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 chapter aims to fill. For 30 industries in 40 economies, I estimate industry relative productivity levels for the period 1995-2011. The results show that convergence was concentrated in manufacturing. An analysis of potential productivity drivers shows that much less is known about what is behind the observed industry convergence.

Introduction

While the recent work of Piketty (2014) and others has drawn great attention to rising inequality of income levels and wealth within many countries, the rapid growth of emerging economies, such as China and India, has led to a decline in global interpersonal income inequality (Milanovic, 2013). Even by the exacting standard of Pritchett (1997) – the ratio of GDP per capita in the US relative to the country with the lowest level of GDP per capita – the Great Divergence that had been ongoing since 1870, seems to have ended around the year 2000. This change in the evolution of world income distribution calls for an explanation. One area of the literature has focused on the role of industry productivity in shaping cross-country income differences, the importance of structural change for aggregate outcomes, and identifying drivers of industry productivity growth and whether these have a different impact depending on the level of technological sophistication.[2]

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 begs the question 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.[3] This begs the question whether a specific sector truly plays an

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

[3] 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 (2014) on the role of agricultural productivity and see Rodrik (2013) on manufacturing.

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.[4]

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.[5] 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, 2015), drawing on detailed surveys of final consumption and investment prices[6] and estimates of relative export and import prices by Feenstra and Romalis (2014). Information on the input-output structure and prices of labour and capital are based on the World Input-Output Database (WIOD, Timmer 2012).

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

[5] On human capital, see Vandenbussche, Aghion and Meghir (2006) and Ang, Madsen and Islam (2011); on 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).

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

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. Of the major sectors of the economy, only productivity levels in manufacturing have moved substantially closer together while in agriculture, services and other goods production the dispersion of productivity levels has changed only little. Agriculture did contribute more substantially to aggregate convergence by shrinking in size, with its average share in value added almost halving over the period and declining most strongly in countries with low levels of agricultural productivity. This points to the importance of agriculture's low productivity and high employment share in explaining cross-country income differences.[7] Overall, structural change has contributed about one-fifth of total convergence.

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.

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[7] As emphasized in Caselli (2005), Restuccia et al. (2008), Herrendorf et al. (2014), Lagakos and Waugh (2013) and Gollin, Lagakos and Waugh (2014).

It should be noted that the broad country coverage of the analysis in this paper comes at clear cost in terms of measurement quality. First, the comparison of industry output prices cannot be of as high a quality as in Jorgenson, Nomura and Samuels (2015), who rely on more extensive and more price comparisons. More in general, the data required to compare prices across countries is much less extensive than for comparing prices over time, while at the same time cross-country price differences tend to be much larger. Second, unlike in the standard KLEMS methodology, information about the asset composition of industry capital inputs could not be taken into account. As discussed in OECD (2009), this is a crucial element in measuring productive capital inputs. Taken together, this implies that the resulting estimates of, in particular, comparative productivity levels should be considered as experimental, rather than definitive. The methodological issues mentioned here will be discussed in more detail in the next section. In discussing the results and drawing conclusions, I will argue that the measurement shortcomings likely lead me to overestimate the degree of productivity convergence, while the regression-based analysis is likely to mostly unaffected.

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. A more detailed exposition of the underlying production theory is given in Inklaar and Diewert (2015). For comparing industry productivity across countries and time, consider an industry production function with outcomes for country c at time t (omitting industry subscripts for simplicity):

(1) $Y_{ct} = F\left(X_{cjt}, A_{ct}\right),$

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. 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) $\ln\left(A_{ct}\right) - \overline{\ln\left(A\right)} = \ln\left(Y_{ct}\right) - \overline{\ln\left(Y\right)} - \frac{1}{2} \sum_{j=1}^{J} \left(v_{jct} - \overline{v}_j\right)\left[\ln\left(X_{jct}\right) - \overline{\ln\left(X_j\right)}\right],$

where an upper bar indicates the arithmetic mean over the set of countries and years and v_{jct} is the share in total costs of input j in country c at time t. Note that this definition of relative productivity levels is specifically tailored to a multi-country setting where an important aim is that the comparison should be transitive, i.e. $\frac{A_c}{A_k} = \frac{A_c}{A_m}\frac{A_m}{A_k}$ for any set of countries c, m and k.

Following CCD, this is achieved by comparing every country to a (hypothetical) average country. Furthermore, to enable a comparison of productivity levels across countries *and* at different points in time, the average of output levels, input levels and cost shares is computed over the countries and year. The approach of comparing a relative output to a relative input level is relevant more generally and is implemented also in Jorgenson, Nomura and Samuels (2015). Their comparison is bilateral, between Japan and the United States, which allows them to achieve a level of industry and input detail that cannot be achieved in the 40-country setting of this paper, but theirs is another example of industry productivity comparisons based on a translog production function. I will discuss the approach to implementing equation (2) – measuring relative industry output and input levels – 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:

$$(3) \qquad \ln(Y_{ct}) - \overline{\ln(Y)} = \left[\ln(V_{ct}^Y) - \overline{\ln(V^Y)} \right] - \left[\ln(P_{ct}^Y) - \overline{\ln(P^Y)} \right]$$

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_{ct}^Y and the relative price P_{ct}^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.

Ideally, these PPPs would be based on producer price data, but the lack of dedicated survey data means that alternative approaches have been followed in the literature. When focused only on manufacturing, some have opted to use exchange rates to compare output from different countries, assuming a relative price of one (e.g. Rodrik, 2013). An argument in favour of this approach is that many manufactured products are traded and thus more exposed to the pressures of the Law of One Price (LOP). But this argument is not fully convincing given the systematic deviations from LOP even for products that are internationally traded (Feenstra and Romalis, 2014; Burstein and Gopinath, 2014) and the very limited trade in some manufactured products, such as ready-mixed concrete (Syverson, 2008).

The main alternative approach, that can also be applied outside manufacturing, is to use relative prices collected as part of the International Comparison Program (ICP). These prices form the basis of the GDP PPPs disseminated by the World Bank (2008, 2014) and are based on prices of consumption and investment goods and services. Relative output prices at the industry level are estimated by selecting and combining the prices of goods that are produced by each, as in Sørensen and Schjerning (2008), van Biesebroeck (2009) and Herrendorf and Valentinyi

(2012). Given its broad application, it can be seen as the standard approach, yet it has drawbacks as well. For one, the prices of goods consumed or invested domestically do not take into account the prices of exported products while they are influenced by the prices of imported goods. Furthermore, final consumption and investment prices are not well-suited for comparing prices of industries that produce mostly intermediate inputs.

The most thorough recent approach to resolving these challenges is discussed in Jorgenson, et al. (2015). They compare prices and productivity between Japan and the US and their estimates of relative output prices rely on a variety of sources, including a dedicated survey of intermediate input prices.[8] Most of this information is not available for the broader range of countries covered in this analysis, so I have to rely on ICP prices and relative prices of exports and imports. This still constitutes an improvement over most studies on industry productivity that only use ICP prices, but is some distance removed from the Jorgenson et al. (2015) 'gold standard'. The possible empirical implications of this will be discussed later.

I take the following approach to estimating industry output prices:[9]

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

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

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[8] See Nomura and Miyagawa (2015) for details.

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

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 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 labour – 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 labour, 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) $\quad \ln\left(P_{ct}^K\right) - \overline{\ln\left(P^K\right)} = \left[\dfrac{r_{ct} + \delta_c - \dot{P}_{ct}^I}{r + \delta - \dot{P}^I}\right]\left[\ln\left(P_{ct}^I\right) - \overline{\ln\left(P^I\right)}\right],$

where r_{ct} is the required rate of return on capital in country c, δ_c is the average depreciation rate, P_{ct}^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.

Ideally, equation (5) would be applied to individual capital assets and the resulting relative rental prices would be aggregated to an overall capital input PPP using capital compensation

shares. This would be the cross-country counterpart of the capital services methodology as outlined in, for example, OECD (2009) and as applied for the Japan-US comparison by Jorgenson et al. (2015). This is, alas, an area where data limitations lead to a serious methodological shortcoming. While data on capital stocks and compensation by asset and industry is available for a growing number of countries, data availability is still limited and would not allow for a full coverage of countries. The possible implications of this methodological shortcoming will be discussed later. Given the lack of data on the asset composition of industry capital input for all countries, we use country-level average depreciation rates in equation (5).

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]

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

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.

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[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.

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:

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

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

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. For information on country input-output structures, I make use of the World Input-Output Database (WIOD). This is a source of harmonised input-output tables, covering 35 industries and 40 countries for the period 1995-2011. 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.

The construction and features of the WIOD are described in detail in Timmer (2012) and the database is also used in Timmer, Los and de Vries (2015) to analyse the development of global value chains (GVC) on competitiveness and the labour market. The WIOD is constructed based on national supply and use tables (SUTs), combined with time series data from country National Accounts to ensure consistency with trends in industry output and overall economic activity. Importantly for GVC analysis, the SUTs are combined with data on trade in goods and services. This way, it is possible to distinguish the composition of intermediate inputs not only in terms of *what* products are used, but also *where* these products are produced and, in many cases,

imported from. For the purposes of this chapter, though, this level of detail is not necessary as only a distinction between domestically-produced and imported intermediate inputs (from any country) is needed. Still, the fact that much effort has gone into harmonizing the industrial classifications across countries makes the WIOD ideally suited for this type of cross-country analysis.

However, a crucial difference with, for example, Timmer et al. (2015) is that the input-output data from WIOD is not sufficient for the analysis in this chapter as these only provide cost shares – the v_{jc} from equation (2) – and nominal output values – V_c^Y from equation (3). We additionally need information on relative prices to allow for comparisons of output and input quantities and thus relative productivity estimates. In part, these are drawn from the Socio-Economic Accounts (SEA) of WIOD. These provide information on the labour compensation and number of hours worked by workers that are high-skilled, medium-skilled and low-skilled (based on their level of education) as well as on capital stocks.[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

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[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 and World Bank (2014) for the 2011 results.

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 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 (2015).

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 labour (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,

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[13] See Inklaar and Timmer (2014) for more details on the mapping procedure and the adjustment for taxes and distribution margins.

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.

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

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

and education, real estate and households. Each country's (log) productivity level is multiplied by the share of factor inputs to give greater weight to (e.g.) China and less to (e.g.) Cyprus.[15] The figure shows a substantial and fairly steady decline in the standard deviation, so that in 2011 it is 26 percent lower than it was in 1995.

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 of factor inputs. Market economy covers all industries except government, health, education, real estate and households.
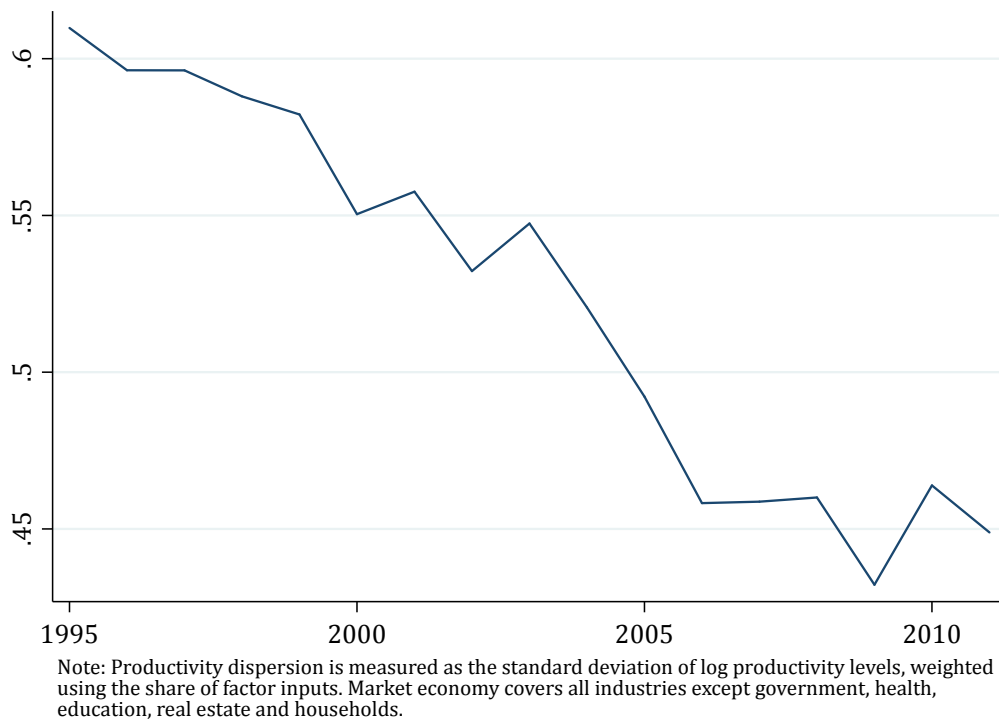
Aggregate convergence is also found if weighting is omitted (−9 percent). Furthermore, the 26 percent decline in Figure 1 is both economically substantial and, using the T^3 test of Carree and Klomp (1997), statistically significant at the 10 percent level. Figure 1 also shows that the finding of convergence is a fairly continuous process so the subsequent comparison will be done by comparing the dispersion in 2011 to that in 1995. Aggregate convergence is due in part to rapidly rising productivity levels in China (increasing from 22 to 34 percent of the US level) and India (27 to 38 percent). However, big increases in relative productivity are also seen in

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[15] See Inklaar and Diewert (2015) for a more detailed exposition.

Turkey (35 to 46 percent) and in Central and Eastern Europe, where big increases can be seen in countries like Estonia (35 to 49 percent) and Poland (42 to 54 percent).

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 almost entirely driven by convergence in manufacturing, where productivity dispersion fell by 48 percent. Dispersion in agriculture and other goods was approximately constant, while market services shows an increase in dispersion.

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

	1995	2011	% Change	
Market economy	0.610	0.449	-26	*
Agriculture	0.852	0.827	-3	
Manufacturing	1.079	0.565	-48	**
Market services	0.375	0.419	12	
Other goods	0.360	0.342	-5	
Market economy at 1995 structure	0.624	0.492	-21	

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 (5) percent level according to the T^3 test of Carree and Klomp (1997).

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) has similar findings. 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 convergence of productivity in services in OECD countries is specific to that group of countries or to the time period rather

than a more general results.[16] The 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 large dispersion is a persistent factor.

The bottom part of the table shows that structural change was an important factor for overall convergence. 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 at 1995 levels 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 21 rather than 26 percent. Structural change can thus be said to account for about one-fifth of aggregate convergence.

The agricultural sector made a positive contribution to overall convergence as the sector's share of (nominal) market economy value added decreased from an average of 8.5 percent in 1995 to 4.7 percent in 2011 and productivity dispersion in the sector is larger than for the market economy as a whole throughout the period. The role of the other sectors is more mixed: there was a clear shift in economic activity away from agriculture and manufacturing (27.8 to 22.9 percent) and towards market services (50.1 to 57.4 percent), but the pattern of dispersion in the beginning and end of the period relative to the market economy makes the overall impact of each sector harder to gauge.

At this point, is helpful to step back and consider how the methodological limitations regarding the measurement of industry output prices and capital input prices that were detailed in the previous could affect these results. Regarding the industry output prices, I compared my detailed Japan-US industry output prices for 2005 to those reported in Nomura and Miyagawa (2015, Table 3) and used in Jorgenson et al. (2015). On an encouraging note, the two sets of

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[16] See e.g. van Ark, Inklaar and Timmer (2008) on diverging productivity growth patterns in market services across Europe and the US after 1995.

industry output prices are positively correlated, but with a correlation of 0.54 there are also notable differences. Some of those differences will cancel out, as there are industries where I find higher relative prices and those where I find lower relative prices than Nomura and Miyagawa (2015). But overall, my estimates seem to overestimate relative industry output pries compared to Nomura and Miyagawa (2015), which would, *ceteris paribus*, lead to lower relative productivity levels in Japan relative to the US in the year 2005. This degree of overestimation of output prices seems to be larger in market services than in manufacturing.

It is harder to draw broader lessons from this comparison for my results regarding productivity convergence. For one, there is no clear pattern or systematic reason for the differences between the two sets of industry output prices, so generalizing the difference for Japan-US in 2005 to other countries and years would not be well-grounded. More generally, for the convergence results to be affected, the degree of overestimation of my estimated industry output prices compared with the 'true' industry output prices would have to be a) larger in manufacturing than in other sectors, b) be larger in lower-income economies, and c) decrease over time. If all these conditions were met, the productivity dispersion in manufacturing at the start of the period would have been overestimated compared to later years and compared to other sectors, potentially overturning the 'faster convergence in manufacturing' result. It is not impossible for these conditions to be met, but there is no evidence pointing in this direction.

It is possible to make a more informed assessment about the potential bias in relative productivity estimates from missing data on the asset composition of industry capital stocks based on economy-wide asset composition. The depreciation rate of structures is low compared to depreciation rates for equipment – around a 2 percent annual geometric rate for structures, compared to 10-35 percent depending on the type of equipment. As a result, structures will tend to account for a relatively large share of the value of the capital stock. This is confirmed when looking at economy-wide (weighted) average depreciation rates – as reported in the Penn World Table (Feenstra et al. 2015) – of, on average, 4 percent. Moving

from a homogenous capital stock to a (more appropriate) capital services measure will give a lower weight to structures, since the user cost of capital increases with the asset depreciation rate (equation (5)). We also know that relative investment prices of equipment tend to differ less across countries than relative prices of structures (see e.g. Hsieh and Klenow, 2007). This is because equipment is largely imported, while investment in structures relies heavily on local (labor) input. As a result of the Balassa-Samuelson effect, the relative price of structures will be lower in lower-income countries. Compared to the capital input prices used in this analysis, lower-income countries would tend to have higher capital services prices and thus higher productivity levels. This would mean that productivity dispersion is overstated in my results, a prediction borne out by the results of Inklaar and Timmer (2009, Table 4). In their sample of mostly high-income countries, productivity dispersion is approximately 15 percent lower when appropriately accounting for the asset composition of industry capital stocks. As lower-income countries grow richer, this degree of overstatement should decrease. In other words, it seems likely that some of the convergence found in my data is due to mismeasured capital input prices. It is not clear, though, that this problem would be more severe in manufacturing than in other sectors, though.

Determinants of productivity growth and convergence
Though the aggregate productivity convergence is clearly broad-based, Table 1 already showed notable differences in the pattern of convergence and divergence of the different sectors. These differences are even larger when analyzing individual industries or countries. In the median industry, productivity dispersion decreased by 21 percent, similar to the market economy rate but productivity dispersion in the textiles and wearing apparel industry decreased by 58 percent, while productivity dispersion in air transport increased by 24 percent. Indeed, 6 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 low at 0.09. 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., 2014):

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

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 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.

Table 2, Potential determinants of productivity growth and determinants

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
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.

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 shows the results of the analysis. The first row shows industries that are closer to the productivity frontier grow less rapidly, though in the more limited samples for R&D (mostly manufacturing and omitting some emerging economies) and FDI (omitting some emerging economies) these are less significant. In the final column, the coefficient is not significantly different from zero and the sample covers only 8 European economies after 2002. Turning to the explanatory variables, the table shows that high-tech imports, R&D and FDI have a significant positive effect on productivity growth, but 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.

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	−0.0279***	−0.0334***	−0.0174*	−0.0185*	0.0369
	(0.00765)	(0.00755)	(0.00957)	(0.0108)	(0.0310)
Explanatory variable	−0.00123	0.162***	0.852***	0.00259**	-0.101
	(0.0386)	(0.0582)	(0.329)	(0.00103)	(0.201)
Interaction	−0.0276	0.0663	−0.478	−0.00283	−0.279
	(0.0338)	(0.0430)	(0.395)	(0.00254)	(0.216)
Observations	13435	13435	5676	4398	1955
Overid. restrictions	0.727	0.404	0.129	0.197	0.0482

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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

If the results had shown that a particular variable had a stronger effect on productivity growth for industries farther from the frontier, this would have been clear evidence 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 have considered 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 pattern of results is the same.

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 evidence that the impact of FDI varies with proximity to the frontier, but is unclear why FDI would have a stronger effect on productivity growth when an industry is close to the productivity frontier in manufacturing and other goods production, but a weaker effect in market services.

It is, again, useful to consider how the measurement of relative prices may influence these results. Given the regression context of this analysis, it is helpful to view this as an error-in-

variables problem: I measure 'true' productivity growth and proximity to the frontier with error. Inklaar, Timmer and van Ark (2008) consider alternative measures of industry productivity growth and comparative levels, based on EU KLEMS data, and I can compare their measures that do not account for differences and changes in asset composition with those that do. The correlation between these two sets of measures is 0.99 for both productivity growth and comparative levels. Their sample of countries is more limited, covering mostly high-income countries, but there is no obvious reason to suspect that the measurement error from not accounting for asset composition differences and changes would be notably different in a broader sample of countries. In other words, there is little reason to suspect that using the methodologically more appropriate capital services methodology would lead to substantively different regression results.

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 sectoral sources of aggregate convergence. Compared with the existing single-sector studies or OECD-sample studies, this analysis offers much more scope for generalizable results.

This analysis showed how only the manufacturing sector contributed to the rapid aggregate convergence. This 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, FDI and high-tech imports intensity – were indeed significantly related to productivity growth, others – high-skilled workers 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? In a volume such as this, a first point for discussion is surely more appropriate data. As I have discussed in some detail, the lack of data on the asset composition of industry capital stocks means that I cannot implement the full KLEMS methodology with a capital services approach. An implication for the convergence analysis of this measurement shortcoming is that I likely overestimate the degree of convergence. Furthermore, the industry output price comparison is based on imperfect source material, which seems to lead to notably difference relative prices than the more extensive price information used by Jorgenson et al. (2015) for the Japan-US 2005 comparison. This is a source of uncertainty, as the differences for one country pair in one year are hard to generalize. So especially for measuring the degree of productivity convergence, more appropriate data on industry output and capital prices are sorely needed. In the context of the regression results, though, there is likely less impact of the lack of a capital services approach in estimating productivity growth and comparative levels, as data based on EU KLEMS show very high correlations between growth and comparative level measures that do and do not apply the capital services methodology.

There are other concerns about the regressions analysis, though. 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 rate 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 labour 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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