Searching for convergence and its causes – an industry perspective

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Abstract

The past 20 years has been a period of rapid growth in emerging economies, leading to convergence in income and productivity levels. Less is known about the industry origins of this development, a gap this papers aims to fill. For 30 industries in 40 economies, I estimate KLEMS-based relative productivity levels for the period 1995-2011. The results show that convergence was particularly rapid in goods-producing industries and that agriculture's shrinking share of activity in emerging economies also contributed to overall convergence. An analysis of potential productivity drivers shows that much less is known about what is behind the observed industry convergence.

Introduction

The rapid economic growth of emerging economies, such as China and India, has led to a remarkable convergence of income levels across countries. Indeed, Milanovic (2013) showed how the period since the late-1990s has been the first since the Industrial Revolution in which global income inequality has decreased. This has coincided with a renewed interest in the role of industry productivity in shaping cross-country income differences, the importance of structural change for aggregate outcomes, and continued efforts to establish whether drivers of productivity have a different impact depending on the level of technological sophistication.[1]

The contribution of this paper is to provide a more comprehensive analysis of the industry sources of aggregate convergence. The current literature in this area either gives a comprehensive coverage of industries, but only for OECD countries. This makes it hard to determine whether rich-country results are applicable to emerging economies as well. Alternatively, studies covers a wide range of countries but only for a specific sector of the economy, such as agriculture or manufacturing.[2] This makes it hard to determine whether a specific sector truly plays an exceptional role in explaining cross-country differences in economic performance. These shortcomings are remedied in this paper by covering 40 economies at a wide range of development levels and 30 industries making up the entire (market) economy.[3]

[1] See e.g. Restuccia, Yang and Zhu (2008), Vollrath (2009), Herrendorf and Valentinyi (2012), Lagakos and Waugh (2013) and Gollin, Lagakos and Waugh (2013) on industry productivity differences; on structural change, see e.g. Duarte and Restuccia (2010), McMillan and Rodrik (2011) and Herrendorf, Rogerson and Valentinyi (2013) and on the moderating role of technological sophistication, see Aghion, Akcigit and Howitt (2014).

[2] See e.g. Bernard and Jones (1996), Inklaar and Timmer (2009) and van Biesebroeck (2009) on industry-level convergence across OECD countries. See e.g. Restuccia, Yang and Zhu (2008), Vollrath (2009) and Gollin, Lagakos and Waugh (2013) on the role of agricultural productivity and see Rodrik (2013) on manufacturing.

[3] Excluded are industries for which the relative output level cannot be determined separately from relative input levels: government, health, education and real estate.

In the analysis in this paper, I will first determine the importance of specific sectors and the role of structural change in accounting for the observed convergence of aggregate productivity. Second, I look at a range of variables that have been suggested to influence productivity growth and (in some cases) to do so differently depending on the industry's distance to the technology frontier. The variables considered are human capital, research and development, (high-tech) imports, foreign direct investment (FDI) and competition.[4] If a particular variable has a larger positive effect on productivity growth in industries that are more distant from the technology frontier, it may help explain convergence.

To estimate relative productivity levels, I estimate prices of industry output and inputs. The data used are comparable to those used in the most recent version of the Penn World Table (see Feenstra, Inklaar and Timmer, 2013), drawing on detailed surveys of final consumption and investment prices[5] and estimates of relative export and import prices by Feenstra and Romalis (2014). Information on the input-output structure and prices of labor and capital are based on the World Input-Output Database (WIOD, Timmer 2012).

The resulting productivity estimates show that economy-wide productivity levels have moved substantially closer together between 1995 and 2011, helped by rapid productivity growth in countries like China, India, Russia and formerly Communist countries in Central and Eastern Europe. All major sectors – agriculture, manufacturing, services – contributed positively to this trend, though with the smallest degree of convergence in agriculture. Agriculture did contribute more substantially to aggregate convergence by shrinking in size, with its average

[4] On human capital, see Vandenbussche, Aghion and Meghir (2006) and Ang, Madsen and Islam (2011); research and development, see Griffith, Redding and Van Reenen (2004); on imports see Cameron, Redding and Proudman (2005) and Keller (2004); on FDI, see Alfaro, Chanda, Kalemli-Ozcan and Sayek (2010), Bloom, Sadun and van Reenen (2012) and Cipollina, Giovannetti, Pietrovit and Pozzolo (2012); and on competition, see Griffith, Harrison and Simpson (2010).

[5] See e.g. World Bank (2008).

share in value added almost halving over the period and declining most strongly in countries with low levels of agricultural productivity. This confirms the importance of agriculture's low productivity and high employment share in explaining cross-country income differences.[6]

To analyse potential drivers of observed industry convergence, I construct multifactor productivity growth rates using data from the Socio-Economic Accounts (SEA) of WIOD. These are KLEMS-type productivity growth rates, except that the changing composition of the capital stock is not taken into account. In regression analysis including a range of productivity-influencing variables, I show that higher spending on R&D, more imports of high-tech intermediate inputs, and more inward FDI are associated with faster productivity growth. However, none of these (or any other) effects vary systematically with proximity to the technological frontier. These results are robust to measurement error in industry productivity levels and robust across major sectors of the economy. So while we observe that industry productivity is converging across countries, we do not have a clear understanding why convergence is taking place and why in some industries and countries and not in others.

In the remainder of this paper, I will first lay out the methodology for measuring industry productivity levels and growth, followed by a description of the data and the results from the analysis. Following the results, I discuss where evidence on the sources of industry convergence might be found and some conclusions.

Methodology

The crucial input for the analysis of convergence is a set of industry productivity level estimates, so this section is mostly devoted to detailing the estimation of industry and aggregate productivity. For comparing industry productivity across countries at given point in

[6] As emphasised in Caselli (2005), Restuccia et al. (2008), Herrendorf et al. (2013), Lagakos and Waugh (2013) and Gollin, Lagakos and Waugh (2013).

time, consider an industry production function with outcomes for country c (omitting industry and time subscripts for simplicity):

(1) $$Y_c = F\left(X_{cj}, A_c\right),$$

where industry output Y is produced using inputs $X_j, j \in J$ and productivity level A. The production function is assumed to be identical across countries, but following Caves et al. (CCD, 1982a) I assume a translog form to allow for a substantial degree of flexibility.[7] Assuming perfect competition in factor and output markets and constant returns to scale, CCD show that relative productivity across countries can be computed as:

(2) $$\ln\left(A_c\right) - \overline{\ln\left(A\right)} = \ln\left(Y_c\right) - \overline{\ln\left(Y\right)} - \tfrac{1}{2}\sum_{j=1}^{J}\left(v_{jc} - \overline{v}_j\right)\left[\ln\left(X_{jc}\right) - \overline{\ln\left(X_j\right)}\right],$$

where an upper bar indicates the arithmetic mean over the set of countries and v_{jc} is the share in total costs of input j in country c. By comparing each country to a hypothetical average country, the resulting index is base country independent. To compare industry productivity at different points in time, this can be achieved by implementing equation (2) for every year. I will discuss the approach to implementing equation (2) – measuring relative industry output and input – in some more detail before turning to the data and results.

Industry output

Starting from input-output data (more on which below), we know the value of industry output at national prices but we need relative prices of industry output to compare the quantity of output across countries:

(3) $$\ln\left(Y_c\right) - \overline{\ln\left(Y\right)} = \left[\ln\left(V_c^Y\right) - \overline{\ln\left(V^Y\right)}\right] - \left[\ln\left(P_c^Y\right) - \overline{\ln\left(P^Y\right)}\right]$$

[7] As shown in Inklaar (2014), this flexibility is important since assuming the more-restrictive Cobb-Douglas production function would lead to biased estimates of convergence.

Equation (3) expresses the quantity of output in country c (for a given industry at a given point in time) as the ratio of the value of output V_c^Y and the relative price P_c^Y. This relative price is commonly referred to as a purchasing power parity (PPP) and it serves the same purpose as a producer price index for comparing the quantity of output of an industry over time.

Yet an index for cross-country producer price comparisons is not directly available. What is instead available are prices of consumption and investment goods from the International Comparison Program (ICP) and prices of exported and imported (merchandise) goods from Feenstra and Romalis (2014). Most studies on industry productivity[8] only use ICP prices, omitting prices of domestically produced but exported goods and ignoring that domestically consumed and invested goods also include imported goods. In this paper, I correct for both problems by estimating industry output prices as follows:[9]

$$\text{(4)} \quad \begin{aligned} \ln\left(P_c^Y\right)-\overline{\ln\left(P^Y\right)} = {} & \tfrac{1}{2}\left(r_c^Q+r_c^Z+\overline{r}^Q+\overline{r}^Z\right)\left(\ln\left(P_c^Q\right)-\overline{\ln\left(P^Q\right)}\right) \\ & +\tfrac{1}{2}\left(r_c^X+\overline{r}^X\right)\left(\ln\left(P_c^X\right)-\overline{\ln\left(P^X\right)}\right) \\ & -\tfrac{1}{2}\left(r_c^M+\overline{r}^M\right)\left(\ln\left(P_c^M\right)-\overline{\ln\left(P^M\right)}\right) \end{aligned} ,$$

where Q refers to goods for domestic final consumption and investment, Z refers to goods for domestic intermediate consumption, X to exports, M to imports, and r^k refers to the share of goods category k in the value of industry output, $r_c^k = V_c^k / V_c^Y$. The r^k's sum to one, satisfying the equality between the value of products supplied – through production or imports – and the value of products used – through (intermediate or final) consumption and investment. Note that only prices for final consumption and investment are available, necessitating the

[8] See e.g. Herrendorf and Valentinyi (2012).

[9] Except for the output price of agriculture, for which direct output price data is available, see the data section for more details.

assumption that prices of products for intermediate consumption equal prices for final consumption. Despite this simplifying assumption, equation (4) represents an important step forward by not having to assume that prices of exported and imported products equal the prices of final consumption and investment.

Industry inputs

Gross output of an industry is produced using factor inputs – capital and labor – and intermediate inputs. Following equation (3) for the relative quantity of output, the value of each input is combined with estimates of relative input prices. In the case of domestically produced intermediate inputs, the assumption is made that the relative price of industry output equals the relative price of an intermediate input from that industry; for imported intermediate inputs, actual price data is available. For labor, the available data allow for a distinction between three types of workers, namely high, medium, and low-skilled, each with information on their relative wage. The price of capital input is computed as the relative rental price of capital, P^K:

(5) $$\ln\left(P_c^K\right)-\overline{\ln\left(P^K\right)}=\left[\frac{r_c+\delta_c-\dot{P}_c^I}{\overline{r+\delta-\dot{P}^I}}\right]\left[\ln\left(P_c^I\right)-\overline{\ln\left(P^I\right)}\right],$$

where r_c is the required rate of return on capital in country *c*, δ_c is the average depreciation rate, P^I is the price of investment goods and a dot indicates a percentage change from one year to the next. The first term on the right-hand-side of equation (5) is the relative user cost of capital, which typically would be computed for each capital asset (so that the depreciation rate would have an asset subscript rather than a country subscript) but for lack of data on the asset composition of industry capital input for all countries, we use country-level average depreciation rates.

Aggregation

With measures of relative industry output and relative industry input, industry productivity can be computed based on equation (2), which results in productivity levels are on a gross output basis. These industry productivity differences have a magnified impact on the economy-wide productivity since part of the industry's output is used by other industries as intermediate inputs. Formally, Hulten (1978) showed that aggregate productivity (for the economy as a whole or for broad sectors) across *N* industries can be computed using Domar (1961) weights *w*:[10]

$$(6) \qquad \ln(A_c) - \overline{\ln(A)} = \sum_{i=1}^{N} \tfrac{1}{2}\left(w_{ic} + \overline{w}_i\right)\left(\ln(A_{ic}) - \overline{\ln(A_i)}\right),$$

where $w_{ic} = V_{ic}^{Y} \Big/ \sum_i V_{ic}^{VA}$ or the value of gross output in industry *i* divided by the sum of value added (gross output minus intermediate inputs) across all *N* industries.

Productivity growth

To measure productivity *growth* based on a translog production function (Diewert, 1976; Caves et al. 1982b), the change in productivity from *t*-1 to *t* (in a specific industry in country *c*) is measured as:

$$(7) \qquad \ln(A_t) - \ln(A_{t-1}) = \ln(Y_t) - \ln(Y_{t-1}) - \tfrac{1}{2}\sum_{j=1}^{J}\left(v_{jt} - v_{jt-1}\right)\left[\ln(X_{jt}) - \ln(X_{jt-1})\right]$$

This methodology is comparatively straightforward as the required data on changes in volumes of gross output, intermediate inputs, labour of different skill types and capital are (more) readily available from country National Accounts or other sources.

Data

[10] The analysis in Domar (1961) and Hulten (1978) refers to comparisons of productivity over time; equation (7) adapts this to a cross-country setting.

The approach to estimating industry productivity levels discussed in the previous section requires data on the input-output structure of each country over time and data on relative prices that can be used to infer industry output and input relative prices. The World Input-Output Database (WIOD) is used as the source of (harmonised) input-output tables, covering 35 industries and 40 countries for the period 1995-2011 (see Timmer, 2012). Together, these countries represent two-thirds of the world population and over 80 percent of world GDP and span much of the development spectrum, from India to the United States.

Importantly, WIOD allows for a distinction between domestically produced and imported intermediate inputs, so that the appropriate relative price can be applied. WIOD, and specifically the Socio-Economic Accounts (SEA), is also used for information on the labor compensation and number of hours worked by workers that are high-skilled, medium-skilled and low-skilled (based on their level of education).[11]

For computing prices of industry output (and hence domestically-produced intermediate inputs), relative prices for consumption and investment and relative prices for exports and imports are used (cf. equation (4)). Consumption and investment prices are from the International Comparison Program (ICP), run by the World Bank, and we use the three surveys covering a global sample of countries that were done in the 1995-2011 period, namely for 1996, 2005 and 2011.[12] We use the most detailed publicly-available data from each of these years and map consumption and investment categories to industries. Aggregating across expenditure categories is done using the CCD index. ICP prices are based on surveys of purchaser prices rather than producer prices, which means that differences in product taxes

[11] Capital compensation is determined as value added minus labor compensation. Aggregate compensation and employment data from PWT is used to extrapolate data from the final year covered in the Socio-Economic Accounts (2009) to 2011; note that this extrapolation is only used to update cost shares, not for estimating industry productivity growth.

[12] See World Bank (2008) for the description of the 2005 survey and results; the 2011 results are preliminary and unpublished.

and distribution margins would lead to a bias in industry output prices. I therefore use tax and margin data from WIOD to adjust the ICP prices.[13] For years not covered by ICP survey data, we use industry deflators to interpolate (for, say, 2007) or extrapolate (e.g. 1995) relative prices, as in Feenstra, Inklaar and Timmer (2013a).

For three of the services industries – government, health and education – the ICP prices do not reflect the prices paid by purchasers of theses services, since public provision or funding makes output prices hard or even impossible to observe. Instead, ICP aims to measure input prices, see Heston (2013). In our framework, this implies equal productivity levels across countries since relative 'output' prices equal relative input prices. These industries are therefore excluded when analysing productivity differences over time. Similarly, the real estate industry is excluded as (for the most part) its output is the imputed rental cost of owner-occupied housing and the 'private households with employed persons' industry is excluded as its dominant (sometimes only) input is labor (as well as incomplete coverage across countries). The remaining set of 30 industries will be referred to as the market economy.

Relative prices of exports and imports are from Feenstra and Romalis (2014), based on quality-adjusted unit values. Quality differences are inferred using a model of demand and supply of quality as an attribute of a traded good between two countries. Demand for quality is deemed high if observed demand is high but prices are not low; supply of quality is deemed high if supply is high despite high trade costs. We distinguish between prices of imported intermediates and imported final goods using the Broad Economic Classification (BEC) system, aggregating over more detailed products using the CCD index. Final good import prices are used when estimating industry output prices (equation (4)) and intermediates import prices are used when estimating industry intermediate input prices.

[13] See Inklaar and Timmer (2012) for more details on the mapping procedure and the adjustment for taxes and distribution margins.

In contrast to other industries, there is direct data on producer prices in agriculture, from the Food and Agricultural Organization (FAO). These have been widely used in studying productivity in agriculture, typically based on the relative prices estimated by Rao (1993).[14] For this analysis, I collected prices and production quantities for crops and livestock directly from FAO and aggregated these to overall agriculture relative output prices for each year using the CCD index.

The relative price of capital – estimated using equation (5) – requires data on investment prices, for which ICP prices can be used directly. The required rate of return is taken as the lending rate, taken from the IMF International Financial Statistics; the depreciation rates are from PWT version 8.0, which provides country-level average depreciation rates in each year; and the investment price change is from WIOD. One drawback is that relative investment prices only cover fixed reproducible assets, so omitting land. This omission can be particularly relevant for agriculture so I also computed relative productivity using the procedure of Vollrath (2009). The results for cross-country differences in agricultural productivity over time are qualitatively similar to those presented below.

Results

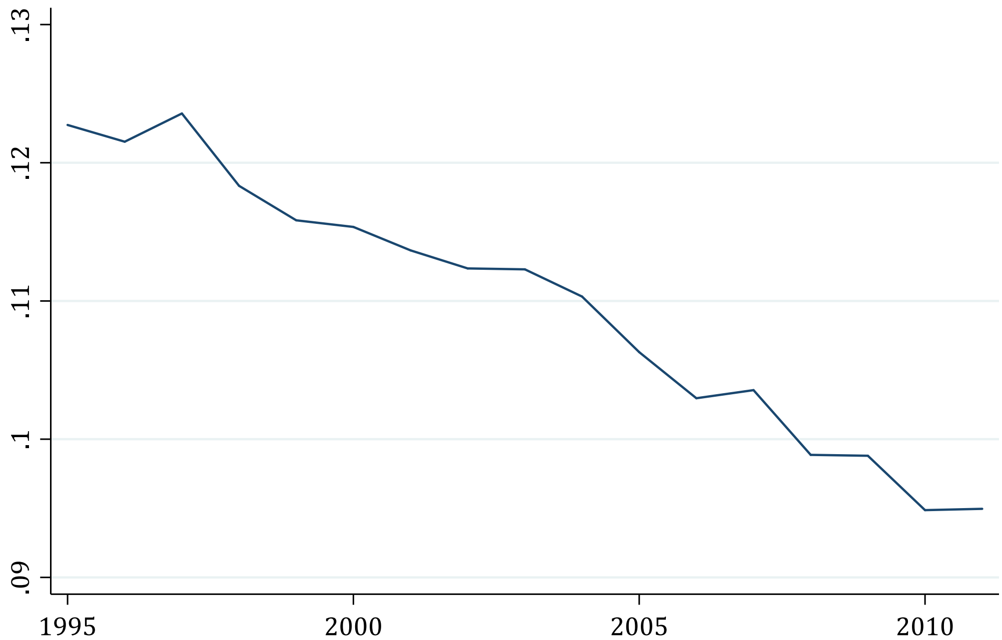
Productivity dispersion

To frame the context of the sectoral analysis, Figure 1 presents the trend in market economy productivity dispersion across the set of 40 countries covered in the analysis. As discussed above, the market economy refers to the aggregate of all industries except government, health and education, real estate and households. Each country's (log) productivity level is multiplied by the share in population to give greater weight to (e.g.) China and less to (e.g.) Cyprus. The figure shows a steady and substantial decline in the standard deviation, so that in 2011 it is 23 percent lower than it was in 1995.

[14] Studies using these data are e.g. Caselli (2005), Vollrath (2009) and Restuccia et al. (2008).

This finding of substantial aggregate convergence is also found if population-weighting is omitted (-20 percent) or when the total economy rather than the market economy is analysed (-26 percent). Furthermore, the 23 percent decline in Figure 1 is both economically substantial and, using the T_3 test of Carree and Klomp (1997), statistically significant at the 10 percent level. Figure 1 also shows that convergence has been a steady, continuous process over this period so that we can analyse convergence by simply comparing productivity dispersion in 1995 and 2011.

Figure 1, Market economy productivity dispersion, 1995-2011



Note: Productivity dispersion is measured as the standard deviation of log productivity levels, weighted using the share in sample population. Market economy covers all industries except government, health, education, real estate and households.

Aggregate convergence is due in part to rapidly rising productivity levels in China (increasing from 16 to 27% of the US level) and India (11 to 19%). However, big increases in relative productivity are also seen in Russia (27 to 44%) and in Central and Eastern Europe, where the 10 countries that joined the European Union in 2004 saw their productivity level increase from an average of 32 to 46% of the US.

To analyse the sectoral pattern of convergence and how these contribute to aggregate convergence, I follow a fairly standard split into major sectors, distinguishing agriculture, manufacturing, market services (transport, distribution, communication, hotels and restaurants, finance and business services) and other goods (mining, utilities and construction). Table 1 summarises this analysis and shows that productivity convergence is a broad-based phenomenon, with all major sectors showing lower dispersion in 2011 than in 1995. In manufacturing and other goods, the degree of convergence is statistically significant and comparable to the pace for the market economy. Market services and in particular agriculture show less convergence.

Table 1, Productivity dispersion in 1995 and 2011 by main sectors

	1995	2011	% Change	
Market economy	0.123	0.095	-23	*
Agriculture	0.223	0.209	-6	
Manufacturing	0.161	0.127	-21	*
Market services	0.082	0.069	-16	
Other goods	0.060	0.045	-25	*
Market economy at 1995 structure	0.123	0.104	-15	
Non-agricultural market economy	0.106	0.081	-24	*
at 1995 structure	0.106	0.082	-23	*

Notes: Table reports the standard deviation of log productivity levels, weighted using country shares in the sample population. * indicates that the indicated change is significant at the 10 percent level according to the T3 test of Carree and Klomp (1997).

Economy-wide convergence analyses for OECD countries have typically shown that productivity in services converges more rapidly than manufacturing productivity; this was the main result of Bernard and Jones (1996) and van Biesebroeck (2009) reports similar results. In contrast, the study of manufacturing productivity for a much broader set of countries by Rodrik (2013) showed clear evidence of convergence. The results in Table 1 suggest that the stronger convergence in services in OECD countries could well be specific to that group of countries.[15] The more sizeable productivity dispersion in agriculture is consistent with the broader literature (e.g. Caselli, 2005) and the relative lack of convergence in this sector shows that this greater dispersion is a persistent factor.

[15] Or to that time period, see e.g. van Ark, Inklaar and Timmer (2008) on diverging productivity growth patterns in market services across Europe and the US after 1995.

The bottom part of the table shows that agriculture has contributed to overall convergence, but mostly through structural change. The line 'Market economy at 1995 structure' shows how productivity dispersion would have changed if the value added shares of the 30 industries in the analysis had remained the same throughout the period in each country. In this counterfactual case, changes in industry productivity levels would still have led to convergence but much less than actually observed: a reduction in the standard deviation of 15 rather than 23 percent. Structural change can thus be said to account for about one-third of aggregate convergence.

The last two rows indicate that this is fully due to agriculture, as convergence in the non-agricultural market economy would have been equally strong if value added shares had remained constant at 1995 levels. The shift of economic activity out of agriculture is pronounced, with its share in value added declining from an average of 6.7 to 3.6 percent of the economy. Furthermore, this shift is most pronounced in countries with low levels of agricultural productivity, with the agricultural share in value added declining by more than 4 percentage points in Romania, Bulgaria, China and India; all countries with low relative productivity levels in agriculture.

Determinants of productivity growth and convergence

Though the aggregate productivity convergence is clearly broad-based, Table 1 already showed notable differences in the pace of convergence of the different sectors. These differences are even larger when analysing individual industries or countries. In the median industry, productivity dispersion decreased by 26 percent, close to the market economy rate but productivity dispersion in the telecommunications industry decreased by 78 percent, while productivity dispersion in land transport increased almost threefold. Indeed, 9 out of 30 industries showed divergence rather than convergence. Also, countries that show larger increases in their aggregate relative productivity levels tend to have more industries with increasing productivity levels, but the correlation is relative low at 0.24. This raises the question what could be driving these differences.

To answer this question, I use the following general model used broadly in the 'Schumpeterian' growth literature (Aghion et al., 2013):

$$(8) \qquad \Delta \ln\left(\frac{A_{ict}}{A_{ict-1}}\right) = \beta_1 \ln\left(\frac{A_{ict-1}}{A^F_{it-1}}\right) + \beta_2 X_{ict-1} + \beta_3 X_{ict-1} \times \ln\left(\frac{A_{ict-1}}{A^F_{it-1}}\right) + \eta_{ic} + \eta_t + \varepsilon_{ict}$$

In this equation, productivity growth for industry *i* in country *c* from year *t*–1 to year *t* (based on equation (7)) is explained using the proximity to the productivity frontier – the productivity level in country *c* relative to the productivity level of the country with the highest productivity level – (computed based on equation (2)) at *t*–1, explanatory variable *X* and an interaction between *X* and the proximity to the productivity frontier. In addition, a full set of country-industry dummies and year dummies is included. We would expect a negative coefficient for β_1, since a greater proximity to the productivity frontier implies fewer opportunities to achieve productivity growth by imitating frontier technologies.

The main interest is in coefficient β_3. If this coefficient is significantly different from zero, it implies that variable *X* has a different effect on productivity growth depending on the proximity to the productivity frontier. So, for example, Griffith et al. (2004) find that in countries that are closer to the frontier, research and development (R&D) spending contributes less to productivity growth, indicating that R&D spending helps both innovation (pushing out the frontier) and imitation (catching up to the frontier).

Table 2, Potential determinants of productivity growth and determinants – definitions and sources

Variable	Definition	Source
High-skilled	The share of university-educated workers in total hours worked	WIOD, SEA
High-tech M	Industry imports of intermediate inputs of chemicals, machinery, electronics & transport equipment as a share of industry gross output	WIOD
R&D	Business enterprise research and development expenditure as a share of industry gross output	OECD, Eurostat

Variable	Definition	Source
FDI	Stock of inward foreign direct investment as a share of gross output	OECD, Eurostat
Lerner	Ratio of price over marginal cost	INDICSER database

Note: WIOD, see www.wiod.org; INDICSER, see www.indicser.com.

Table 2 defines and describes the set of *X*-variables that are considered in the analysis. The first is the share of hours worked by high-skilled workers, which according the Vandenbussche et al. (2006) should contribute positively to productivity growth only in settings of close proximity to the frontier since more high-skilled workers would stimulate the rate of innovation. The second is the share of high-tech imports. As the survey of Keller (2004) discusses, imports of more advanced inputs are an important source of technology transfer, so these imports would be expected to have a greater impact on productivity growth for industries that are farther from the productivity frontier. Note that 'high-tech' uses the OECD definition of high and medium-high technology industries. The third variable is R&D, which according to Griffith et al. (2004) would have a greater impact in industries farther from the productivity frontier since R&D helps both innovation and imitation. The fourth variable is FDI, which – again – following Keller (2004) could be a source of foreign technology and thus help growth in industries more distant from the frontier. The final variable is the Lerner index, or price-cost margin, where a higher Lerner index implies less intensive competition. As discussed in Aghion et al. (2014), fiercer competition would be particularly beneficial for industries close to the frontier as those industries rely more on innovation for growth and (unless competition turns too cut-throat) competition is beneficial for growth.

Given these predictions, equation (8) can be estimated for each of the variables of interest. As indicated in the equation, the regressions include dummies for each country/industry pair to account for unobserved heterogeneity and year dummies to account for common shocks. In addition, I use two further lags of the explanatory variables (so at t–2 and t–3) as instruments in a two-step GMM procedure to reduce endogeneity concerns. Though more truly exogenous variables, such as the introduction of the European Single Market Program exploited by Griffith et al. (2010), would be preferable, these are typically hard to find. Finally, standard errors are clustered by country-industry pair to allow for correlation of errors within each cross-section.

Table 3, Explaining productivity growth and convergence – regression results

	(1) High-skilled	(2) High-tech M	(3) R&D	(4) FDI	(5) Lerner
Proximity to the frontier	-0.0273**	-0.0264**	-0.0496	0.0321	-0.00934
	(0.0118)	(0.0112)	(0.0371)	(0.0969)	(0.0237)
Explanatory variable	-0.000732	0.193**	0.943**	0.00186	0.297
	(0.0470)	(0.0803)	(0.393)	(0.00211)	(0.264)
Interaction	-0.0373	0.0355	-1.597	0.00328	0.256
	(0.0578)	(0.102)	(1.036)	(0.00593)	(0.186)
Observations	13435	13435	5676	4398	1955
Overid. restrictions	0.435	0.0469	0.146	0.256	0.437

Notes: each column represents a separate regression explaining productivity growth using the proximity to the productivity frontier, the explanatory variable that is identified in the column header and an interaction between the proximity to the frontier and the explanatory variable, see also equation (8) for the specification and Table 2 for definitions of the explanatory variables. Each regression includes country/industry dummies and year dummies and two lagged values of the independent variables are used as instruments in a two-step GMM procedure. Standard errors, clustered by country/industry pair, are in parentheses. 'Overid. restrictions' gives the p-value of the Hansen J statistic on the overidentifying restrictions of all instruments. *** p<0.01, ** p<0.05, * p<0.1

Table 3 shows the results of the analysis. The first row shows that in the full sample (columns 1 and 2), industries that are closer to the productivity frontier grow less rapidly. In the more limited samples for R&D (mostly manufacturing and omitting some emerging economies), FDI (omitting some emerging economies) and Lerner (only 8 European economies after 2002) these coefficients are not significantly different from zero. Turning to the explanatory variables, the table shows that high-tech imports and R&D intensity have a significant positive effect on productivity growth, yet the effect does not vary depending on the proximity to the productivity frontier. In fact, none of the interaction coefficients is significantly different from zero, thus failing to contribute to our understanding of why some industries show faster convergence than others.

Although finding for a particular variable that is has a stronger effect on productivity growth for industries farther from the frontier would be a clear indication that this variable enhances the rate of convergence, a more indirect way would be if that variable has a direct effect on productivity growth and takes on higher values in industries farther from the frontier. The high-tech import share is negatively correlated with the proximity to the frontier but at -0.04, the relationship is weak. In contrast, R&D intensity is positively correlated with proximity to the frontier and, at 0.11, this relationship is somewhat stronger. So, if anything, the high-tech import share is a force of convergence, while R&D would lead to divergence. However, it is unclear whether these correlations have systematic drivers or are a coincidence.

To establish the robustness of the results in Table 3, I first consider that the industry proximity to the frontier could be measured with error and that, due to the persistence in this variable, this is not adequately addressed by using lagged values of industry proximity. In the first sensitivity analysis, I therefore use two lagged values of the aggregate proximity to the productivity frontier as instruments for industry proximity to the frontier. These are clearly weaker instruments, as indicated by first-stage F-statistics, and the test on overidentifying restrictions is rejected in two of the five specifications, indicating that the aggregate instrument is not valid. The other three specifications show broadly similar results and no significant interaction terms.

In the second sensitivity analysis, I run the regressions for major sectors, i.e. subsets of industries rather than all industries together. Specifically, I run regressions for manufacturing, market services and other goods (including agriculture, as well as mining, utilities and construction). This provides some weak evidence that high-skilled workers contribute more to productivity growth in market services industries farther from the frontier; that high-tech imports contribute more to productivity growth in other goods industries farther from the frontier but that FDI contributes less to growth in those same industries.

Discussion and conclusions

In this paper, I have analysed productivity convergence from an industry perspective for an unusually detailed and broad set of countries and industries: 40 economies across the development spectrum and 30 industries covering the market economy (i.e. excluding those industries where no sensible productivity measures could be computed). The first aim was to document the industry sources of aggregate convergence, moving beyond the single-sector studies, to determine who their results fare compared to those of other sectors, and OECD-sample studies, to establish to what extent the findings from those studies can be generalised to emerging economies as well.

This analysis showed how all major sectors – agriculture, manufacturing, services, other goods production – contributed to the rapid aggregate convergence. Convergence was strongest in manufacturing and other goods-producing industries, somewhat weaker in services and weakest in agriculture. The stronger convergence in manufacturing suggests that some of the evidence showing (faster) convergence in services in OECD countries does not generalise to the current broader set of countries and more recent period. Conversely, the results are more in line with the findings of Rodrik (2013) of (unconditional) convergence of manufacturing productivity.

The second aim of this paper was to establish why some industries show more rapid convergence than others by testing whether a variety of variables have a greater effect on productivity growth in industries that are more distant from the productivity frontier. While some variables – R&D and high-tech imports intensity – were indeed significantly related to productivity growth, others – high-skilled worker, FDI and competition – were not. More importantly, none of the variables showed a significantly different effect on productivity growth depending on the proximity to the productivity frontier.

So where to look to better understand productivity convergence? It could be that the specification chosen here is not appropriate; for instance it could be that learning takes place in proportion to actual trade or investment between specific countries (e.g. Keller, 2004) instead of a common pace of learning from the frontier industry. Beyond that, a first set of alternative candidates are sector or industry-specific regulations, such as import tariffs and other trade restrictions (e.g. Lileeva and Trefler, 2010) or barriers to entry (Nicoletti and Scarpetta, 2003). Other candidates are macro variables whose effects differ across industries, such as financial development (Rajan and Zingales, 1998), infrastructure (Fernald, 1999) or labor market institutions (Bassanini, Nunziata and Venn, 2009). A third possibility would be that a variable considered here has a different effect depending on some other variable that is related to, but not perfectly correlated with (industry) productivity. For example, Alfaro et al. (2010) find that FDI has a larger effect on productivity in countries with a greater level of financial development.

All these alternatives are potentially important and may provide further insights into observed convergence patterns. However, existing evidence tends to be limited in terms of countries or industries covered or obtained in empirical frameworks that make it hard to draw firm conclusions on productivity convergence. So given this state of our knowledge, the best we can do is be grateful for any productivity convergence that occurs.

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