

Income Convergence and R&D Intensity in OECD Manufacturing Industries: A Panel Study[†]

Nicholas Vasilakos*
Department of Economics
University of Birmingham
Birmingham, B15 2TT
Tel: +44 (0)121 415 8642
Email: *n.vasilakos@bham.ac.uk*

Nikolay Zubanov
Bureau for Economic
Policy Analysis (CPB)
Den Haag 2508GM
Tel: +31 70 3383 384
Email: *n.zubanov@cpb.nl*

Abstract

This paper evaluates the impact of R&D investment on income convergence for a cross section of manufacturing industries in 12 OECD countries over the time period 1987-1999. We apply dynamic panel estimation techniques to obtain a speed of convergence which, when conditioned to R&D expenditure, is significantly greater than the conventional 2%. In particular, the inclusion of the R&D variable results to a speed of convergence of 7-9% per year, suggesting that convergence is faster between equally technologically advanced industries. A further implication from our results is that differences in the industry mix can be important in explaining the speed of income convergence between countries.

JEL CODES: C33, J24, O32, O47.

KEYWORDS: income growth, beta convergence, R&D investment.

[†]Nicholas Vasilakos acknowledges the receipt of financial support for this project (in the form of travel grants) from the Department of Economics of the University of Birmingham. All views expressed in this paper are ours alone.

*Corresponding author.

1 Introduction

Income convergence, or a tendency for richer economies to grow slower and for poorer economies to catch up with the rich, has been studied extensively in the empirical growth literature. A large part of this literature has investigated the issue of cross-country income convergence on the assumption of some given, exogenously determined rate of technological progress, as specified in the Solow (1956) model. This model predicts that per-capita income in economies with equal rates of population growth, investment and total factor productivity should converge to a given steady state, because the marginal product of capital is higher in poorer economies where capital is scarcer. Some earlier country-level empirical studies (see, for instance, Barro and Sala-i Martin, 1991, 1992a,b) confirm this prediction, calculating a speed of income convergence at around 2% per year. Others, however, find little or no evidence to support the notion of convergence.

The insight from the “new growth theory”, namely that advances in technology increase the marginal product of physical capital in already capital-rich economies, helps explain why one may fail to observe convergence between economies at different stages of technological development. The mechanism ensuring convergence in the Solow model – higher marginal product of capital in poorer countries – fails unless technological sophistication is controlled for. For instance, Quah (1994) shows that Solow convergence, conditional only on population growth and investment, is only observed within samples of similarly developed economies, also known as “convergence clubs”.

In this study, we try to reconcile conflicting empirical evidence on income convergence with the basic tenets of the Solow model by conditioning convergence on technological sophistication. One way of conditioning convergence is to allow each country to have its own “fixed effect”. Doing so leads to much higher estimates of the speed of convergence in the region of 5 to 11% per year (Islam, 1995; de la Fuente, 2002). We do observe this tendency in our estimations as well, but, as we will show, there are econometric problems with the fixed-effects specification of the convergence equation, which we ad-

dress. Therefore, valid controls for technological sophistication should be used instead of relegating all unobserved heterogeneity to the fixed effects.

Still, relegating all unobserved heterogeneity to the fixed effects may not be enough because some steady state determinants evolve with time. Identifying appropriate controls to characterise the steady state can be problematic. Earlier attempts to do so by using years of schooling have proved inconclusive (see for instance Barro and Lee, 1993; Mankiw et al., 1992; Islam, 1995). One reason for the disappointing performance of schooling in convergence regressions is that it is measured with a considerable error which attenuates its regression estimates. A more fundamental reason, however, which would also apply even if technological sophistication were perfectly measured, is that the abovementioned studies were carried out at the country level. We argue that, because national economies are naturally a mix of low-tech (such as agriculture) and high-tech (such as aviation) industries, a country-level convergence analysis may suffer from aggregation bias. Accordingly, following the footsteps of industry-level studies (Dollar and Wolff, 1988; Bernard and Jones, 1996a,b; Cameron et al., 2005), we estimate a convergence equation using data from individual industries.

We proxy technological sophistication with research and development (R&D) expenditure per worker. Common intuition suggests that, if R&D is indeed a significant determinant of the steady-state per-capita income, industries will converge to their appropriate steady states faster than – if at all – to some kind of “average” steady state across the industries that differ in terms of technological sophistication. Our results show that this is indeed the case. We find that R&D expenditure per worker is strongly and positively correlated with per-worker value added growth, and that including it in the convergence equation increases the speed of convergence considerably. Therefore, convergence is faster the more similar the industries are in terms of technological sophistication.

The rest of the paper is organised as follows. Section 2 presents a summary of the key findings in the convergence literature. Regression specification and estimation issues are discussed in section 3. Section 4 provides a descriptive summary of the data and the

main variables used in our study. Section 5 shows and discusses our estimation results and links them to earlier findings. Section 6 concludes.

2 Previous studies

The origin of the idea of income convergence can be traced back to the basic properties of the neoclassical growth models, which practically ensured the existence of a transitional growth path to a steady state level of income (Solow, 1956). If the steady state income is the same for all economies, convergence is said to be unconditional (Barro and Sala-i-Martin 1992). This being seldom the case, convergence may still exist conditional on the variables determining for every economy its own steady state. As we will show, technological sophistication is one of such variables. Although there are several other definitions and methodologies to measure income convergence, the two empirical measures that are most often used in this class of studies are: (1) beta-convergence, or a negative correlation between growth and initial level of income (Baumol, 1986); and (2) sigma-convergence, or a reduction in the dispersion of per capita income between economies (Quah, 1993). This paper is about beta-convergence.

Historically, empirical studies of convergence started with the analysis of cross-sectional data from countries or regions. In a series of studies, Barro and Sala-i Martin (1991, 1992a,b, 1995) find convergence at a rate of about 2% per year for 48 US states over the period 1880-1890, 10 Canadian provinces (1961-1991), 47 Japanese prefectures (1955-1990), 90 European regions (1950-1990) and various combinations of OECD countries. Similar estimates were reported in Levine and Renelt (1992), Neven and Gouyette (1995), Hofer and Wörgötter (1997) and Martin (2001). The 2% per year speed of convergence, implying that it would take a region 35 years to eliminate half the initial gap from the steady state income level, was justified on the grounds of high costs of implementing new technologies (Sala-i Martin, 1996), but was often criticised as arising from inappropriate measurement of variables and application of estimation techniques (Vasudeva Murthy and Chien, 1997) and omission of steady state determinants (Andres et al., 1996).

One way of gaining control over steady state determinants is to allow for country-specific fixed effects, which was made possible by the arrival of large internationally comparable panel data, such as the Penn World tables. Panel data studies do indeed report faster convergence. Islam (1995), for instance, using OECD panel data and a model with country fixed effects, obtains estimates of the rate of convergence varying between 4.3 and 9.3%. More recent panel data estimates tend to report even higher convergence rates, in certain cases as high as 20% (de la Fuente, 2002; Cuadrado-Roura et al., 1999; Tondl, 1999). Other studies which take into account the endogeneity of the lagged income level in the convergence equation report somewhat lower estimates for the speed of convergence (Caselli et al., 1996); and 3-5% in Hoeffler (2002). Our results suggest that correcting for this endogeneity is important.

Mankiw et al. (1992) and Islam (1995) present an augmented version of the classical Solow convergence equation, that has the advantage of controlling for human capital, as a measure of technological differences between countries and regions. They find that the speed of convergence tends to increase once average years of schooling was included in the regression (though this variable itself was often found to be insignificant). A number of studies followed a less structural approach, adding a variety of potential determinants of economic growth. Examples include financial institutions (Collender and Shaffer, 2003), and political stability (Savvides, 1995), fiscal policy and openness to trade (Haveman et al., 2001). The evidence here is mixed, but meta-analytical results in Abreu et al. (2005) suggest that the inclusion of these variables does lead to higher estimates for the speed of convergence ¹.

The role of technology development itself in the convergence process has also been in the centre of attention in a number of empirical studies, although it has often suffered from the usual limitations imposed by data aggregation and variables selection. Earlier contributions in the wider growth literature, have attempted to proxy the role of technology with the inclusion of measures of human capital accumulation (Abramovitz, 1986;

¹In their recent meta-study of income convergence, Abreu et al. (2005) show that, though peaking at the "legendary" 2% per year, the estimates of the speed of convergence vary. Thus, they cite more than 600 studies reporting estimates ranging from -3.8% to 65.5% per year. They show, however, that a considerable part of this variation can be explained through addressing relatively few issues surrounding the estimation procedure.

Mankiw et al., 1992; Behnabib and Spiegel, 1994). More recent ones include more direct controls for technological differences between regions, in order to examine the effect of technology defusion (spillovers) or “research capacity” (Coe and Helpman, 1995; Helliwell, 1992; Parente and Prescott, 1994; Cameron et al., 2005). Our paper falls to the latter category, using a particular measure of sectoral research intensity to control for the effect of differences in technological sophistication between countries.

Parente and Prescott (1994) present a model in which the ability to adopt new technologies relates directly to the growth potential of the economy. Their empirical calibration of this model shows that cross-country differences in the capability to adopt new technologies can explain a significant part of the existing growth and income differentials, and that an increase in the “adaptability” of the laggards can stimulate rapid growth and catch-up. Similar findings are reached by Cameron et al. (2005) at a more disaggregated setting. Using a panel of 14 UK manufacturing industries over the period 1970-1992, they find standardised R&D expenditure to be a significant determinant of innovation and, ultimately, productivity growth and convergence.

3 Model Specification

The basic convergence model as derived in Solow (1956) is based on a constant returns to scale Cobb-Douglas production function with two inputs, labour and capital, and exogenous rates of technological progress. Mankiw et al. (1992) add human capital in the production function (maintaining the assumption of constant returns to scale). Islam (1995) extends the convergence equation to include country or industry-specific effects. Drawing on these frameworks, we estimate an extended version of the convergence equation, with a control for technological sophistication added as follows:

$$(1) \quad \ln (INCOME_{it_2}) = e^{-\lambda\tau} \ln INCOME_{it_1} + (1 - e^{-\lambda\tau}) \frac{\alpha}{1 - \alpha} \ln \frac{S_{it}}{EMP_{it} + g + \delta} \\ + (1 - e^{-\lambda\tau}) \frac{\phi}{1 - \alpha} \ln r_{it} + (1 - e^{-\lambda\tau}) \ln A_i + g(t_2 - e^{-\lambda\tau}t_1)$$

where i and t are industry and time period identifiers, t_1 and t_2 denote the beginning and end, respectively, of a four year period (so $\tau = 4$)². *INCOME* is defined as value added worker; s is the share of capital investment in total output; *EMP* is the growth rate of workers in a particular industry; and r is R&D expenditure per worker, which we use as a measure of technological sophistication. The parameter α measures the share of physical capital in the production function, ϕ is the share of the technology input in the production function, τ is the length of a period, g and δ measure the rate of exogenous technological progress and physical capital depreciation, respectively (following common practice, $g + \delta$ is assumed to be equal to 0.05), and A_i is the unobservable industry-specific term. Finally, λ measures the speed of convergence, i.e. the average rate at which the gap between per-worker incomes in different industries is reduced each year.

The empirical counterpart of (1) is

$$(2) \quad \ln(INCOME_{it_2}) = \gamma \ln INCOME_{it_1} + \beta_1 \ln(s_{it}) + \beta_2 \ln(EMP_{it} + g + \delta) \\ + \beta_3 \ln r_{it} + \alpha_i + \rho_t + e_{it}$$

where e_{it} is a random error and ρ denotes a vector of period dummies. We estimate equation (2) on an industry-level panel dataset of 12 OECD countries³ over the period 1987-1999. The structural parameters of interest, λ , α and ϕ can be recovered from the regression estimates as follows:

$$\lambda = -\frac{\ln \gamma}{4}, \\ \alpha = \frac{\beta_1}{1 - \gamma + \beta_1} \\ \phi = \frac{\beta_3}{1 - \gamma + \beta_1}$$

²See section 4 for a discussion of the choice of time periods

³The countries included in our sample are: Australia, Belgium, Canada, Finland, France, Italy, Netherlands, Norway, Spain, Sweden, UK, US.

Equation (1) also implies a testable restriction, that the coefficients of $\ln(s_{it})$ and $\ln(EMP_{it} + g + \delta)$ are of equal magnitude and opposite signs. Wald tests carried out on our data generally do not reject this restriction.

Equation (2) is then estimated with a selection of estimators, namely pooled least squares, fixed effects, instrumental variables and GMM. A pooled least squares estimator assumes that the observed variables (s , EMP , r) fully define the relevant income steady state, so, given these, there should be no systematic differences in steady states across industries. This assumption is bound to fail in the presence of a variety of industry-specific factors, important for economic growth but either unobservable or poorly measured (e.g. institutions, overall level of economic development, geographic determinants) and therefore concealed in the term A_i which this estimator ignores. As a result of assuming away the persistent differences induced by unobservables, one gets too few income steady states, so that the average distance to the nearest identified steady state becomes large and the estimate of the speed of convergence low ⁴.

The fixed-effect estimator can accommodate industry-specific unobservable effects, although it may also lead to incorrect inferences about the speed of convergence. Thus, the fixed-effects estimator assumes the existence of an income steady state peculiar to each cross-section unit (and thus estimates an $\hat{\alpha}_i$ for every i), but at the same time washes out a great deal of inertia in income dynamics, which may exaggerate the estimated speed of convergence, leading again to erroneous conclusions ⁵.

A number of estimation techniques have been proposed to correct the bias in the estimation of a dynamic regression such as equation (2) with fixed effects. These include instrumental variables (Anderson and Hsiao, 1982), various versions of the Arellano-Bond

⁴In more technical terms, the unbiasedness of an estimate requires $\gamma = E(\hat{\gamma})$. In the case of OLS, this equality does not hold. The initial level of total factor productivity, which is part of the term α_i , is positively correlated with subsequent levels of labour productivity. Thus $cov(\ln INCOME_{it_1}, \alpha_i) > 0$, which results in $\hat{\gamma} > E(\gamma)$ and underestimated speed of convergence since $\lambda = -\frac{\ln \hat{\gamma}}{\tau}$.

⁵The fixed-effects estimator works by subtracting each variable's cross-section average from every observation and running OLS on the residuals. In our case (skipping the rest of the variables), the transformed regression equation would be $\ln INCOME_{it_2} - \ln \overline{INCOME}_i = \ln INCOME_{it_1} - \ln \overline{INCOME}_{i,-1} + e_{it} - \bar{e}_i$. $\ln INCOME_{it_2}$ is positively correlated with its contemporaneous error, e_{it} , by construction, so $\ln INCOME_{it_1}$ would be positively correlated with e_{it-1} and hence with \bar{e}_i . Therefore, $cov(\ln INCOME_{it_1}, e_{it} - \bar{e}_i) < 0$, resulting in $\hat{\gamma} < E(\gamma)$ and overestimated speed of convergence.

GMM estimator, bias-corrected fixed effects (Kiviet, 1995), minimum distance (Chamberlain, 1982), as well as limited- and full-information maximum likelihood estimators. However, the short span of our data severely limits the choice of the estimators we can apply, thus ruling out the use of more advanced Arellano-Bond type estimators (see Blundell and Bond, 1998), as they would require more than three periods per cross section. Similarly, the use of non-IV estimators, such as maximum likelihood, would require more time periods than we have to ensure consistency. We therefore use basic IV and Arellano-Bond estimators to obtain consistent estimates for equation (2)'s parameters.

To assess the performance of these two techniques, we run simple Monte Carlo simulations (results presented in Appendix 1). Applying the GMM estimator, we are aware of the possibility of it carrying a bias because of the weak instruments problem. This problem is the result of GMM using all available instruments for a given observation, some of which may be weak, particularly when the dependent variable is persistent (Blundell and Bond, 1998). Indeed, as our simulations show, the bias of our GMM estimator exceeds that of IV.

We use the second lag of the dependent variable and lags of regressors as (excluded) instruments. These instruments are sufficiently strongly correlated with the lagged dependent variable $\ln INCOME_{it_1}$ and they pass the Sargan-Hansen overidentification test. Each estimator is tried on two specifications of the regression equation. The first includes only the log initial level of value added per worker, employment and investment growth rates. The second augments it with our measure of technological sophistication - R&D expenditure per worker. The difference in the estimates for the speed of convergence from these two specifications is instructive and suggests that industries similar in terms of technological sophistication converge faster.

4 Data

Our sample is drawn from OECD's Structural Analysis (STAN) database. This is one of the most comprehensive internationally comparable data sources on industry-level performance currently available. We extract from this dataset information on value added,

R&D expenditure, investment and employment for a number of manufacturing industries in 12 OECD countries. All variables have been transformed to real per capita values. The number of available industries varied from 31 (Netherlands) to 45 (Australia). Not all data were available for all industries and countries, so the complete sample consists of 326 country-industry pairs.

Because convergence is expected to occur over a period of several years, to reduce the importance of business cycle component in our data, we operate with three periods of four years each: 1987-90, 1991-94, and 1995-99⁶. This time period length is comparable to the ones used in previous studies. In particular, some of our preliminary estimations confirm that the OLS speed of convergence estimates do not differ significantly when the model is estimated over the entire sample period as opposed to period by period (i.e. one observation per country-industry pair). This similarity has also been reported in earlier studies (see for instance Islam, 1995, 2003).

Table 1 goes about here.

Table 1 summarises our regression variables. Value added per worker averages at around \$45,000 and has been rising over time. Although declining in size and economic importance, the manufacturing sector in OECD economies has enjoyed steady growth in value added per worker amounting to 2.5% per year over the observed period, which is somewhat higher than the OECD average GDP annual growth of approximately 2.1% over our sampling period.

⁶The correct implementation of the IV and GMM estimation techniques that we follow, requires at least three time periods.

With many industries in decline, the overall employment growth rate is also falling at a rate of -0.7% per annum. Given that the total employment growth in OECD is averaging at 0.15% per annum, this figure is indicative of the shift of employment from manufacturing to other sectors of the economy (mainly services). Despite the overall reduction in employment, investment per worker averages a positive 2.2% per annum. R&D expenditure averages at \$3,601 per worker, or 8% of value added, with a pronounced upward trend reflecting the increasing technical sophistication of production processes.

R&D varies greatly across industries and countries. Its variance between types of industries accounts for 51% of the total, suggesting that R&D intensity is largely industry-specific and depends on returns to technology innovations across different groups of products. Our data enable us to capture this important source of variation in technological sophistication. At the same time, differences in R&D intensities by industry suggest differences in the degree of importance of R&D for sectoral productivity growth.

The variation in R&D's country averages accounts for 6% of the total. Although the driving forces behind this variation are not fully clear, it would be reasonable to suppose that a considerable part of it is due to differences in industry mix across countries. Differences in R&D intensities between industries and in industry mix between countries imply that, if R&D is to matter for growth, countries may or may not converge depending on how similar their industry mix is.

Figure 1 goes about here.

Figure 1 gives a first impression of unconditional income convergence. The term 'unconditional convergence' is used here to imply the absence of controls for factors other

than the initial level of value added. The slope coefficient of the fitted regression line has the expected sign and magnitude, implying that less productive industries seem to grow faster on average. Thus, industry productivity growth appears to reduce its gap with the sample average by 1.4% per year. This rate is within the range of country-based estimates found in cross-sectional convergence studies at the country level (Barro and Sala-i Martin, 1991, 1995; Islam, 1995).

There is one important difference, however, between our estimate from Figure 1 and earlier cross-sectional studies, namely that we operate with individual industries. As similar industries are likely to converge faster (because, for instance, similar technology can be more easily adopted), going from the industry to the country level can reduce the estimated speed of convergence if countries differ in terms of industry mix. Indeed, as we aggregate our data up to the country level, we find lower in magnitude (1.1%) and insignificant speed of convergence. It is therefore conceivable that aggregation may have been one of the reasons that led earlier, country-level, studies to report low or insignificant rates of convergence.

5 Estimation Results

Table 2 reports our estimation results for the convergence equation (2) from a variety of estimators. The pooled OLS estimates suggest a speed of convergence in the region of 2-3% per year. All variables have intuitive signs, and overall significance is high. The restriction that the coefficients of EMP and s are equal and of opposite signs is not rejected by the data. The estimate for the share of capital in total output is somewhat above the benchmark of $1/3$, but it comes closer to it as the R&D variable is introduced in the equation. Introducing R&D also leads to the increase in the speed of convergence estimate, which supports conditioning convergence on the steady state parameters other than employment growth and investment rate.

Table 2 goes about here

The fixed-effects estimator renders faster speed of convergence and lower share of capital input, but their magnitudes are improbable: 54.3% per year and 15% of output, respectively. As we showed in section 3, the short time dimension of our panel (only three observations per industry-county pair) induces the correlation between the fixed-effects transformed lagged dependent variable and the error term, and creates an upward bias to the speed of convergence estimate. We observe the same tendency when simulating the performance of the LSDV estimator in Appendix 1.

The IV and GMM estimates for the speed of convergence are between the OLS and fixed-effects. They are higher than OLS, as we allow for industry-specific steady state effects. But they are also lower than fixed-effects estimates, because the correlation between the lagged dependent variable and the error term is reduced by instrumenting $INCOME_{it_1}$ with its second lag. The diagnostic tests warrant the validity of the restriction imposed on EMP and s , as well as the choice of the instruments. The results of the overidentification test imply that there is no unaccounted inertia in the error term, otherwise earlier lags of value added per worker, used as instruments, would be correlated with it. Therefore, the estimate γ for $INCOME_{it_1}$ is not downward-biased, and the speed of convergence is not overestimated.

R&D is an important determinant of economic growth. Thus, according to our regressions, a 10% increase in the share of R&D is associated with an additional 0.5-0.6% of per-worker value added growth, the same as the 0.6% implied by de la Fuente's (2003) estimates for the share of R&D expenditures in GDP ⁷. The addition of R&D increases the speed of convergence from 4-6% to 7-9% per year, as conditional convergence would imply. It also reduces the estimate for the share of capital in output, implying that more

⁷de la Fuente's estimate of the speed of convergence is lower than ours (in the region of 3.4% per year), but his reported results are indeed consistent with our preliminary estimates on the speed of convergence between economies rather than industries.

capital-intensive industries are also more R&D intensive. The implied average share of physical capital in total output is now around 0.3, which is close to the benchmark. The implied share of the R&D input in total output, also averaged across industries, is about 14-16%.

Even though we took a different approach from most of the earlier literature, our findings are consistent with it, especially if we take data aggregation issues into account. Our pooled OLS estimates for the speed of convergence are comparable with those reported in cross-sectional studies employing the same design (Barro and Sala-i Martin, 1992a,b; Mankiw et al., 1992). That they are slightly on the right side of the spectrum could be explained through differences in data aggregation levels, as we demonstrated in section 4. As in Mankiw et al. (1992), we too observe an increase in the speed of convergence once the measure of technological sophistication (R&D intensity in our case) is added in, and, as in Islam (1995), we find an increase in the speed of convergence when adding fixed effects. Both effects are strongly grounded in theory.

The difference between our OLS and fixed-effects estimates, however, is far greater than in Islam (1995). Part of the explanation for this is that we have fewer time periods (three versus five), which increases the correlation between the initial level of value added and the fixed effect⁸. Data aggregation level could be yet another explanation for the smaller difference between the OLS and fixed-effects results in Islam (1995). Given the pairwise correlations between value added in a certain country-industry pair and its fixed effect, aggregating industry data up to country level reduces this correlation and thus the difference between OLS and fixed effects estimates.

6 Conclusions

Our main motivation for this study was to provide a more direct assessment of the impact of structural and technological differences between countries to the process of income convergence. To this end, we have estimated a simple conditional income conver-

⁸As we increase the number of time periods in our simulations, this correlation, and hence the upward bias to the speed of convergence, becomes smaller.

gence model in the spirit of Mankiw et al. (1992) and Islam (1995) using industry-level data for a sample of twelve OECD countries. Our findings can be summarised as follows. We demonstrate that technological sophistication is an important determinant of income growth. We also find that conditioning on technological sophistication increases the speed of convergence between industries. Consequently, our results imply that, because industries differ in terms of technological sophistication, economies with different industry mix will converge slower than more similar ones.

Our results yield support to the results reported by earlier studies at the macro level, arguing the importance of technological sophistication in the process of income convergence. We also show the importance of differences in the industry mix for convergence between national economies. While industries do differ in terms of R&D intensity, the mainstream, country-level, research on convergence cannot address such differences in industry mix between countries, which may partly explain the absence of or very slow convergence results that are reported in some of these studies. We, therefore, conclude that sufficient conditioning should be applied at the right level of aggregation to demonstrate convergence.

Turning to policy implications, aspiring economies should not only emulate the leaders in stimulating R&D spending but also pay attention to their industry mix. Large variation in R&D intensity by industry type suggests industry-specific returns to new technology. Therefore, policies to promote technological innovation will be more successful if applied to the right industries.

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Appendix 1: Simulating bias performance of selected panel-data estimators: OLS, Fixed Effects, IV, GMM

To investigate empirically the bias properties of the estimators applied in this study, we run Monte Carlo simulations on our assumed convergence regression model (equation (2)). As is often done in the literature (Hauk and Wacziarg, 2009), we simulate the variables in the regression model - the beginning-of-period value added per worker, share of investment in total output, population growth and per-worker R&D expenditure - so that the moments, pairwise and auto-correlations of the simulated data resemble those of the corresponding observed variables. The dependent variable, the end-of-period value added per worker is simulated via equation (2) with an added error term. The error term is simulated as a series of independent, normally distributed random variables with variance resembling the empirically observed variance of the error term on our sample.

The parameter values are set close to the regression estimates on which we base our main story: $\gamma = 0.7$, $\beta_1 = -\beta_2 = 0.1$, and $\beta_3 = 0.06$. Instrumenting for the IV and GMM estimators is done in exactly the same way as in the main estimations. The structure of our simulated data - three time periods and 300 cross-sectional units - also closely resembles our original dataset.

After simulating the data and applying a random error term to the dependent variable, we estimate equation (2) on a newly generated dataset with all four estimators,

recording regression coefficients and their standard errors (useful to study efficiency properties of the estimators). The procedure is repeated 1000 times. We compare the mean of the estimate with the true coefficient, calculating the bias as a percentage deviation. Table 3 reports the results.

Table 3 goes about here

Our simulation results agree with econometric intuition as outlined in section 3. The OLS estimator overstates persistency in the dependent variable, producing underestimated speed of convergence, 1.6% compared to the true 8.9% per year. The FE estimator, on the other hand, assigns too much explanatory power to the fixed effects, overstating persistency in the per worker value added, which leads to too high an estimate for the speed of convergence.

The IV and GMM estimates allow for fixed effects, unlike OLS, and, unlike FE, instrument the lagged dependent variable to prevent its correlation with the error term that the fixed effects transformation involves. These estimates are much closer to the parameters' true values. The GMM estimates are larger than IV but only because of the greater bias that the GMM estimates carry. The bias of the GMM estimator is presumably because of the weak instruments problem, as we anticipated in section 3. GMM performs worse than IV in terms of the precision of the estimates, also a consequence of weak instruments.

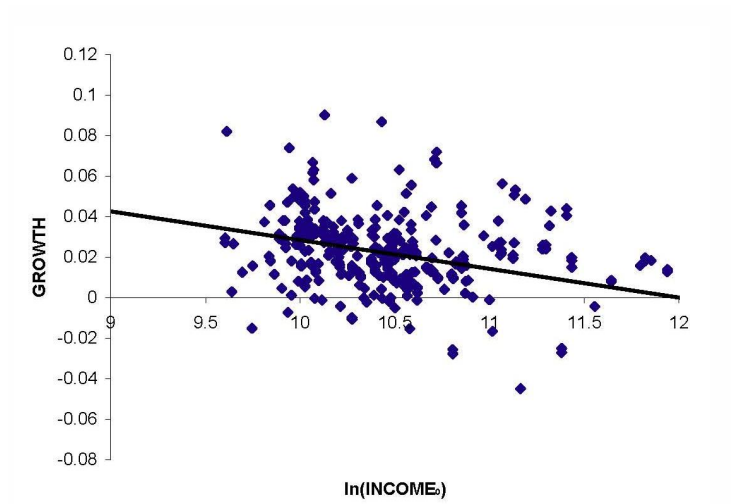


Figure 1: Unconditional Convergence, whole sample. The fitted line depicts the estimated equation $GROWTH = -0.014INCOME_0 + 0.171$, corresponding to an average speed of convergence of 1.4% per year.

Table 1: Descriptive Statistics for the Key Variables

Variable	No of Obs.	Mean	Std. Dev.	Min	Max
$\Delta INCOME_t$	956	0.025	0.049	-0.235	0.213
$INCOME_{t_1}$	960	43026	43138	7912	777264
$INCOME_{t_2}$	992	46896	46215	9308	777264
s_t	750	0.022	0.084	-0.474	0.31
ΔEMP_t	895	-0.007	0.036	-0.309	0.321
r_t	858	3601	6273	5	77542

Notes: $\Delta INCOME$: the average annual growth of value added per worker; $INCOME_{t_1}$: Start of period value added per worker, in PPP equivalent US\$, adjusted for CPI inflation; $INCOME_{t_2}$: End of period value added per worker; s_t : Growth rate of share of capital investment per worker, adjusted for CPI inflation; ΔEMP : Growth rate of employment; $R\&D$: R&D spending per worker, in PPP equivalent US\$, adjusted for CPI inflation.

Table 2: Regression Results

Dependent variable: $\ln \text{INCOME}_{t_2}$	OLS		LSDV		IV		GMM	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
$\ln(\text{INCOME}_{t_1})$	0.901 (0.015)	0.868 (0.017)	0.118 (0.117)	0.103 (0.113)	0.792 (0.157)	0.760 (0.053)	0.838 (0.186)	0.710 (0.237)
$\ln(s)_t - \ln(\text{EMP}_t)$	0.075 (0.012)	0.075 (0.012)	0.010 (0.034)	0.011 (0.034)	0.097 (0.012)	0.090 (0.014)	0.101 (0.042)	0.095 (0.041)
$\ln(\tau_t)$		0.019 (0.004)		0.058 (0.025)		0.045 (0.012)		0.061 (0.021)
λ	0.026	0.035	0.534	0.568	0.058	0.069	0.044	0.086
α	0.431	0.362	0.011	0.012	0.318	0.272	0.385	0.247
ϕ		0.092		0.064		0.137		0.157
Observations	710		710		384		384	
Industries	326		326		220		220	
Restriction validity test (p -value)	0.358	0.405	0.453	0.405	0.115	0.275	0.097	0.436
Overidentification test (p -value)					0.542	0.867	0.182	0.296

Note: INCOME_t : value added at time t ; $\ln(s)_t - \ln(\text{EMP}_t)$: log of investment net of the log of employment growth; $\ln(\tau_t)$: log of R&D per worker at time t ; λ : implied speed of convergence; α : implied share of physical capital; ϕ : implied share of R&D capital. Standard errors in brackets.

Table 3: Simulation Results

	True coefficient	OLS mean	std. error	LSDV mean	std. error
Dependent variable: $\ln \text{INCOME}_{t_2}$					
$\ln(\text{INCOME}_{t_1})$	0.7	0.94	0.008	0.224	0.033
$\ln(s_t) - \ln(\text{EMP}_t)$	0.1	0.063	0.022	0.09	0.034
$\ln(r_t)$	0.06	0.011	0.003	0.055	0.035
implied speed of convergence	0.089	0.016		0.374	
implied share of physical capital	0.25	0.512		0.104	
implied share of R&D capital	0.15	0.092		0.064	
	True coefficient	IV mean	std. error	GMM mean	std. error
$\ln(\text{INCOME}_{t_1})$	0.7	0.662	0.124	0.603	0.292
$\ln(s_t) - \ln(\text{EMP}_t)$	0.1	0.097	0.038	0.097	0.041
$\ln(r_t)$	0.06	0.057	0.037	0.059	0.039
implied speed of convergence	0.089	0.103		0.127	
implied share of physical capital	0.25	0.223		0.196	
implied share of R&D capital	0.15	0.132		0.12	