Knowledge Spillovers and Productivity Differences

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Abstract

A large part of cross-country variation in per capita income is left unexplained by differences in physical and human capital, so that the hypothesis of a common world technology should be rejected and a theory of productivity differences is needed. We study two possible structures of cross-country knowledge spillovers that have the potential to account for observed productivity differences: appropriate technology knowledge spillovers and backward knowledge spillovers, in which countries face a barrier in extracting technical knowledge due to their factor intensity relative to the technological leader. We find that both spillovers structures can explain over an half of observed cross-country productivity differences, but the backward spillovers one is more consistent with the observed world income distribution.

1 Introduction

Observed per capita income differences across countries are enormous: in 1996 average per capita income of the richest country in the world (USA) was about 50 times that of the poorest country (Ethiopia), while observed income dispersion across the 90-10 percentiles was given by a factor of 17. A successful theory of growth and development should at least be able to account for cross-country income differences, i.e. to explain the actual shape of the world income distribution (WID): the conclusion of a decade of theoretical and empirical research is that, either through development accounting or using calibration techniques, the standard neoclassical framework is unable to explain observed income differences. In the development accounting approach, summarized in Caselli(2005), one introduce a particular functional form for the production function and uses cross-country data on per capita income and on factors of production to assess the relative contribution of observables input and unobservable efficiency backed out as a residual: the general consensus is that observed differences in physical and human capital stocks are not big enough to match observed differences in income, and differences in efficiency account for about an half of income dispersion. Rich countries seem to be rich not only because of bigger stocks of physical and human capital, but largely because of a more efficient use of these stocks: the hypothesis of a common world technology should be rejected while theory is left to explain the existence and patterns of technology differences. Calibration exercises like those performed by Prescott (1998) reach the same conclusion: using plausible parametrizations of a neoclassical growth model, one with a common world technology and constant returns to scale in accumulable factors, differences in saving rates for physical and human capital accumulation needed to generate observed cross-country income dispersion are way too high to be consistent with observed differences in investment rates. As Prescott concludes, a theory of total factor productivity differences is needed.

First generation endogenous growth model à la Romer (1990) or Aghion and Howitt (1992) based on an explicit modeling of an R&D sector do provide a theory of TFP differences, but they predict that any parameter change that influences the steady-state value of the R&D volume directly translates in a variation of the long run growth rate. On the other hand a number of empirical studies, such as Evans (1996), suggest that for many countries growth rate differences show very little persistence over time despite the existence of large cross-country variation in rates of investment in physical and human capital, and Klenow and Rodriguez (2004) interpret this as an evidence of "very large international spillovers at the heart of the long run growth process", driving the world economy toward a common long-run growth rate and an equilibrium WID with long-run differences in income levels. Howitt (2000) builds a Schumpeterian model of the world economy in which all R&D performing countries converge to the same long-run growth rate but differences in per capita income and aggregate productivity survive because of different long-run investment rates: the stability of the long-run WID is obtained through a technology diffusion process, showing that knowledge spillovers are essential in reconciling Schumpeterian growth theory with the empirical evidence.

In Gerosa (2007) we develop a general equilibrium analysis of a world economy characterized by the existence of cross-country knowledge spillovers: the model predicts the existence of a long run WID, an equilibrium in which every country grows at the same rate but differences in efficiency, factor intensity and per capita income survive because of the existence of knowledge spillovers. Here we perform, using cross-country data, a first empirical evaluation of that theoretical framework aimed at testing the consistency of two knowledge spillovers structures. In particular we test a specification of the traditional technology index, that generalizes that of Eeckhout and Jovanovic (2002) aimed at explaining the distribution of firm size, that allows for two possible structure of knowledge diffusion consistent with empirical evidence on TFP levels: appropriate knowledge spillovers and backward spillovers.

The main insight of the appropriate technology literature, originated with the seminal paper by Atkinson and Stiglitz (1969), is that a neoclassical production function, which maps factor intensity into output levels, is just the continuous limit of an increasing number of production processes, each one expressed by a unique capital-labor ratio; as Atkinson and Stiglitz point out:

> "different points on the curve still represent different processes of production, and associated with each of these processes there will be certain technical knowledge specific to that technique [...] if one brings about a technological improvement in one of this blue-prints this may have little or no effect on the other blueprints"

so that it is realistic to assume a relative independence of each technique: technological change should be modeled not as a general shift of the production function, but as a localized shift which affects only a neighborhood of the improved technology and consequently only a part of the production function, and knowledge spillovers between interacting economies are likely to be local rather than global. This argument can be applied by assuming that a country whose technological state is measured, as in Basu and Weil (1998), by the factor intensity k, which must be interpreted as an aggregate of human and physical capital, can only have access to the knowledge of countries that are in a neighborhood of k, simply because this is the only useful knowledge with respect to its technology level: in this way the factor accumulation process and the dynamics of productivity are linked, and the growth experience of every country depends on the entire cross-section distribution of factor intensity, the world factor distribution (WFD), and not on a predetermined target, such as its average as in Lucas (1988) or the maximum of the support as in Aghion-Howitt (1998).

The traditional representations of knowledge spillovers suppose that followers can freely access technical knowledge created by the technological leader and often model technology diffusion, in line with the seminal contribution by Nelson and Phelps (1966), as an increasing function of the distance from the technological frontier: but this *advantage of backwardness hypothesis*, originally formulated by Gerschenkron (1962), seems to be challenged by the persistence of cross-country productivity differences and by the fact that even growth miracles such as those of some East Asian countries (Taiwan, Hong Kong, South Korea, Singapore) or of China have been shown by Young (1995)(2003),using careful growth accounting analysis, to be cases of rapid factor accumulation rather than of exceptional productivity growth. The empirical evidence documented by Hall and Jones(1999) and more recently by Caselli (2005) shows that low-k countries display also low TFP levels.

We then examine another possible structure of technological spillovers, that reverts conventional wisdom about cross-country knowledge diffusion, analyzing the case in which spillovers are an increasing function of a country factor intensity: an economy can spill free knowledge only about technologies it has already developed, so that the more advanced a country the greater the information flow it can intercept. As Boldrin and Levine (2005) suggest, if the non rival character of ideas is a property of their immaterial nature, there exist also a cost associated with learning and implementing ideas into an actual production process: it is more likely that an advanced economy can integrate, freely or at near zero-cost, knowledge about inferior technologies into its framework rather than the contrary. Another channel through which knowledge spillovers might flow from low to high factor intensity countries is international migration: Docquier and Marfouk (2006) show that, for a given source country, emigrants are almost universally more skilled than non emigrants, while Beine, Docquier and Rapoport (2001) show that the net effect of this brain-drain phenomenon is negative for the majority of developing countries.

It is also possible to interpret this knowledge spillovers structure in a more conventional way, as representing the existence of barriers to technology adoption, as in Parente and Prescott (1994): low-k countries can search a limited portion of the distribution of existing technologies, since they lack the physical and human capital infrastructures needed to adopt them, the barrier being aggregate capital intensity *relative* to the country with the maximum observed factor endowment, the technological leader.

We formalize these two knowledge spillovers structure and we test them using cross-country data on income and factor endowments (physical and human capital) along two dimensions: their ability to explain static observed cross-country productivity differences at a point in time and their consistency with the shape of the observed world income distributions. We find that both knowledge spillovers structures are able to explain over an half of observed static productivity differences but we also show that backward spillovers are more successful in generating a theoretical WID close to the observed one.

The rest of the paper is organized as follows. Section 2 presents the dataset, the observed pattern of productivity differences and the relationship between observed WID and WFD (world factor distribution). Section 3 introduces the two knowledge spillovers structures and derives the static relationship between relative productivity and relative factor intensity at a point in time. Section 4 present the estimation results and an analysis of the relationship between observe and theoretical WID for both spillovers structures. Section 5 concludes.

2 The World Income Distribution and Productivity Differences

The more direct way to assess the relative contribution of observables input and unobservable efficiency in shaping cross-country income differences is the development accounting technique, of which Klenow and Rodriguez (1997) and Hall and Jones (1999) are early examples and Caselli (2005) is a recent summary: by choosing a functional form for the production function and measuring inputs for a cross-section of country at a point in time, it is possible to extract total factor productivity (TFP) as the residual part of income left unexplained by factors of production.

We follow Caselli (2005) and specify per-worker production as

$$y = Ak^{\alpha}h^{1-\alpha} \tag{1}$$

where k is the per worker capital stock, h is average human capital and A is efficiency or, in a wide sense, technology. With data on y, k and h, and given a value for the capital share α, efficiency or total factor productivity can be backed out and the structure of cross-country productivity differences can be analyzed.

Data are taken from a variety of sources:

- y is real GDP per worker in PPP adjusted international dollars, and it is taken from version 6.1 of the Penn World Tables (PWT 6.1 - Heston, Summers, and Aten (2002)).
- aggregate capital stock K is taken from Caselli (2005) who calculate it using the perpetual inventory equation $K_t = I_t + (1 - \eta)K_{t-1}$, where I_t is investment and η is the depreciation rate of physical capital. I_t is measured from PWT 6.1 as real aggregate investment in PPP and η is set equal to 0.06. K is then divided by the number of workers, taken again from PWT 6.1, to finally obtain per worker capital stock k.
- h is average per worker human capital and is constructed as in Hall and Jones (1999). Since with competitive markets for factors (1) implies that the wage ω of a worker is such that $\ln \omega \propto \ln h$ and since the wage-schooling relationship is widely thought to be log-linear, then it is natural to specify $h = \exp\{\phi(s)\}$ where $\phi^{'}(s)$ is the return to schooling estimated in a Mincerian regression of $\ln \omega$ on years of schooling s. Finally, since international data on education-wage profile documented in Psacharopulos (1994) show a cross-country convexity across countries, with the return to an extra-year of schooling being higher in low-average schooling countries, $\phi(s)$ is specified as piecewise linear in s with slope 0.13 for $s \leq 4$, 0.10 for $4 < s \leq 8$, and 0.07 for $8 < s$, consistently with Psacharopulos estimates for sub-saharan Africa, the world average and OECD countries. Data on average years of schooling for each country are taken from the Barro and Lee (2001) dataset.
- the capital share of GDP α is set equal to 0.3, roughly consistent with cross-country evidence documented in Gollin (2002): the mean labor share for a sample of 31 countries oscillates between 0.65 and 0.75, depending on the type of correction for the inclusion of the income of self-employed into the labor share of GDP.

There are 82 countries in our sample for which all relevant data are available for the year 1996. Table 1 list all the countries in the sample and presents across countries differences in income, factor intensity and productivity (TFP) resulting from a decomposition of (1) as in Hall and Jones (1999). We normalize everything with respect to the values of the country which displays the maximum observed $k^{\alpha}h^{1-\alpha}$ (Norway): in Gerosa (2007) and in the following we interpret factor intensity as an index of the technological state of an economy and propose a specification for the efficiency index which depends on a country factor intensity *relative* to the technological leader, so that it is useful to observe the pattern of cross-country income and TFP from the point of view of relative factor intensity $z = k^{\alpha}h^{1-\alpha}/K_t$, where $K_t = \max\left\{\text{observed } k^{\alpha}h^{1-\alpha} \text{ in } t = 1996\right\}$.

Denoting, as in Caselli(2005), with $y_{kh} \equiv k^{\alpha}h^{1-\alpha}$ the component of income explained by observables (physical-human capital), one can evaluate the ability of the neoclassical-common world technology approach in explaining observed income differences. Backing-out A for each country using y_{kh} it is possible to pursue a variance decomposition approach since

$$Var\left[\ln\left(y\right)\right] = Var\left[\ln\left(y_{kh}\right)\right] + Var\left[\ln\left(A\right)\right] + 2Cov\left[\ln\left(A\right), \ln\left(y_{kh}\right)\right] \quad (2)$$

and if technology does not differ across countries, then $Var\left[\ln\left(A\right)\right] = Cov\left[\ln\left(A\right), \ln\left(y_{kh}\right)\right] = 0$ and the dispersion of incomes should be fully explained by the dispersion of factors endowments.

One can judge the explanatory power of the neoclassical-common world technology approach by evaluating the ratio $Var\left[\ln\left(y_{kh}\right)\right]/Var\left[\ln(y)\right]$, the fraction of observed income dispersion explained by differences in observable factor stocks. In our sample $Var\left[\ln\left(y_{kh}\right)\right]/Var\left[\ln(y)\right] = 0.36$, meaning that less than 40% of observed static dispersion in per worker income is explained by factor endowments: cross-country productivity differences are large and they systematically amplify income differences produced by factor differences. Indeed the correlation between the observed TFP residual and y_{kh} is very high ($Corr\left[\ln\left(A\right), \ln\left(y_{kh}\right)\right] = 0.7852$), meaning that high-$y_{kh}$ countries display at the same time higher levels of technological efficiency.

This simple approach relates a moment, the variance, of two observed distribution, the world income distribution and the world factor distribution, but it is consistent with various possible shapes and local properties of both the WFD and the WID. As Quah (2007) convincingly argues, focusing on single moments of observed distributions of income, factor intensity or efficiency, or on conditional moment as in panel or cross-section regressions, might miss important static or dynamic features of those distribution. Collapsing in a single measure an entire distribution may be useful and in some cases appropriate, but it is uninformative of what is taking place in different subsets of the distribution support and may eventually conceal the existence of theoretically significant properties as multimodality or different degrees of polarization.

As an example, Caselli (2005) shows that the ratio $Var\left[\ln\left(y_{kh}\right)\right]/Var\left[\ln(y)\right]$, which measures the success of growth models that rely exclusively on factor accumulation, does vary significantly across different subsets of the distribution: factor accumulation seems to play a major role in OECD countries where $Var\left[\ln\left(y_{kh}\right)\right]/Var\left[\ln(y)\right] \simeq 0.6$, while in non-OECD countries $Var\left[\ln\left(y_{kh}\right)\right]/Var\left[\ln(y)\right] \simeq 0.3$ and in general the ratio is higher for above the median income countries than for below the median income ones.

A simple and intuitive way to consider the global relationship between income and factor accumulation consists in comparing directly the two observed distribution, appropriately normalized.

We define

$$y_r = \frac{y}{y_{\max}} \tag{3}$$

and

$$z = \frac{y_{kh}}{y_{kh}^{\max}} \tag{4}$$

as respectively per capita income and relative factor intensity relative to the observed maximum, so that both variables take values in $[0, 1]$.

We then estimate the observed densities $h_y(y_r)$ and $h(z)$ using a gaussian kernel and an "optimal" bandwidth following Silverman (1986) rule of thumb incorporated in Stata 8.2: Figure 1 shows the relationship between the observed WFD and WID[1]. Several features of this figure deserve comments. First, the 1996 WID displays the "twin peaks" property originally described by Quah (1993): an emergent bimodality that points to the possibility of the clustering of the world economy into a group of low-income and a group of high-income countries. Second, in this static representation of cross-country income differences, this bimodality seems to be driven by factor endowments since the observed WFD, the normalized distribution of y_{kh} across countries, shows the same twin peaks property of the WID: the low-z peak, around which is concentrated a large density mass of the world economy, corresponds to the low-income cluster, while the high-z peak corresponds to the (smaller) high-income cluster. Third, technological efficiency acts in a systematic way over the WFD to transform it into the WID: cross-country productivity differences give rise to the WID by stretching the WFD to the left, widening its support and shifting density mass back along it. This is just another representation of the failure of the common world technology assumption: if the world economy was characterized by a common technology, then the WID would simply mirror the WFD or, with z-independent technology shocks, would not systematically act on the WFD to deform it into the WID.

3 The Structure of Knowledge Spillovers and Productivity Differences

Taken together, these observations suggest a representation of the technology index A as a function $A(z)$ of relative total factor intensity, with the property

[1] The unit of observation is the single country: we don't weight each data point by its population size and we neglect within country inequality. We see this as a natural choice if one thinks of the world economy as composed of different realizations of a model economy: population weighting assigns a disproportionate role to a few large economies in shaping the distribution of all relevant quantities.

that $A^{'}(z) > 0$. Interpreting factor intensity as a measure of a country technological state (the higher total factor intensity the more advanced the technology operated) a natural possibility is a representation in terms of cross-country knowledge spillovers, linking both statically and dynamically factor accumulation and productivity, in which $A = A(z, h(z))$ and the entire cross-section

distribution of factor intensity is an argument of the technology index.

Suppose, as in a continuous-time version of Gerosa (2007), that the world economy is composed by a unit mass of countries and that income per worker of a country with y_{kh}units of aggregate capital, where $y_{kh} \equiv k^{\alpha}h^{1-\alpha}$ as in (1), is given by

$$y(z,t) = A(z,t)y_{kh} \tag{5}$$

and total factor productivity is given by

$$A(z,t) = S(z,t)^{\beta}G(t)^{1-\beta} \equiv \left[1 + \int_{D} \alpha(z)h(z,t)dz\right]^{\beta} G(t)^{1-\beta} \tag{6}$$

where $G(t)$ is an efficiency index which grows at the constant and exogenous rate g shared by each country, $z = \frac{y_{kh}}{y_{kh}^{\max}}$is the country factor intensity relative to the supremum $y_{kh}^{\max}$ of the distribution of y_{kh} among countries, $H(z,t)$ is the distribution function of z defined over $[z_{\min}, 1]$, $h(z,t) = H^{'}(z,t)$ is the density of z, β is a parameter which measures the intensity of the spillover force, $\alpha(z)$ is a positive bounded function that expresses the direction of copying (if $\alpha^{'} > 0$ copying is directed toward the high-k countries, if $\alpha^{'} < 0$ it is directed toward the low k ones, if $\alpha(z) = \alpha$ copying is undirected) and D is the domain over which spillovers act.

Equation (6) specifies a country technology level as a Cobb-Douglas aggregate of two technical knowledge components: a common general part $G(t)$ which is not country-specific and that can be thought as general knowledge, and a knowledge spillovers component $S(z,t)$ that comes from cross-country interactions. The knowledge spillovers part of (6) is totally deterministic, but it can be interpreted as an expectation of the amount of knowledge a firm can copy drawing from the subset $D \subseteq [z_{\min}, 1]$ of the support of $h(z,t)$: , interpreting $h(z,t)$ as a probability density, the integral in $S(z,t)$ represent the mean of the copying function $\alpha(z)$ conditional on the fact that $z \in D$. Note that the knowledge spillovers component of technology is bounded from below by 1.

The crucial step is the choice of the subset D over which spillovers flow:

- if $D = [z_{\min}, 1]$ then A depends on the average level of the copying function $\alpha(z)$ over the entire relative cross-country factor distribution, as in the single country model of Lucas (1988), in which there is an externality based on the economy-wide average level of human capital, and in Romer

(1986) . With those kind of *general or non-localized knowledge spillovers* $\partial A/\partial z = 0$, there is no correlation between relative factor intensity and productivity and there is a common world technology shared by each country. Productivity can grow over time through cross-country interactions if $h(z,t)$ changes so that the mean value of $\alpha(z)$ increases (e.g. with undirected copying $\alpha(z) = \alpha$ and productivity grows if average relative factor intensity grows), but at a point in time this specification cannot explain systematic productivity differences.

- if $D = [z, 1]$, as in Eeckhout and Jovanovic (2002), then each country is supposed to freely extract useful technical knowledge from all countries that operate superior technologies. In this case the spillover force is negatively related to factor intensity: low z-countries have access to the knowledge of a large part of the cross-country distribution of techniques, while high z-countries can't copy much and have to rely more on investment. With this kind of *forward knowledge spillovers* $\partial A/\partial z < 0$ and relative factor intensity and TFP are negatively related: low-z country should display higher levels of efficiency. This is why the Eeckhout-Jovanovic model cannot explain neither the positive correlation between income levels, levels of physical and human capital and TFP, nor the observed relationship between the WFD and the WID.

- if $D = [\underline{\delta}z, \overline{\delta}z]$, where $\overline{\delta} = (1+\delta)$ and $\underline{\delta} = (1-\delta)$, then A is characterized by *appropriate technology knowledge spillovers*: a country with relative factor intensity z extracts useful knowledge only from countries that are technologically near, where the amplitude of the technological neighbourhood over which spillovers flow is proportional to z and is controlled by the parameter δ (Figure 2). Note that since $h(s,t) = 0$ outside of $[z_m, 1]$, very low-z and very high-z countries don't have a complete technological neighbourhood and the intervals over which the integral is computed are $[z_m, \overline{\delta}z]$ for $z \in \left[z_{\min}, \frac{z_{\min}}{\underline{\delta}}\right]$ and $[\underline{\delta}z, 1]$ for $z \in \left[\frac{1}{\overline{\delta}}, 1\right]$. We argue in Gerosa (2007) that the fact that technological neighbourhoods are increasing in z, meaning that high-z countries spill knowledge from a larger portion of $h(z,t)$, seems empirically plausible: advanced economies operate a larger set of technologies and can integrate in their framework also inferior technologies and related knowledge. In this case the sign of $\partial A/\partial z$ depends both on the shape of $h(z,t)$ and on the value δ: it follows that such a representation has the potential to account for static observed productivity differences.

- if $D = [z_m, z]$ then each country is supposed to extract free knowledge only from countries operating technologies it has already developed and we have *backward or technology improving knowledge spillovers.* This specification emphasizes the existence of *barriers to technology adoption* based on factor intensity: a country with low physical-human capital can't have access at zero cost to a large set of existing technologies, simply since it lacks the infrastructures and skills needed to implement them. In this case $\partial A/\partial z > 0$ so that also this representation of knowledge spillovers can account for static productivity differences.

We test both the appropriate technology and the technology improving knowledge spillovers structures, along two dimensions: their ability to account for observed static dispersion of productivity and their ability to reproduce the observed WID. We restrict the analysis to the case, extensively studied in Gerosa (2007), of undirected copying with $\alpha(z) = \alpha$: this assumption removes one degree of freedom and assigns exclusively to the WFD and to the free parameter β controlling the strength of spillovers the task of explaining observed productivity differences.

With appropriate technology spillovers, TFP at time t of a country i with relative factor intensity z is given by

$$A_i(z,t,\delta) = S(z,t,\delta)^{\beta} G_i(t)^{1-\beta} \equiv \left[\alpha \int_{\underline{\delta}z}^{\overline{\delta}z} h(s,t)ds\right]^{\beta} T(0)e^{\gamma t+\xi_i} \tag{7}$$

where $T(0) = G(0)^{1-\beta}$ with $G(0)$ the initial level of the common part of technology , $\gamma = (1-\beta)\,g$ being the common TFP growth factor and ξ_i a country specific technology shock reflecting differences in initial conditions due to other factors (e.g. geography or institutions). We also changed slightly the definition of TFP by removing the additive constant 1 from $S(z,t)$,so that we let the lower bound of accessed knowledge being freely determined.

Normalizing with respect to the technological leader, the country $i = L$ with $z = 1$, one obtains the relative TFP:

$$a_i(z,t) \equiv \frac{A_i(z,t,\delta)}{A_L(1,t,\delta)} = \left[\frac{\int_{\underline{\delta}z}^{\overline{\delta}z} h(s,t)ds}{\int_{\underline{\delta}}^{1} h(s,t)ds}\right]^{\beta} e^{\xi_i-\xi_L} \tag{8}$$

and passing to logs

$$\ln a_i(z,t) = C + \beta \ln D_{\delta}(z) + \nu \tag{9}$$

where $C = -\beta \ln \left[\int_{\underline{\delta}}^{1} h(s,t)ds\right]$, $D_{\delta}(z) = \left[\int_{\underline{\delta}z}^{\overline{\delta}z} h(s,t)ds\right]$ and $\nu = \xi_i - \xi_L$.

Then, for each choice of the amplitude δ of the neighbourhood over which spillovers flow, one can obtain an estimate of β by regressing observed relative TFP levels, extracted as residuals from (1), on the observed quantity $D_\delta(z) = H(\overline{\delta}z) - H(\underline{\delta}z)$, which is simply the density mass included in each technological neighbourhood given by the observed cumulative distribution of relative factor intensity $H(z)$. It is then possible to evaluate the ability of appropriate technology spillovers in explaining productivity differences by looking at, for each choice of δ, the explanatory power of the regression, that measures the fraction of observed dispersion in $a(z,t)$ accounted by a country position along the WFD, and by the implied predicted shape of the WID.

For each choice of δ we estimate the associated $\widehat{\beta}$ and we calculate the theoretical or counterfactual income level relative to the technological leader for each country as

$$y^{th}_{R,\delta} = \frac{y^{th}_i(z,t,\delta)}{y^{th}_L(1,t,\delta)} = \left[\frac{\int_{\underline{\delta}z}^{\overline{\delta}z} h(s,t)ds}{\int_{\underline{\delta}}^{1} h(s,t)ds}\right]^{\widehat{\beta}} z \tag{10}$$

and normalizing with respect to the maximum of $y^{th}_{R,\delta}$ (that may not coincide with $y^{th}_L(1,t,\delta)$), we obtain for each choice of the free parameter δ the theoretical world distribution of relative income levels $h^{th}_y(y^{th}_{r,\delta})$ that can be compared to the observed one $h_y(y_r)$.Theoretical or counterfactual relative income is the relative income generated by knowledge spillovers *in the absence of shocks*, that in our interpretation represent differences in initial levels of technological efficiency: that is, theoretical relative income is the level of income predicted by observed factor differences and cross-country knowledge diffusion as described by our specification of knowledge spillovers.

With backward spillovers, or with barriers to technology adoption measured by factor intensity according to the preferred interpretation, TFP of a country i with relative factor intensity z is given by

$$A_i(z,t) = S(z,t)^\beta G_i(t)^{1-\beta} \equiv \left[1 + \alpha \int_{z_m}^{z} h(s,t)ds\right]^\beta T(0)e^{\gamma t + \eta_i} \tag{11}$$

and TFP relative to the technological leader is

$$a_i(z,t) \equiv \frac{A_i(z,t)}{A_L(1,t)} = \left[\frac{1 + \alpha \int_{z_m}^{z} h(s,t)ds}{1+\alpha}\right]^\beta e^{\xi_i - \xi_L} \tag{12}$$

since $\int\limits_{z_m}^{1} h(s,t)ds = 1$.

Supposing that $\alpha \gg 1$ and passing to logs, it is possible to approximate (12) by

$$\ln a_i(z,t) \simeq \beta \ln H(z) + \epsilon \tag{13}$$

where $H(z) = \int\limits_{z_m}^{z} h(s,t)ds$ is simply the observed density mass of the world economy that lies behind country i along the technology ladder represented by the WFD, while $\epsilon = \xi_i - \xi_L$ is an error term.

It is possible to check the consistency of the assumption $\alpha \gg 1$, needed to identify β separately from α while keeping a specification of $A(z,t)$ in which the lower bound of $S(z,t)$ is non-zero, noting that the theoretical productivity relative to the technological leader of the less advanced country l with $z = z_m$ is

$$a(z_m,t) = \frac{A_l(z_m,t)}{A_L(1,t)} = \left[\frac{1}{1+\alpha}\right]^{\beta} \tag{14}$$

In our sample the technological leader with $z = 1$ is Norway, while the country with the lowest total capital stock is Mozambique with $z_m = 0.091$ with an observed relative productivity $a_{obs}(z_m,t) = 0.26$. With an estimated $\widehat{\beta}$ obtained from (13), it is possible to recover the normalizing constant $\widehat{\alpha}$ by matching theoretical and observed $a(z_m,t)$, so that $\widehat{\alpha}$ should be given by $\widehat{\alpha} = \left(\frac{1}{0.26}\right)^{1/\widehat{\beta}} - 1$, so that we can check the mutual consistency of $\widehat{\beta}$ and of the assumption $\alpha \gg 1$.

With the estimates $\widehat{\alpha}$ and $\widehat{\beta}$ we then calculate the theoretical or counterfactual income level relative to the technological leader for each country as

$$y_r^{th} = \frac{y_i^{th}(z,t)}{y_L^{th}(1,t)} = \left[\frac{1+\widehat{\alpha}\int\limits_{z_m}^{z} h(s,t)ds}{1+\widehat{\alpha}}\right]^{\widehat{\beta}} z \tag{15}$$

which in this case simply coincide with income relative to the theoretical maximum. We can finally compare the theoretical distribution of relative income with backward spillovers $h_y^{th}(y_r^{th})$ with the observed one $h_y(y_r)$.

It should be noted that our specification of knowledge spillovers can be also tested with panel data about cross-country TFP growth rate differences over time. Time-differentiating (7) we obtain the TFP growth rate at time t of a country i withe relative factor intensity z with appropriate technology spillovers

$$\frac{\overset{\bullet}{A}(z,t,\delta)}{A(z,t,\delta)} = (1-\beta)\,g + \beta\frac{\int_{\underline{\delta}z}^{\overline{\delta}z} \overset{\bullet}{h}(s,t)ds}{\int_{\underline{\delta}z}^{\overline{\delta}z} h(s,t)ds} + \beta\left[\frac{\overline{\delta}h(\overline{\delta}z(t),t)}{\int_{\underline{\delta}z}^{\overline{\delta}z} h(s,t)ds} - \frac{\underline{\delta}h(\underline{\delta}z(t),t)}{\int_{\underline{\delta}z}^{\overline{\delta}z} h(s,t)ds}\right]\overset{\bullet}{z} \quad (16)$$

where the first term captures the common growth rate of TFP due to increase in general knowledge, the second term the effect on knowledge spillovers due to the evolution of the WFD, the third term the effect on spillovers of the variation in a country relative factor intensity.

With backward spillovers one obtains

$$\frac{\overset{\bullet}{A}(z,t,\delta)}{A(z,t,\delta)} = (1-\beta)\,g + \beta\frac{\int_{z_m}^{z} \overset{\bullet}{h}(s,t)ds}{\int_{z_m}^{z} h(s,t)ds} + \beta\left[\frac{h(z,t)}{\int_{z_m}^{z} h(s,t)ds}\overset{\bullet}{z} - \frac{h(z_m,t)}{\int_{z_m}^{z} h(s,t)ds}\overset{\bullet}{z_m}\right] \quad (17)$$

that has the same interpretation.

We leave for future research the test of the ability of our specification of cross-country interactions in explaining differences over time in TFP growth rates: here we focus only on the ability of our specification of technology in replicating observed cross-country differences in TFP levels at a point in time.

4 Estimations and Results

The two equations we estimate are equation (9) and (13). Data on productivity levels A (TFP) and relative factor intensity z are obtained as described in Section 2: absolute TFP levels are normalized with respect to the country with the maximum observed value of total factor intensity (Norway), to obtain relative productivity levels $a_i(z,t)$ for all 82 countries in the sample. $H(z)$ is simply taken to be the empirical distribution function of z, calculated by Stata 8.2 using the 82 observed data points, while $D_\delta(z) = H_\delta(\overline{\delta}z) - H_\delta(\underline{\delta}z)$ is constructed as follows:

- We let δ vary in $[0,1]$ taking the possible values $\{0.1, 0.2, ..., 0.9\}$.
- For each possible value of δ we add to the 82 observed values of z, the values $\overline{\delta}z$ and $\underline{\delta}z$ (obviously if $\underline{\delta}z < z_m$ or $\overline{\delta}z > 1$ we don't include those values).

- Finally we compute for each δ a new empirical distribution function $H_\delta(z)$, different from $H(z)$ since it is obtained through the inclusion of unobserved data points, from which we compute $D_\delta(z) = H_\delta(\overline{\delta}z) - H_\delta(\underline{\delta}z)$ (obviously if $\underline{\delta}z < z_m$ then $H_\delta(\underline{\delta}z) = H_\delta(z_m)$ and if $\overline{\delta}z > 1$ then $H_\delta(\overline{\delta}z) = 1$).

The last assumption, formulated in order to justify OLS estimates of (9) and (13), is that the error terms ν and ϵ are uncorrelated with $H(z)$ and $D_\delta(z)$: initial differences in technology should not be correlated with the actual shape of the world distribution of factor intensity. Controlling for fixed country effects would require a panel data analysis, but here we are focusing on a first check of the consistency of our specification.

Table 2 presents the OLS regressions of (9) for each of the 9 possible values taken by δ:

- The intercept is always positive as predicted by (8), with the single exception for $\delta = 0.9$, but it is statistically significative only in 5 cases. The estimated $\widehat{\beta}$ is always significant at the 1% level, but its magnitude varies between 0.47 and 0.97 with the choice of δ. The interpretation of $\widehat{\beta}$ within the appropriate technology framework is relatively straight forward: given an amplitude δ of the technological neighbourhood over which spillovers flow, a 1% increase in the density mass of the world economy contained in $D_\delta(z)$ generates a $\widehat{\beta}$% increase in the relative productivity of a country with relative factor intensity z: it follows that the estimated impact of a 1% increase in $D_\delta(z)$ varies between 0.47% and 0.97% with the choice of δ.

- The R^2 of the regressions, that measure the fraction of observed productivity differences explained by appropriate knowledge spillovers, varies with δ: in particular the R^2 seems to be U-shaped in δ, starting from 0.39 for $\delta = 0.1$, then decreasing monotonically and reaching a minimum of 0.21 for $\delta = 0.5$ and finally increasing monotonically toward its maximum value of 0.54 for $\delta = 0.9$.

Table 3 presents the OLS regression of the backward/technology improving specification of knowledge spillovers (13)

- The intercept is near zero as predicted by (13), even if not statistically significant. The estimated $\widehat{\beta}$ is equal to 0.39 and it is highly significant: a 1% increase in the fraction of the world economies with relative capital intensity lower than z generates a 0.39% increase in the relative productivity of a country with relative factor intensity z.Here the linkage between factor accumulation and productivity is more direct than with appropriate technology spillovers, where the circular shape of the domain over which spillovers act introduces some ambiguity: by raising its own z and advancing its own technological state relative to the frontier through accumulation of physical and human capital, a country also raises the quantity of accessed knowledge and its own relative productivity. Finally the R^2 of the regression is 0.55: backward/technology improving spillovers (or knowledge spillovers with barriers measured by relative capital intensity) can explain more than half of the observed cross-country dispersion in TFP levels.

- The estimated $\widehat{\beta}$ entails a value of $\widehat{\alpha}$ consistent with the assumption $\alpha \gg 1$ used to obtain the regression equation (13): in fact $\widehat{\alpha} = \left[\left(\frac{1}{0.26}\right)^{1/0.39} - 1\right] \simeq 61$, so that $\widehat{\beta}$ and the assumption $\alpha \gg 1$ are mutually consistent. We will use this value $\widehat{\alpha}$, together with the estimated $\widehat{\beta}$, in the computation of theoretical relative income levels given by (15).

An evaluation of the two knowledge spillovers structures based on their ability to explain static observed productivity differences is unable to discriminate between them: both the appropriate technology (with large enough technological neighborhoods, $\delta = 0.9$) and the backward spillovers frameworks are able to account for slightly more than an half of the observed dispersion in relative TFP, hence a significative fraction.

The second dimension over which we evaluate these representation of knowledge spillovers is their consistency with the actual shape of the WID: a conditional mean approach, like the one pursued above in the OLS regressions, identifies a single moment of the distribution of relative productivities and an identical predicted dispersion may translate in different implied shape of the distribution itself.

We use the OLS estimates $\widehat{\beta}$ and observed values for $D_\delta(z)$ and $H(z)$ to calculate relative income levels with appropriate technology and backward spillovers, using respectively (10) and (15): Figures 3 and 4 display observed and theoretical kernel density estimations of the world income distribution, respectively for appropriate technology (for each value of δ) and backward spillovers.

It is evident that the appropriate technology framework fails in the replication of the observed WID for almost every choice of δ: predicted relative productivity differences are clearly too high and act on the observed WFD shifting density mass inconsistently with the actual shape of the WID. Even the common world technology hypothesis, that predicts that the WID should simply mirror the WFD, performs better, as Figure 1 shows. Only for $\delta = 0.9$ the predicted WID is similar to the observed one: the WFD is deformed by shifting mass backwards while keeping the original bimodality and its support is enlarged consistently with the observed WID.

Backward knowledge spillovers seem to perform much better than AT spillovers in predicting the WID, even if the R^2 of the OLS regression of the two representations is almost identical when $\delta = 0.9$: the theoretical WID is almost indistinguishable from the observed one for the upper part of the support, while the two distributions slightly differ in the central and lower parts since the theoretical WID overpredicts the density mass of the world economy concentrated in the middle-income part.

To give a formal and quantitative meaning to the visual analysis of the "closeness" of the theoretical and observed WID, we perform a Kolmogorov-Smirnov test of the equality of the two distributions. The two-sample KS test is a nonparametric and distribution free test that assigns a probability distribution to the variable $\Delta = \sup_x |F_n(x) - G_m(x)|$ that measures the maximal distance between two empirical cumulative distributions $F_n(x)$ and $G_m(x)$ generated from unknown distributions F and G, where n and m are the number of observations in each sample: it is then possible to calculate explicitly a P-value for a properly normalized Δ-statistics, and the hypothesis of the equality of the two distributions is rejected if P is "small". In general, it is possible to compute a threshold value for Δ under which the null hypothesis $F = G$ is accepted, but here we report simply the observed Δ and the P-value of the test: the higher the P-value, the closer the observed and theoretical WID.

Table 4 shows the results of the KS test of the equality of the observed WID $H_y(y_r)$ and the theoretical WID whith appropriate technology, $H_y^{th}(y_{r,\delta}^{th})$ given by (10) for each choice of δ, and backward spillovers, $H_y^{th}(y_r^{th})$ given by (15). We include also the test of the equality between the WID and the WFD, predicted by the common world technology hypothesis, as a benchmark for the performance of our specification of technology differences. The null hypothesis of the equality of the observed and theoretical WID is accepted at the 5% level only for three values of δ (0.1, 0.8 and 0.9) for the appropriate technology case, for the common world technology hypothesis WID=WFD and for backward spillovers: the highest P-value is obtained for the backward spillover specification (0.645), followed by the appropriate technology one with $\delta = 0.9$ (0.384).

5 Conclusion

The existence of large and systematic cross-country differences in TFP calls for a rejection of the common world technology assumption and for a theory of productivity differences. We introduce a simple specification for cross-country knowledge spillovers, that generalizes Eeckhout and Jovanovic (2002) and that has been extensively studied in Gerosa (2007), and that has the potential to account for observed productivity differences. If a country capital intensity is an index of its technological state, then every economy receive useful knowledge spillovers by sampling a portion of the world distribution of total factor intensity: either from a neighborhood of technologically close economies (appropriate technology spillovers), or from economies operating technologies already adopted (backward spillovers or spillovers with barriers based on factor endowments). In both cases factor accumulation and TFP levels are linked in a fundamental way, since the position of a country in the WFD determines the amount of technical knowledge it can access. We show that both knowledge spillovers structures are able to explain over an half of observed static productivity differences. We then evaluate the consistency of our specification with the observed WID: we show that backward spillovers are more successful in generating a theoretical WID close to the observed one. A further empirical test left for future research should be a panel data analysis of our technology specification, aimed at explaining cross-country differences in TFP growth rates over time.

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Table 1 - Relative Factor Intensity, Relative Income and Relative Productivity

Country	Code	$k^{\alpha}h^{1-\alpha}$	y	A
Norway	NOR	1	1	1
United States	USA	0.9415	1.1389	1.2096
Switzerland	CHE	0.9186	0.8782	0.9559
Canada	CAN	0.8914	0.9011	1.0107
Sweden	SWE	0.8643	0.7981	0.9233
Australia	AUS	0.8476	0.9236	1.0896
Japan	JPN	0.8419	0.7550	0.8968
Finland	FIN	0.8390	0.7878	0.9390
Denmark	DNK	0.8374	0.8980	1.0723
New Zealand	NZL	0.8340	0.7472	0.8959
Belgium	BEL	0.8223	1.0064	1.2239
Austria	AUT	0.8071	0.9114	1.1292
Netherlands	NLD	0.8022	0.9137	1.1390
Hong Kong	HKG	0.8001	1.0278	1.2847
Republic of Korea	KOR	0.7923	0.6838	0.8631
France	FRA	0.7859	0.8981	1.1426
Singapore	SGP	0.7795	0.8584	1.1011
Israel	ISR	0.7784	0.8711	1.1190
Iceland	ISL	0.7523	0.7809	1.0380
United Kingdom	GBR	0.7287	0.8079	1.1087
Italy	ITA	0.7212	1.0156	1.4081
Ireland	IRL	0.7133	0.9542	1.3377
Greece	GRC	0.6961	0.6231	0.8950
Spain	ESP	0.6737	0.7763	1.1524
Cyprus	CYP	0.6698	0.6785	1.0130
Argentina	ARG	0.5863	0.5114	0.8723
Malaysia	MYS	0.5813	0.5194	0.8934
Barbados	BRB	0.5642	0.5957	1.0558

Table 1 (continued)

Name	Code	$k^{\alpha}h^{1-\alpha}$	y	A
Romania	ROM	0.5216	0.1996	0.3826
Chile	CHL	0.5163	0.4623	0.8954
Portugal	PRT	0.5097	0.5984	1.1738
Mexico	MEX	0.5031	0.4264	0.8476
Panama	PAN	0.4988	0.3045	0.6105
South Africa	ZAF	0.4928	0.4365	0.8857
Trinidad and Tobago	TTO	0.4749	0.4828	1.0166
Uruguay	URY	0.4617	0.4137	0.8948
Thailand	THA	0.4568	0.2661	0.5827
Venezuela	VEN	0.4496	0.3959	0.8805
Jordan	JOR	0.4294	0.3226	0.7512
Peru	PER	0.4294	0.2036	0.4743
Ecuador	ECU	0.4217	0.2518	0.5972
Mauritius	MUS	0.4155	0.5193	1.2497
Brazil	BRA	0.4132	0.3738	0.9047
Costa Rica	CRI	0.3983	0.2647	0.6646
Iran	IRN	0.3897	0.3565	0.9147
Botswana	BWA	0.3863	0.3588	0.9288
Turkey	TUR	0.3747	0.2948	0.7868
Algeria	DZA	0.3743	0.2994	0.7997
Philippines	PHL	0.3727	0.1551	0.4161
Guyana	GUY	0.3553	0.1549	0.4359
Syrian Arab Republic	SYR	0.3479	0.3216	0.9243
Tunisia	TUN	0.3479	0.3531	1.0148
Jamaica	JAM	0.3456	0.1529	0.4426
Paraguay	PRY	0.3431	0.2426	0.7069
Dominican Republic	DOM	0.3340	0.2487	0.7446
Colombia	COL	0.3245	0.2422	0.7464

Table 1 - (continued)

Name	Code	$k^{\alpha}h^{1-\alpha}$	y	A
Indonesia	IDN	0.3044	0.1729	0.6469
Sri Lanka	LKA	0.2934	0.1344	0.5218
Zimbabwe	ZWE	0.2870	0.1029	0.4086
El Salvador	SLV	0.2857	0.2370	0.9446
Nicaragua	NIC	0.2708	0.0995	0.4184
Honduras	HND	0.2696	0.1198	0.5062
Bolivia	BOL	0.2672	0.1170	0.4989
Lesotho	LSO	0.2521	0.0493	0.2228
Guatemala	GTM	0.2509	0.2343	1.063
Zambia	ZMB	0.2446	0.0437	0.2038
India	IND	0.2319	0.0946	0.4648
Papua New Guinea	PNG	0.2204	0.1306	0.6749
Pakistan	PAK	0.2144	0.1221	0.6487
Bangladesh	BGD	0.2000	0.1092	0.6217
Cameroon	CMR	0.1807	0.0671	0.4232
Kenya	KEN	0.1711	0.0453	0.3015
Ghana	GHA	0.1669	0.0465	0.3174
Togo	TGO	0.1506	0.0381	0.2885
Senegal	SEN	0.1491	0.0540	0.4128
Malawi	MWI	0.1425	0.0294	0.2349
Haiti	HTI	0.1339	0.0732	0.6225
Central African Republic	CAF	0.1338	0.0328	0.2796
Mali	MLI	0.1145	0.0295	0.2941
Niger	NER	0.1111	0.0288	0.2954
Uganda	UGA	0.0935	0.0307	0.3747
Mozambique	MOZ	0.0917	0.0305	0.3799

Table 2 - Relative Productivities and Appropriate Technology Knowledge Spillovers

	Technological Neighbourhood Amplitude				
	$\delta = 0.1$	$\delta = 0.2$	$\delta = 0.3$	$\delta = 0.4$	$\delta = 0.5$
Constant	0.9410196^{***} (0.1678781)	0.4680726^{*} (0.1864839)	0.3651233^{**} (0.1224665)	0.1304574 (0.0977648)	0.0877904 (0.086854)
$\ln D_\delta(z)$	0.5520611^{***} (0.0755041)	0.4732244^{***} (0.1102956)	0.5326067^{***} (0.089457)	0.4545924^{***} (0.0874277)	0.5315591^{***} (0.0935024)
R^2	0.3928	0.3025	0.2414	0.2119	0.2090
Obs.	82	82	82	82	82
	$\delta = 0.6$	$\delta = 0.7$	$\delta = 0.8$	$\delta = 0.9$	
Constant	0.1035439 (0.0927429)	0.0938162 (0.0742824)	0.3651233^{**} (0.1224665)	-0.0849079^{*} (0.0399052)	
$\ln D_\delta(z)$	0.7002127^{***} (0.1247104)	0.8833711^{***} (0.1255699)	0.9791215^{***} (0.1212171)	0.5988725^{***} (0.066256)	
R^2	0.2424	0.3283	0.4800	0.5446	
Obs.	82	82	82	82	

Note: OLS estimates of equation (9). Dependent variable is TFP relative to the technological leader (Norway). Robust standard errors in parentheses. *,** and *** mean significantly different from 0 at the $10\%, 5\%$ or 1% level.

Table 3 - Relative Productivities and Backward/Technology Improving Knowledge Spillovers

Constant	0.0212248 (0.0475042)
$\ln H(z)$	0.3930646*** (0.0512411)
R^2	0.5534
Obs.	82

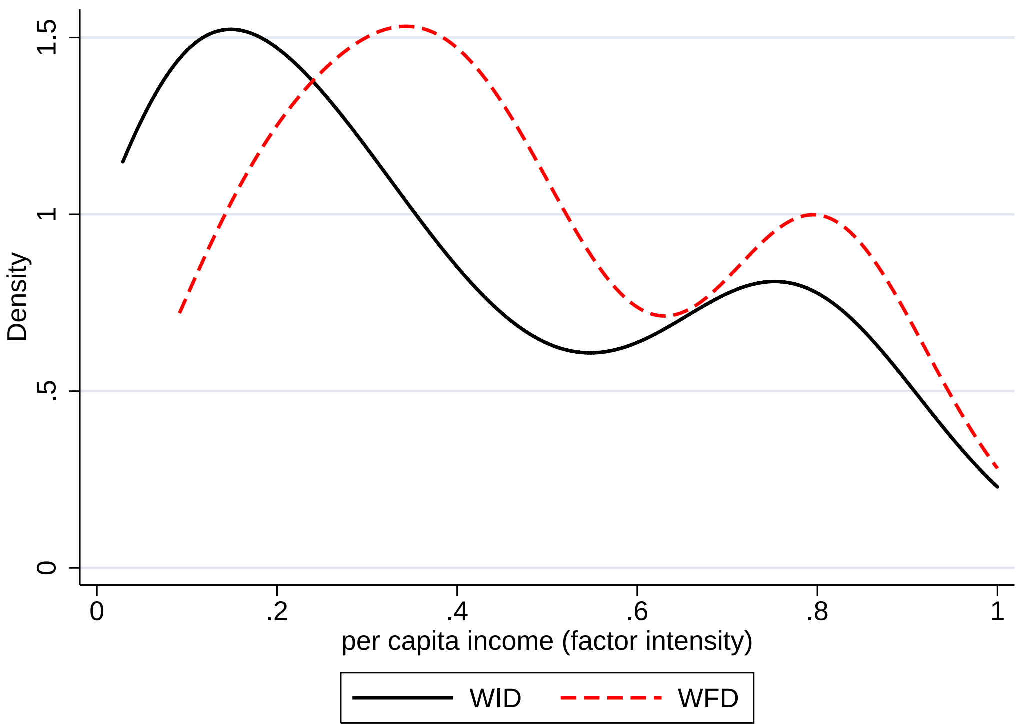
Note: OLS estimates of equation (13). Dependent variable is TFP relative to the technological leader (Norway). Robust standard errors in parentheses. *,** and *** mean significantly different from 0 at the $10\%, 5\%$ or 1% level.

Table 4 - Kolmogorov-Smirnov Test for the Equality of Observed and Theoretical WID

	Technological Neighbourhood Amplitude				
	$\delta = 0.1$	$\delta = 0.2$	$\delta = 0.3$	$\delta = 0.4$	$\delta = 0.5$
Δ	0.2195	0.2927	0.3171	0.3293	0.3415
$P - value$	0.026	0.001	0.001	0.000	0.000
	$\delta = 0.6$	$\delta = 0.7$	$\delta = 0.8$	$\delta = 0.9$	
Δ	0.3415	0.3049	0.2439	0.1341	
$P - value$	0.000	0.001	0.010	0.384	
	Backward Spillovers	WFD			
Δ	0.1098	0.2561			
$P - value$	0.645	0.006			

Note: Kolmogorov-Smirnov test for the equality of the observed and theoretical WIDs with appropriate technology and backward spillovers. Δ is the maximum distance between the two distribution and $P - value$ is the corrected P computed by Stata 8.2. WFD is the observed cross-country distribution of relative factor intensity $h(z)$, constructed as explained in the article. Sample of 82 countries for the year 1996.

Figure 1: World Income Distribution and World Factor Distribution



Note: Kernel density estimation of per worker income (WID) taken from PWT 6.1 and physical-human capital aggregate $y_{kh} = k^{\alpha} h^{1-\alpha}$(WFD), constructed as described in the main text, both relative to the observed maximum for the sample of 82 countries in the year 1996. Gaussian kernel and optimal bandwidth selected by Stata 8.2 in accord with Silverman (1986).

Figure 2: Appropriate Technology Spillovers

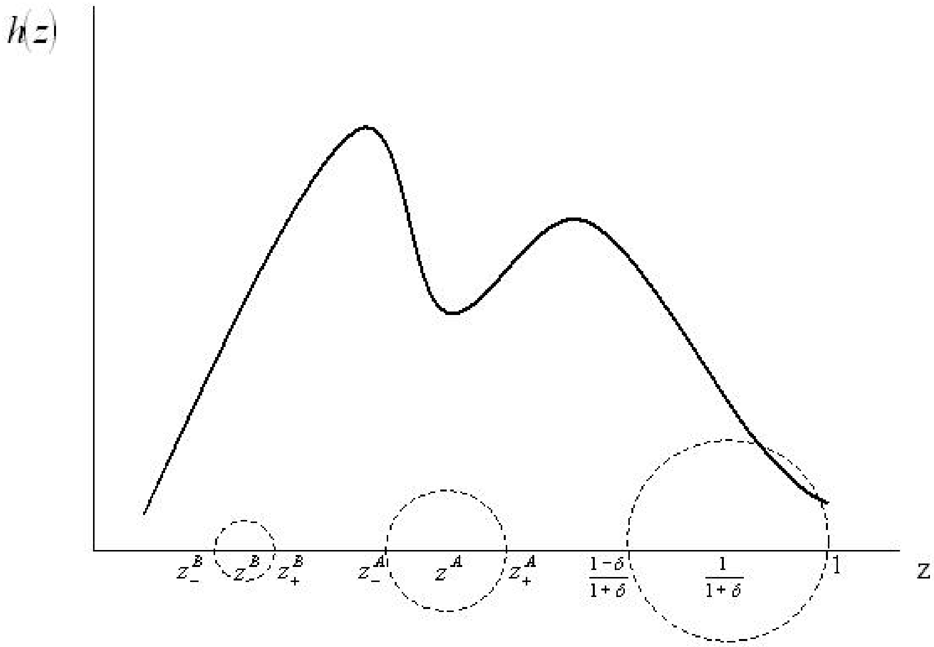


Figure 3:

Figure 3 - Observed vs Theoretical WID with Appropriate Technology Knowledge Spillovers

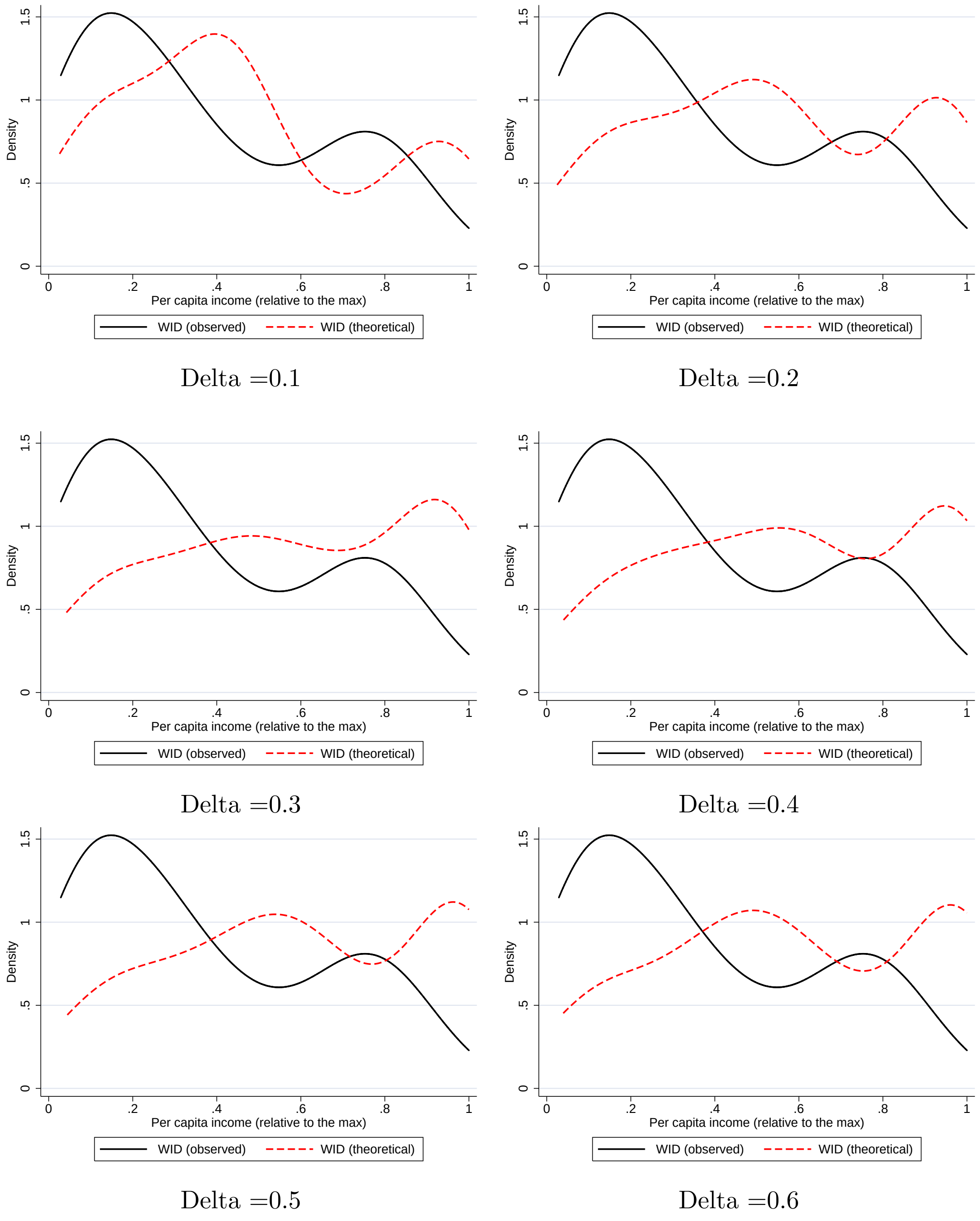
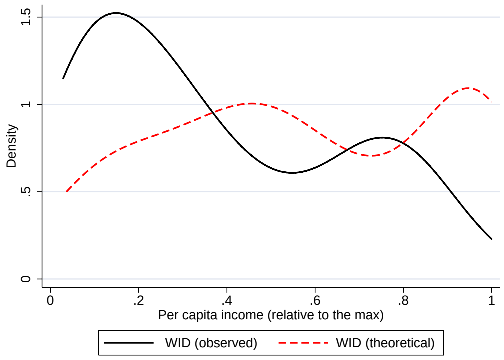
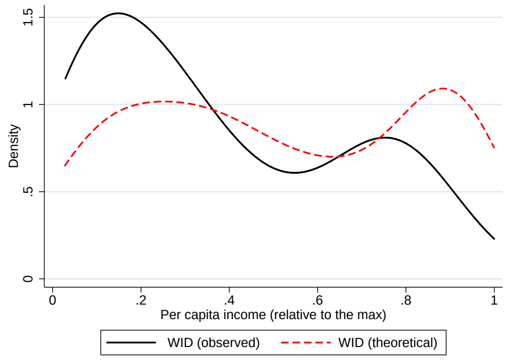


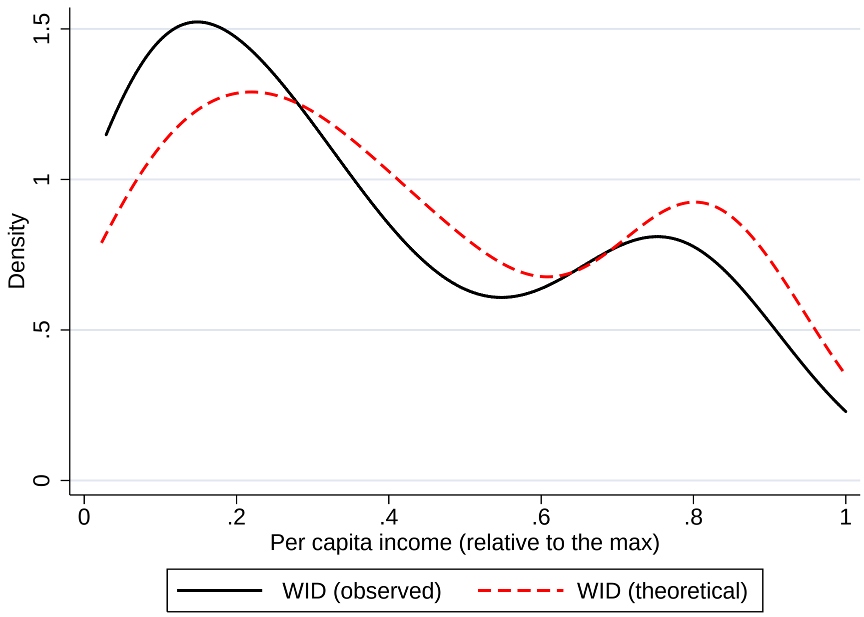
Figure 3 - Observed vs Theoretical WID with Appropriate Technology Knowledge Spillovers (continued)



Delta=0.7



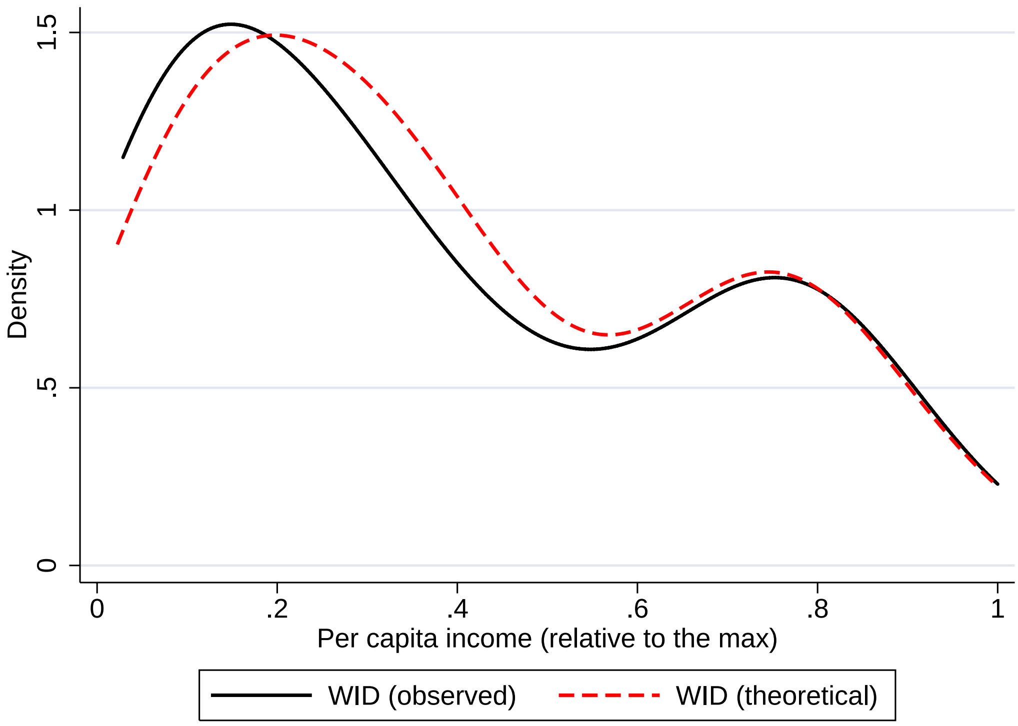
Delta=0.8



Delta=0.9

Note: Kernel density estimation of observed per worker income (WID) taken from PWT 6.1 and theoretical per worker income, described by equation (10) in the main text, relative respectively to the observed and theoretical maximum for the sample of 82 countries in the year 1996 described in the main text. Gaussian kernel and optimal bandwidth selected by Stata 8.2 in accord with Silverman (1986).

Figure 4 - Observed and Theoretical WID with Backward Knowledge Spillovers



Note: Kernel density estimation of observed per worker income (WID) taken from PWT 6.1 and theoretical per worker income, described by equation (15) in the main text, relative respectively to the observed and theoretical maximum for the sample of 82 countries in the year 1996. Gaussian kernel and optimal bandwidth selected by Stata 8.2 in accord with Silverman (1986).