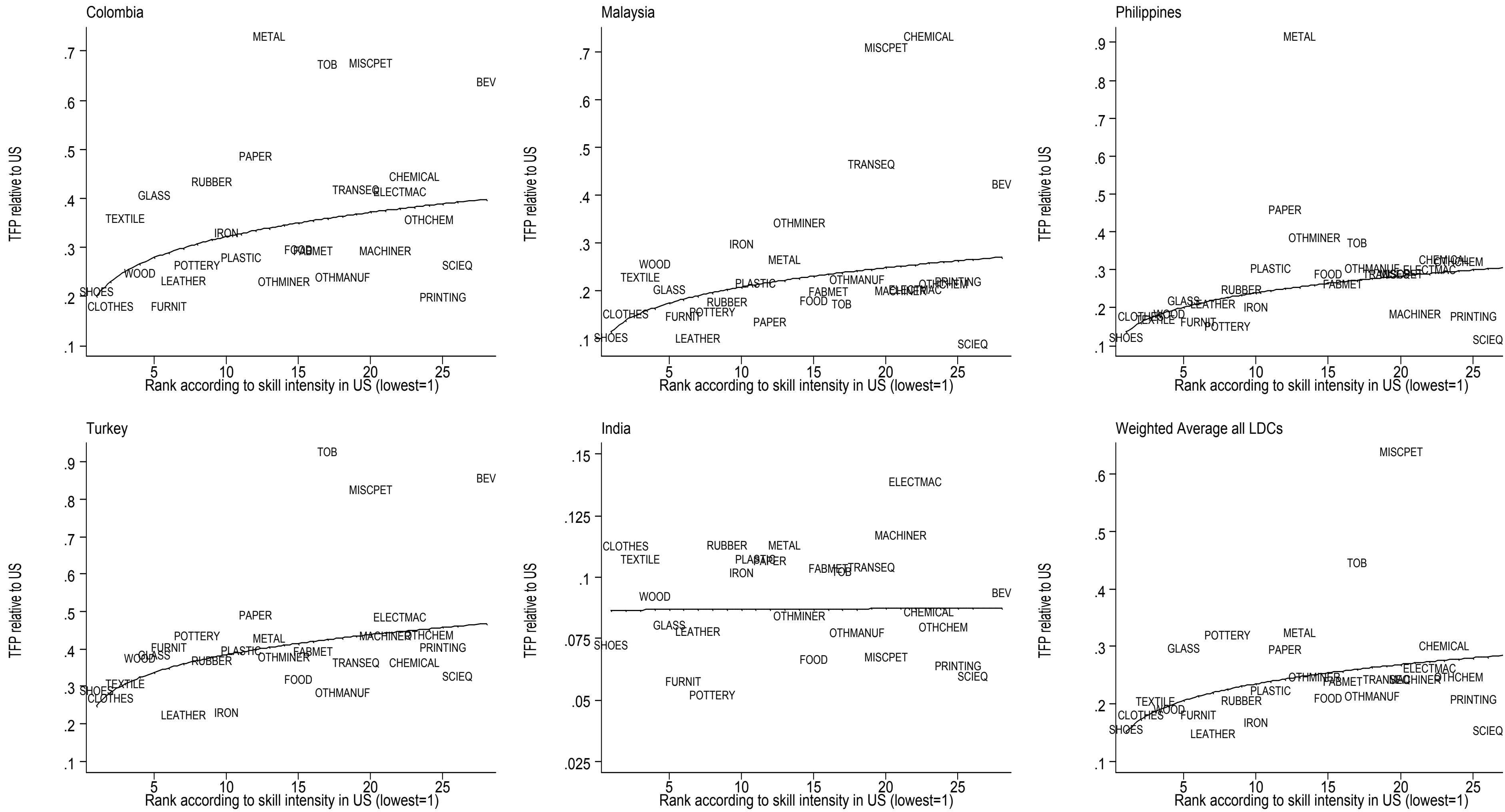


Figure 2: Patterns of Physical Productivity

Figure 3. TFP gap across 27 industries in selected LDCs



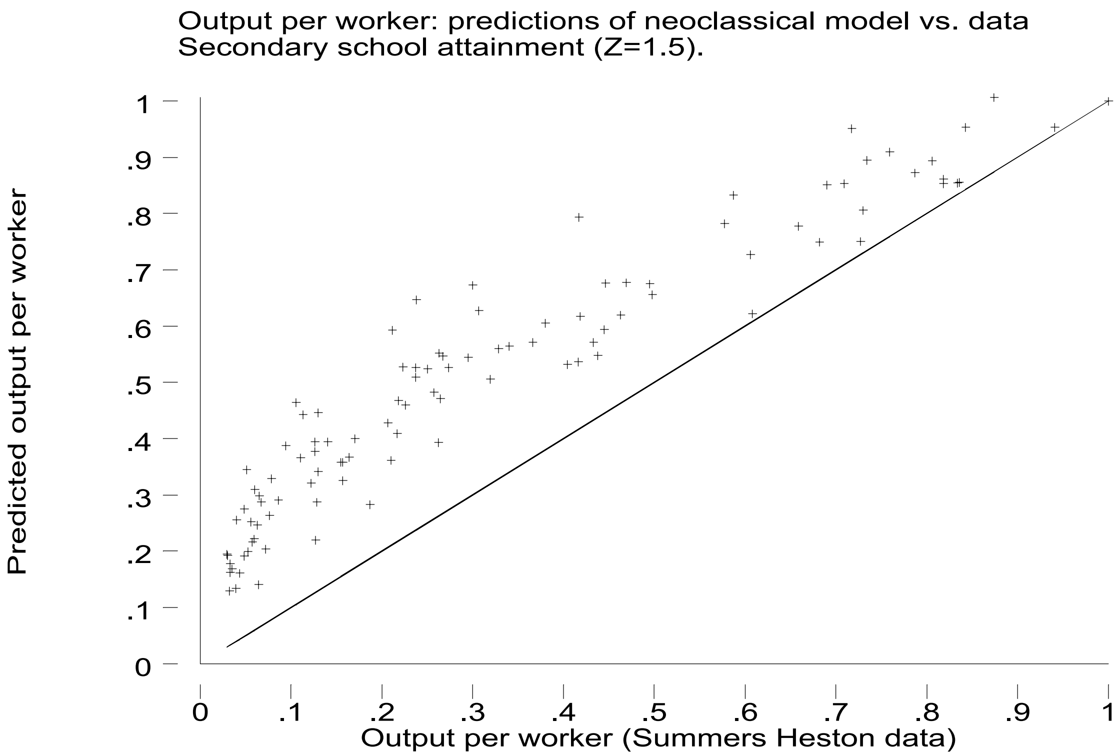


Figure 4: Output per worker: y^c_{NC} vs. y^c.

Figure 5: Output per worker: y^c_{AZ} vs. y^c.