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Abstract

We infer sectoral productivity from trade and production data and test the hypothesis that technological catch-up is slower in tacit knowledge intensive sectors, operationalised by measures of complex task intensity. Furthermore, we examine whether catch-up is slower in sectors with a large skill intensity, a high degree of export sophistication and high income elasticity. Employing Comtrade and UNIDO data between 1960 and 2000 covering manufacturing sectors, we find that catch-up is slower in more tacit knowledge intensive sectors, as well as in skill intensive and export sophisticated sectors. With more recent data from 1997 to 2011 from GTAP we find instead that catch-up is faster in more tacit knowledge intensive manufacturing sectors, whereas catch-up is slower in more tacit knowledge intensive services sectors. Catch-up is consistently faster in income elastic sectors, both for manufacturing and services.

Keywords: sectoral TFP, tacit knowledge, technological catch-up

JEL classification: F14, F43, I25

CONTENTS

1 Introduction

As recently pointed out in a European Commission report (EC (2015)) EU manufacturing exports to traditional high-income markets of North America and Europe tend to be substituted by products from emerging industrial powers. Stehrer, et al. (2016) report the decrease in world market shares for manufacturing sectors between 1995 and 2013 in EU, US and Japan, while in China and other Asia an increase is observed. In the US the share of manufacturing production has fallen substantially. Kehoe, et al. (2017) point out that the share of labor compensation in goods (relative to services and construction) has fallen from 19.7% to 12.5% between 1992 and 2012. Mathews (2006) suggests that countries that have done best in raising their share of global manufacturing value added are those that have mastered the intricacies of medium- and high-technology manufacturing industry. Bloom, et al. (2016) examine the impact of Chinese import competition on technical change in twelve European countries and find that in sectors more exposed to Chinese exports high tech firms are relatively sheltered while in low-tech firms jobs and survival rates fell. Whereas productivity growth in the United States significantly accelerated since the mid 1990s, the European Union has experienced a slowdown. This leads to increasing calls for revival of industrial policy in the EU. The question is, however, which sectors the industrialized countries should promote.

In this paper we focus on differences in the competitive pressure faced by the rich countries, because of technological catch-up of the emerging countries. Rich countries specializing in sectors insulated from competition will see their welfare better maintained. We hypothesize that differences in the relevance of tacit knowledge across sectors are crucial for technological catch-up. In most countries foreign sources of technology account for the biggest part of productivity growth (Keller , 2004). Thus, the speed of catch-up depends on how fast that foreign technology diffuses to the domestic economy. Although the information and communcations technology (ICT) revolution has made the transfer of knowledge easier, not all knowledge can be transferred at zero cost through IT or through imports of capital equipment. Some of it is tacit by nature and is transferred only through extensive personal contact (Gertler , 2003). The impossibility or difficulty to codify such knowledge slows down technology diffusion and thus catch-up.

In this paper we test the hypothesis that catchup is slower in sectors where tacit knowledge is more important. Furthermore, we test hypotheses that catch-up is slower in sectors with larger export sophistication, in more skill-intensive sectors, and in sectors with a higher income elasticity. Following recent approaches in the trade literature (Costinot, et al. (2012), Chor (2010), Shikher (2012), Levchenko and Zhang (2016)), we use trade and production data to infer sectoral productivity. We estimate sectoral gravity equations employing the importer fixed effects of the gravity equation as a combined measure of productivity and the price of input bundles. Using data on the price of input bundles we obtain then technology parameters relative to a reference country. Using TFP data in the reference country, the US, makes it possible to obtain revealed productivity measures for each country in the dataset. We implement this approach to infer sectoral productivity with datasets from two time-periods, Comtrade and UNIDO data for 1960-2000 for manufacturing sectors and GTAP data for 1997 to 2011 for both manufacturing and services.

We construct tacit knowledge intensity measures using data on tasks and occupations. We choose the task approach to measure the intensity of tacit knowledge in a sector because complex tasks that are difficult to codify reflect the tacit nature of a work activity. The skills of complex work activities as tacit knowledge are acquired by experience and are difficult or impossible to codify, thus the transfer of it needs an extensive face-to-face interaction.

We get four main results. First, in line with our hypothesis we find that technological catchup is significantly slower in tacit knowledge intensive manufacturing sectors with a high tacit knowledge intensity, skill intensity, and export sophistication, using the earlier data from 1960-2000 from UNIDO and Comtrade. Second, contrary to our hypothesis we find with the later GTAP data that catch-up is faster from 1997-2011 in the tacit knowledge and skill intensive and sophisticated manufacturing sectors. Third, catch-up is found to be slower in tacit knowlege, skill intensive and sophisticated manufacturing sectors with the later data. Fourth, contrary to our hypothesis based on the home market effect but in line with the strategy in particularly observed in Asian countries to concentrate on exports to high-income markets and product development we find that catchup is faster in sectors with a higher income elasticity.

We discuss three potential explanations for the changing association of catchup with tacit knowledge intensity when moving from the older data to the more recent data. First, in the recent period, foreign direct investment (FDI) to emerging countries has hugely increased. According to UNCTAD (2014) FDI flows to developing economies reached a new high in 2013 and totaled 54 % of the global flows. A positive role of FDI inflows from the advanced countries in increasing the economic growth of developing countries is supported by Kim, et al. (2003). Xu (2000) finds strong evidence of technology diffusion from US MNE affiliates in developing countries once those countries reach a minimum human capital threshold level. Moreover, Chen et al. (2008) using data on Chinese firms find that in locations with strong clustering of innovative foreign invested firms, local firms benefit from knowledge spillovers and are themselves more likely to introduce product innovations. Second, an ICT-revolution has taken place creating possibilities for easier transfer of knowledge. Third, increased mobility by students and trainees from developing countries seeking international educational and/or initial job experience in advanced countries. The management literature continues to recognize international migration as a significant channel for knowledge transfer (Williams , 2007). The study by Filatotchev, et al. (2009) examines the role of returnee entrepreneurs in an emerging economy. They define the returning entrepreneurs as scientists and engineers returning to start up a new venture in their native countries, after several years of business experience and/or education in the USA or other OECD countries. Their results suggest that the presence of a returnee entrepreneur and also entrepreneur-specific factors such as global networks and knowledge transfer from abroad are positively related with export orientation and export performance. Also migrants and return migrants other than top managers possess distinctive knowledge and may be potential knowledge brokers (Williams , 2007). These phenomena have made it easier to transfer knowledge, also in more task complex sectors. However, the effects of increased FDI and ICT seem to be limited to the manufacturing sectors, as much knowledge in the complex services sectors is transferred through interpersonal contacts and cannot be simply transmitted by ICT. And the scale of knowledge transfer over migration might be not sufficiently large to overcome difficulties in transferring tacit knowledge in service sectors.

A large literature in growth economics studies aggregate country-level productivity differences. However, there are only few studies that are conducted at the sector level, including the study by Rodrik (2013) who investigated convergence for value added per worker, the revealed comparative advantage study by Hausmann and Klinger (2007), and the paper by Levchenko and Zhang (2016) who analyze productivity convergence. Levchenko and Zhang (2016) find convergence in a pooled regression with all countries and sectors included. They also check differences in convergence, estimating convergence regressions for groups of countries showing that non-OECD countries display higher convergence. We add to their research by analyzing what drives the differences of speed of convergence across sectors.

The rest of the paper is organized as follows. In the next section present out our hypotheses. Then we map out the approach to estimate productivity in Section 3. Section 4 presents the data and Section 5 describes the empirical findings. Section 6 concludes.

2 Hypotheses on scope for technological catchup

In this section we formulate hypotheses regarding the scope for technological catchup across sectors, focusing on the importance of tacit knowledge. We discuss the role of task complexity and product sophistication of exports to measure the importance of tacit knowledge and then also add the roles of skill intensity and income elasticity in the scope and pattern of catchup.

In a world in which access to codified knowledge is fairly easy, the possession, creation, and access to tacit knowledge is of crucial importance for competitive success. Tacit knowledge is difficult to transfer because it defies codification. Moreover, it is effectively transferred over face-to-face interactions within small groups of people who share values, language and culture. Thus, it is difficult to share this type of knowledge even between the affiliates of the same organization located in different countries (Gertler , 2003).

Work activities of different occupations contain different amounts of tacit knowledge. The more complex the activity is, the more difficult it is to codify it, thus tacit knowledge intensity can be measured by complex task intensity. For example, work activities of a sewing machine operator in the textile industry can be precisely documented and thus the know-how can be easily transfered between companies or countries. On the other hand, a computer programmer who works in electronics is involved a lot in problem solving activities and it would be difficult or impossible for her/him to exactly define what she/he is doing. Hence, the transfer of the know-how she/he has acquired would take much more effort and time. "The best way to convey such knowledge is through demonstration and experience, such as in the classic master-apprentice relationship in which observation, imitation, practice, and correction are employed in the learning process" Gertler (2003).

These properties of tacit knowledge, namely spatial stickiness [1], make us believe that it is hard for the technologies of well developed tacit knowledge intensive sectors in advanced

[1] As in Gertler (2003) spatially sticky knowledge refers to the property of tacit knowledge to stay local.

economies to diffuse to emerging economies, which in turn slows down the convergence in these sectors. We formulate the following hypothesis:

Hypothesis 1 *Convergence is slower in more tacit knowledge intensive sectors.*

In addition to the task approach we also employ the income approach to measure the complexity of a sector. We use the quantitative index PRODY, by Hausmann, et al. (2007), which ranks goods in terms of how prevalent such goods are in the export baskets of higher vs. lower income economies. The index is an endogenous complexity measure that uses the fact that richer countries have more collective knowhow and use it to produce a greater variety of complex goods. Thus, the goods that are exported by the rich countries get ranked higher than the goods that are exported by poorer countries.

The know-how possessed by the richer countries is at least partially tacit, so their products are difficult to copy for the poorer countries. As a result the catch-up is also slower. We thus formulate the following hypothesis:

Hypothesis 2 *Convergence is slower in sectors where large share of goods are exported by rich countries.*

One can expect that complex tasks are performed by high skilled workers, thus, we also analyze the relationship between sectoral skill intensity and the speed of catch-up. In general, an educated labor force is better at creating, implementing, and adopting new technologies, thereby generating growth (Benhabib and Spiegel (1994)). In a setting where total factor productivity depends on a nation's human capital stock level Benhabib and Spiegel (1994) find that countries with higher education tend to close the technology gap faster than others. They also find that human capital growth has an insignificant and usually negative effect in explaining per capita income growth. In contrast, Madsen (2014) finds that changes in educational attainment and the interaction between education and the distance to the frontier have been influential for productivity growth, measured as growth in output per hours worked as well as growth in TFP. Castellacci (2011) shows that there is convergence in human capital and finds that more advanced education levels are indeed correlated with GDP per capita growth and that tertiary education is progressively becoming more crucial to explain cross-country differences in economic performance. The findings of these studies support the statement above, that an educated labor force is a prerequisite for achieving economic growth. At the sector level Ciccone and Papaioannou (2009) find that countries with higher initial education levels experienced faster value-added and employment growth in schooling intensive industries. This suggests that the countries with less educated labor force, which tend to be the more backward countries in terms of productivity, are less capable to catch up with the more productive economies and it is even more difficult for them in high skill intensive sectors. We thus come to the following hypothesis:

Hypothesis 3 *Convergence is slower in sectors that require highly skilled labor.*

The literature on the patterns of trade has shown that trade flows are characterized by a home market effect. The Linder-hypothesis postulates that countries specialize in goods with a large demand in their own market. Fajglbaum (2011) for example develop a model of non-homothetic preferences predicting that rich countries specialize in high-quality goods with high income elasticity. Caron et al. (2015) focus on innovation and develop a model of innovation and non-homothetic preferences featuring a home market effect, predicting that technology improvements in rich countries are biased towards luxury goods. Although these models do not examine technological catchup as such, the implications for catch-up are straightforward. Imposing a general tendency of convergence in all sectors of poorer countries, technological catchup of poor countries will be slower in goods with high income elasticity. Phrased differently: convergence will be slower in high income elastic goods, because rich countries specialize in these goods given their sales experiences on their home markets. Our discussion is summarized in the following hypothesis:

Hypothesis 4a *Convergence is slower in sectors producing products that show high income elasticity*

The opposite result is possible if developing countries concentrate on exports to high-income markets, collect sales experience there and thus could do well in high-income elastic products. This was an explicit development and export strategy of Japan after WWII and then emulated by other Asian economies. As pointed out by Fagerberg and Godinho (2006) Korea, Singapore and Taiwan are the prime examples of developing Asian countries that considered the policies and practices pursued by the Japanese as a possible model for their own catch-up towards Western levels. In all countries, targeting production for exports and rewarding successful export performance was very important. (Fagerberg and Godinho , 2006) Their aggressive promotion of international trade and strong pursuit of FDI have given them great capacity for structural change and allowed their economies to develop rapidly. (Dowlinga and Cheang , 2000) The government of Japan emphasized not just the importance of economies of scale but also continuous improvements of products and processes through learning. (Fagerberg and Godinho , 2006) The continuous improvement of products and their quality further eases the process of meeting the standards of the demand in high-income countries. Hence we can formulate a modified Linder hypothesis:

Hypothesis 4b *Lower-/medium income countries can counteract the home market effect on their exports by targeting high-income markets early on in their catching-up process.*

In the next section we move on to the model used which allows us to obtain sectoral productivity levels and convergence equations.

3 Trade model to infer productivity

Based on the multi-sector Eaton and Kortum model, the literature on international trade has developed a methodology to infer productivity from international trade data (Costinot, et al. (2012), Chor (2010), and Shikher (2012)). In this section we first sketch the multi-sector Eaton and Kortum model with non-homothetic preferences as in Fieler (2011) and Caron, et al. (2014). Second, we map out how trade flows can be used to infer sectoral productivity based on the approach in Levchenko and Zhang (2016). Third, we show how income elasticities can be estimated with this framework. Fourth, we show how the productivity convergence and the sectoral determinants of convergence are estimated.

3.1 Economic Model

3.1.1 Demand

We follow Caron, et al. (2014) and work with a multi-sector Eaton and Kortum model with non-homothetic preferences across sectors. There is a mass of consumers L_j in country j with identical preferences given by:

$$U_j = \sum_s \alpha_{1s} q_{js}^{\frac{\sigma_s - 1}{\sigma_s}} \tag{1}$$

This utility function has been introduced into the literature by Hanoch (1975) and employed by Fieler (2011) in the context of international trade. With $\sigma_s = \sigma$ preferences would be homothetic and constant elasticity of substitution (CES), but with heterogeneous σ_s preferences are non-homothetic. Following the Eaton and Kortum setup sector s composites in country j, q_{js}, consist of a CES continuum of varieties ω of mass 1:

$$q_{js} = \left(\int_0^1 q_{js}(\omega)^{\frac{\xi_s - 1}{\xi_s}} d\omega \right)^{\frac{\xi_s}{\xi_s - 1}} \tag{2}$$

With corresponding price index:

$$p_{js} = \left(\int_0^1 p_{js}(\omega)^{1-\xi_s} d\omega \right)^{\frac{1}{1-\xi_s}} \tag{3}$$

Given the sectoral price index defined in (3), individual expenditures on good s in country j, $x_{js} = p_{js} q_{js}$, are equal to:

$$x_{js} = \lambda_j^{-\sigma_s} \alpha_{2,s} p_{js}^{1-\sigma_s} \tag{4}$$

λ_j is the Lagrangian multiplier associated with the budget constraint and cannot be solved for analytically. The income elasticity of good s in country j is equal to:

$$\eta_{js} = \sigma_s \frac{\sum_{s'} x_{js'}}{\sum_{s'} \sigma_{s'} x_{js'}} \tag{5}$$

Equation (5) indicates that the ratio of income elasticities of two goods is constant, $\eta_{js}/\eta_{js'} = \sigma_s/\sigma_{s'}$ and that the income elasticity of any good falls as income rises, since the expenditure x_{js} on goods with high σ_s rises with income.

3.1.2 Production

All countries can potentially produce all goods with a productivity z implying a marginal cost of $\frac{c}{z}$ with c the price of input bundles. There is perfect competition in the product market and to ship goods from i to j iceberg trade costs τ_{ijs} have to be paid. The price of a good shipped from country i to j is thus given by:

$$p_{ij}(\omega) = \frac{\tau_{ijs} c_{is}}{z_{is}(\omega)}$$

c_{js} is a Cobb-Douglas composite of the price of labor and capital, respectively w_j and r_j, and the price of intermediate inputs, p_{jr}, in the different supplying sectors:

$$c_{js} = w_j^{\alpha_s \beta_s} r_j^{(1-\alpha_s)\beta_s} \left(\prod_{r=1}^{S} p_{jr}^{\gamma_{rs}} \right)^{1-\beta_s} \tag{6}$$

β_s is the share of value added in gross output, a_s the share of labor in value added and γ_{rs} is the share of intermediate r in intermediates employed by sector s.

Productivity z is drawn in each country from a country-specific Frechet distribution function with z_{is} a measure of absolute advantage of country i in sector s and θ_s a (inverse) measure of the strength comparative advantage:

$$F_{is}(z) = \exp\left(-\left(\frac{z_{is}}{z} \right)^{\theta_s} \right) \tag{7}$$

We follow the exposition in Caron, et al. (2014) and raise the technology parameter z_{is} also to the power θ_s. Given the Frechet distribution of productivities z in equation (7) the price p of a good sold from country i to j is also Frechet distributed:[2]

$$G_{ijs}(p) = 1 - \exp\left(\frac{z_{is} p}{\tau_{ijs} c_{is}} \right)^{\theta_s} \tag{8}$$

The realised price of variety ω in country j is the minimum price of all potential suppliers:

$$p_{js}(\omega) = \min \left\{ p_{1js}(\omega), .., p_{Jjs}(\omega) \right\} \tag{9}$$

Therefore, the distribution of prices in country j is given by:[3]

$$G_{js}(p) = 1 - \prod_{i=1}^{J} (1 - G_{ijs}(p)) = 1 - \exp\left(-\Phi_{js} p^{\theta_s} \right) \tag{10}$$

With Φ_{js} defined as:

$$\Phi_{js} = \sum_{i=1}^{J} z_{is}^{\theta_s} \left(\tau_{ijs} c_{is} \right)^{-\theta_s} \tag{11}$$

Φ_{js} is a measure of the competitiveness of importer market j and a function of technology and

[2] Substituting the expression for p_{ij} into the productivity distribution gives: $G_{ijs}(p) = 1 - F_{is}\left(\frac{(1+ta_{ijs})\tau_{ijs} c_{ijs}}{p} \right)$

[3] The probability that a price in country j is smaller than p is equal to 1 minus the probability that none of the suppliers has a price smaller than p.

input costs in the countries selling to market j, z_{is} and c_{is}, deflated by trade costs τ_{ijs}.

The probability that country i delivers a good of sector s to country j is equal to:

$$\pi_{ijs} = \frac{z_{is}^{\theta_s} \left(\tau_{ijs} c_{is}\right)^{-\theta_s}}{\sum\limits_{k=1}^{J} z_{ks}^{\theta_s} \left(\tau_{kjs} c_{ks}\right)^{-\theta_s}} \tag{12}$$

It can be shown that the price distribution of goods bought from country i in country j is equal to the general distribution of prices in country j, $G_{js}(\varphi)$. This implies that average expenditure in country j does not vary by source as pointed out by Eaton and Kortum, since expenditure can only vary by source because of price differences. Therefore the import share of country i in country j is equal to the probability that goods are sourced from country i in country j, $\frac{x_{ijs}}{x_{js}} = \pi_{ijs}$.

3.1.3 Equilibrium

Total expenditures by consumers on sector s, D_{js} can be expressed as follows:

$$D_{js} = L_j \lambda_j^{-\sigma s} \alpha_{2,k} \left(P_{js}\right)^{1-\sigma_s} \tag{13}$$

e_j is per capita income implying:

$$L_n e_n = \sum_k D_{nk} \tag{14}$$

Total demand (final and intermediate) for sector s goods in country j are given by:

$$X_{js} = D_{js} + \sum_r \gamma_{sr} Y_{jr} \tag{15}$$

Y_{jr} is the value of gross output in country j in sector r.

3.2 Gravity estimation to infer productivity

To infer productivity z_{js} relative to a reference based on gravity estimation, we follow the methodology in Levchenko and Zhang (2016) and Shikher (2012). Dividing the import share fom country i, π_{ijs}, in equation (12) by the share of domestic production, π_{jjs}, and taking logs gives the ratio of trade values in logs:

$$\frac{X_{ijs}}{X_{jjs}} = \left(\frac{\frac{\tau_{ijs} c_{is}}{z_{is}}}{\frac{c_{js}}{z_{js}}}\right)^{-\theta_s} \tag{16}$$

We have imposed $\tau_{jjs} = 1$. x_{ijs} is the trade value shipped from i to j.

We write iceberg trade costs, τ_{ijs}, for $i \neq j$, as a function of the observable trade costs distance, d_{ij}, a dummy variable indicating whether the two countries share a common border, $contig_{ij}$, a currency union dummy, CU_{ij}, and a regional trade agreement dummy, RTA_{ij}, an exporter fixed effect υ_{is},[4] and an error term ε_{ijs}:

$$\tau_{ijs} = \exp\left(\beta_{1s} \ln d_{ij} + \beta_{2s} contig_{ij} + \beta_{3s} CU_{ij} + \beta_{4s} RTA_{ij} + \upsilon_{is} + \varepsilon_{ijs}\right) \tag{17}$$

Including exporter and importer fixed effects, η_{is} and ζ_{js}, the gravity equation to be estimated becomes:[5]

$$\frac{X_{ijs}}{X_{jjs}} = \exp\left(\beta_{1s} \ln d_{ij} + \beta_{2s} contig_{ij} + \beta_{3s} CU_{ij} + \beta_{4s} RTA_{ij} + \eta_{is} + \zeta_{js} + \varepsilon_{ijs}\right) \tag{18}$$

The ratio of imported to domestically produced goods is determined by the cost of input bundles, state of technology and trade costs. The trade costs are accounted for by the bilateral observables while the country fixed effects contain information on technology and the cost of input bundles. $\left(\frac{z_{is}}{c_{is}\exp(\upsilon_{is})}\right)^{-\theta_s}$ is accounted for by an exporter fixed effect and $\left(\frac{c_{js}}{z_{js}}\right)^{\theta_s}$ by an importer fixed effect. Since one country dummy has to be omitted and is henceforth zero, the exponentiated importer fixed effect can only be identified relative to a reference country k:

$$\exp\left(\zeta_{js}\right) = \left(\frac{z_{js}}{z_{ks}} \frac{c_{ks}}{c_{js}}\right)^{\theta_s} \tag{19}$$

To obtain the input prices p_{jr}, the share of total spending on domestic goods is written as a function of the price index p_{js}:

$$\frac{X_{jjs}}{X_{js}} = \left(\Gamma \frac{z_{js}}{c_{js}} p_{js}\right)^{\theta_s} \tag{20}$$

x_{js} is total spending in country j on sector s goods and $\Gamma = \left[\boldsymbol{\Gamma}\left(\frac{\theta_s+1-\sigma}{\theta_s}\right)^{\frac{1}{1-\sigma}}\right]$, where $\boldsymbol{\Gamma}$ is the Gamma function. Dividing the share of total spending on domestic goods in country j by the share of total spending on domestic goods in the reference country and substituting equation

[4] As in Waugh (2010).

[5] Following the recent literature, we estimate the gravity equation with PPML.

(19) gives:

$$\frac{\frac{X_{jjr}}{X_{jr}}}{\frac{X_{kkr}}{X_{kr}}} = \left(\frac{z_{jr}}{z_{kr}} \frac{c_{kr}}{c_{jr}} \frac{p_{jr}}{p_{kr}}\right)^{\theta_r} = \exp\left(\zeta_{jr}\right)\left(\frac{p_{jr}}{p_{kr}}\right)^{\theta_r} \tag{21}$$

Hence, we can determine the price level in sector s of country j relative to the reference country as follows:

$$\frac{p_{jr}}{p_{kr}} = \left(\frac{\frac{X_{jjr}}{X_{jr}}}{\frac{X_{kkr}}{X_{kr}}} \frac{1}{\exp\left(\zeta_{jr}\right)}\right)^{\frac{1}{\theta_r}} \tag{22}$$

Substituting equation (22) into equation (6) and the result into equation (19), we can express technology relative to the reference country, $\frac{z_{js}}{z_{ks}}$, as follows:

$$\begin{aligned} \frac{z_{js}}{z_{ks}} &= \exp\left(\frac{\zeta_{js}}{\theta_s}\right)\frac{c_{js}}{c_{ks}} \\ &= \exp\left(\frac{\zeta_{js}}{\theta_s}\right)\left(\frac{w_j}{w_k}\right)^{\alpha_s\beta_s}\left(\frac{r_j}{r_k}\right)^{(1-\alpha_s)\beta_s}\left(\prod_{r=1}^{S}\left(\frac{\frac{X_{jjr}}{X_{jr}}}{\frac{X_{kkr}}{X_{kr}}}\frac{1}{\exp\left(\zeta_{jr}\right)}\right)^{\frac{\gamma_{rs}}{\theta_r}}\right)^{1-\beta_s} \end{aligned} \tag{23}$$

We have written the price of input bundles in country j relative to the price in reference country k using equation (6).

To complete the estimation of sectoral productivities we need the productivity levels of a reference country, z_{ks}. The observed TFP level, Λ_{kst}, is obtained as a residual from a standard production function:

$$\ln \widetilde{Y_{ks}} = \ln \Lambda_{ks} + \beta_s\alpha_s lnL_{ks} + \beta_s(1-\alpha_s)lnK_{ks} + (1-\beta_s)lnM_{ks} \tag{24}$$

$\widetilde{Y_{ks}}$ denotes the volume of gross output in sector s of reference country k and L_{ks}, K_{ks}, and M_{ks} stand for labor, capital and intermediate inputs, respectively. To get productivities z_{ks} from the observed TFP levels, Λ_{ks}, we take into account that open economies have a higher productivity level than measured by TFP, since the varieties in which the country has a comparative disadvantage will be imported (Finicelli (2013)):

$$z_{ks} = \frac{\Lambda_{ks}}{\left(1 + \sum_{i \neq k} \exp\left(\eta_{is}\right)\tau_{iks}^{-\theta_s}\right)^{\frac{1}{\theta_s}}} \tag{25}$$

3.3 Estimating sectoral income elasticities

We follow Caron, et al. (2014) to estimate income elasticities using data on imports, production and expenditure. We proceed in two steps. In the first step we estimate a gravity equation for each industry and in the second step we use the estimated parameters to control for supply-side effects in the final demand in each sector. In particular, we control for differences in price levels across countries affecting demand. We employ the reduced-form approximation mapped out in the online appendix of Caron, et al. (2014).[6]

The value of trade from i to j, X_{ijs}, can be written as follows, based on the expressions for Φ_{js} and π_{ijs} in (11)-(12) and using $\frac{X_{ijs}}{X_{js}} = \pi_{ijs}$:

$$X_{ijs} = z_{is}^{\theta_s} \left(\tau_{ijs} c_{is}\right)^{-\theta_s} \frac{X_{js}}{\Phi_{js}} \tag{26}$$

Using the expression for τ_{ijs} in (17) we convert the theoretical gravity equation (26) into the following empirical gravity equation:

$$X_{ijs} = \exp\left(\gamma_{1s} \ln d_{ij} + \gamma_{2s} contig_{ij} + \gamma_{3s} CU_{ij} + \gamma_{4s} RTA_{ij} + \chi_{is} + \nu_{js} + \varepsilon_{ijs}\right) \tag{27}$$

As before the exporter fixed effect captures technology, the price of input bundles and exporter-specific trade costs, $\chi_{is} = \left(\frac{z_{is}}{c_{is}\exp(\upsilon_{is})}\right)^{\theta_s}$. The importer fixed effect ν_{js} captures expenditures and competitiveness, $\nu_{js} = \frac{x_{js}}{\Phi_{js}}$.

Using equation (11) we can construct an expression for competitiveness Φ_{js} based on the estimated coefficients in (27):[7]

$$\widehat{\Phi_{js}} = \sum_i \exp\left(\widehat{\gamma_{1s}} \ln d_{ij} + \widehat{\gamma_{2s}} contig_{ij} + \widehat{\gamma_{3s}} CU_{ij} + \widehat{\gamma_{4s}} RTA_{ij} + \widehat{\chi_{is}}\right)$$

In the second step we convert the expression for individual expenditures per industry, x_{js}, in equation (4) into an estimable equation using the following approximation for the Lagrangian associated with the budget constraint, $log\lambda_j \approx \rho_1 loge_j + \rho_0$ and using the proxy for competitiveness $\widehat{\Phi_{js}}$. Individual expenditures per industry x_{js} are thus regressed on an industry fixed effect, ϖ_s, individual expenditures e_j and competitiveness $\widehat{\Phi_{js}}$:

[6] These authors find a 98 % correlation between the estimates from the reduced form and the benchmark structural estimates.

[7] This approach was first introduced by Redding and Venables (2004).

$$logx_{js} \approx \varpi_s + \rho_1\sigma_s loge_j + \mu_s\widehat{\Phi_{js}} + \epsilon_{js} \tag{28}$$

Estimating (28) with OLS enables us th obtain the σ's up to a constant for each sector, $\widehat{\rho_1\sigma_s}$.

Using fitted values on individual expenditures and the estimated coefficient $\widehat{\rho_1\sigma_s}$ gives the following approximation for income elasticities:

$$\eta_{js} \approx \widehat{\rho_1\sigma_s} * \frac{\sum\limits_{s'} \hat{x}_{js'}}{\sum\limits_{s'} \widehat{\rho_1\sigma_{s'}}\hat{x}_{js'}} \tag{29}$$

3.4 Convergence and its sectoral determinants

We follow Levchenko and Zhang (2016) and determine the degree of comparative advantage by estimating a convergence equation of technology z_{js}:

$$\Delta \log z_{js} = \beta \log z_{js_0} + \delta_j + \delta_s + \varepsilon_{js} \tag{30}$$

With convergence we should have $\beta < 0$: countries and sectors starting with a higher level of technology should display slower growth.

To analyze the impact of tacit knowledge intensity on catch-up we introduce an interaction term of a proxy for tacit knowledge intensity and base period productivity to the model:

$$\Delta \log z_{js} = \beta \log z_{js_0} + \gamma \operatorname*{complex}_s * \log z_{js_0} + \delta_j + \delta_s + \varepsilon_{js} \tag{31}$$

If our hypothesis that convergence is slower in more complex sectors is true, then γ should be positive. The negative impact of initial productivity on productivity growth should be smaller, implying a positive coefficient for the interaction term.

To ease interpretation of the results we also report the speed of convergence in the bottom of each table of convergence estimations, calculated according to the Barro and Sala-i-Martin (1992) formula: $\beta = e^{-\lambda T} - 1$, where β is the regression coefficient on the initial value of productivity, T is number of decades (years) between the initial and a particular final period, and λ is the convergence speed. In the estimations where an interaction term with complexity variable is included we report the speed of convergence for the least, the average and the most complex sectors.[8]

[8]The formula adjusting for the complexity level can be written as: $\beta + \gamma * complex_{min/avg/max} = e^{-\lambda T} - 1$.

To account for possible within-country correlation of errors when estimating convergence equations we cluster standard errors by country. The cluster-robust standard errors are precise estimates of correct standard errors only when many clusters are available. Cameron and Miller (2015) suggest that 50 clusters with roughly equal sizes are enough for accurate inference. However, in out dataset there are too few sectors to cluster at sector level. In addition, the model includes country and sector fixed effects, which account for the within cluster correlations driven by common shocks.

4 Data

In this section we discuss in turn the data needed to estimate sectoral productivity levels and income elasticities based on trade and production data, the complexity measures, and measures of skill intensity.

4.1 Data to estimate productivity and income elasticity

We estimate productivity with two datasets. First, we estimate TFP levels for 16 manufacturing sectors spanning five decades using trade flows from the Comtrade database, output data from UNIDO (2017), and other data. The number of countries range from 43 to 68 for each decade. The exact list of countries and periods is in Table B1 and the list of sectors in Table B3. Further details on the COMTRADE and UNIDO data are in the online appendix.

Second, we estimate productivity with GTAP data to have a wider coverage of sectors at a cost of having shorter time frame. In this dataset we have 1 agriculture, 12 service, and 15 manufacturing sectors. The number of countries range from 66 to 107 for the years from 1997, 2001, 2004, 2007, and 2011. Given short time intervals of this dataset we have to take into account that the results could be affected by cyclical effects. The country and sector lists are given in tables B2 and B4 respectively.

The gravity variables are from the following sources. The geographical distance between coutnries, d_{ij}, and a dummy variable indicating whether the two countries share a common border, $contig_{ij}$, are from the CEPII database (Mayer and Zignago , 2011). The currency union dummy, CU_{ij}, and regional trade agreement dummy, RTA_{ij}, are from de Sousa (2012). We let the iceberg trade costs differ across sectors, by running the gravity equation for each sector separately. Following Eaton and Kortum (2002) the dispersion parameter, θ, is set to 8.28.

As reference country we choose the US. To get the productivity parameters relative to the US, we need information on the cost of the input bundles relative to the US and input coefficients (equation (23)). Production function parameters α_s and β_s are estimated using UNIDO data. To get α_s, we calculate the share of the total wage bill in value added, and take a simple median across countries. β_s is a median of value added divided by total output across countries. Intermediate input coefficients, γ_{rs}, are from the Direct Requirements Table for the US (1997 Benchmark Detailed Make and Use Tables (converted to ISIC Rev. 3 from NAICS 1997 using a concordance table)) We assume that they are the same in all countries [9] and revoke this assumption while estimating productivity parameters using GTAP data. To get the relative wage rates, $\left(\frac{w_j}{w_{us}}\right)$, we use UNIDO data where we divide the total manufacturing sector wage bill by total manufacturing employment in each country, and take that value relative to the US. In less than 10% of country-decade observations the data is missing and we use GDP per capita relative to the US data from the World Bank national accounts data to proxy wages. To get the information on the relative return to capital, $\left(\frac{r_j}{r_{us}}\right)$, we assume that the following aggregate market clearing condition holds: $r_j/w_j = ((1-\alpha)L_j)/(\alpha K_j)$, with the aggregate labor share, α, set at 2/3. By using the data from Penn World Tables 8.0. (Feenstra, et al. (2015)) on the number of persons engaged in each country, L_j, and the total capital stock K_j we get the returns to capital estimates for each country.

To finish the estimation of productivity levels we need the data for US productivity in each sector. To get the sectoral productivity parameters for the US we use the NBER-CES Manufacturing Industry Database (Bartelsman and Gray (1996)) which offers information on output, and inputs of labor, capital, and intermediates, along with the deflators for each, needed to get sectoral total factor productivities. The values for $\exp(\eta_{is})\,\tau_{iks}^{-\theta_s}$ in equation (25) come from the fitted values of the gravity equation in (18).

The estimated revealed productivity levels averaged across sectors and the productivity growth are presented on maps in Figures C1 and C2 for the UNIDO-Comtrade and GTAP datasets, respectively. Table 1 shows that high income countries have on average higher sectoral productivity levels in all time periods.B5 shows that based on the GTAP dataset the strongest increases in productivity levels from 1997 to 2011 on average are in service sectors of medium income countries.

[9] Levchenko and Zhang (2016) find that using country-specific IO matrices source from GTAP yield slightly higher average productivities, but the variation is similar to the baseline and the correlations are very high.

Table 1: Summary statistics of log(TFP) by income groups

	Low income			Medium income			High income		
Decade	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**
1960s	3.966	3.232	240	4.650	3.092	224	6.587	2.688	224
1970s	4.835	3.564	303	5.406	2.926	288	8.284	2.636	288
1980s	4.832	3.304	319	5.348	2.757	320	7.746	2.507	304
1990s	2.830	3.311	367	3.458	3.201	368	7.196	2.498	352
2000s	3.489	2.704	367	4.580	2.773	352	7.840	2.668	352

Countries divided to low, medium and high income countries using GDP per capita, PPP for year 2000 from the World Bank data.

Summary statistics on the estimated income elasticity show that there is wide variation in the income elasticity with higher elasticities for services than for manufacturing goods. (See Table B18). The correlation with the O*NET measures of tacit knowledge is positive, in the range of 0.3 to 0.4 for the different measures. (See Table B19).

4.2 Measuring Tacit Knowledge

To construct tacit knowledge intensity proxies we employ cognitive non-routine O*NET work activities used by Acemoglu and Autor (2011) and Oldenski (2012). These tasks are difficult to codify, thus the knowledge acquired by the employees is difficult to transfer. In sectors where employees are actively engaged in cognitive non-routine activities, like problem solving or creative thinking, the tacit component of knowledge is larger. Employees can often not specify precisely what they are doing, thus their acquired knowledge is impossible or very difficult to codify. The non-codified knowledge is often transferred through person-to-person demonstrations and instructions. (David (1992)) And the most effective way to do it is face-to-face interaction, which makes the transfer slow and costly.

In particular we use five work activities from which three are analytical tasks, important for engineering and science, such as “Analyzing data/information”, “Thinking creatively”, and “Interpreting information for others”, and other two complex tasks: “Making decisions and solving problems”; and “Communicating with supervisors, peers, or subordinates.” As a counterpart we also include manual tasks that can be easily codified and learned in relatively short time: “Controlling machines and processes”, “Operating vehicles, mechanized devices, or equipment”, “General physical activities”, and “Handling objects.”

These indicators range from 0 to 100, 100 indicating high importance of the task for an occupation. The indicators are measured at the occupation level and henceforth have to be converted to the industry level. Following Oldenski (2012), we aggregate these scores to the industry level by employing data from 2001 on the shares of occupations used in the industry from the US Bureau of Labor Statistics Occupational Employment Statistics. The importance of work activity a in an industry s, M_{as} is defined as

$$M_{as} = \sum_{c} o_{sc} l_{ac}$$

c indicates occupation, o_{sc} is the share of occupation c employed in industry s and l_{ac} is the importance score of a task for an occupation. To get the share of a task in the total task inputs in an industry, I_{as}, we can divide M_{as} by the sum of importance scores for each task in the industry:

$$I_{as} = \frac{M_{as}}{\sum\limits_{b} M_{bs}}$$

The tasks are matched to the sectors classified by 1987 US Standard Industrial Classification (SIC) and then converted to ISIC rev. 3 classification using the correspondence table provided by United Nations.

The analytical and other complex tasks are highly correlated. (See Table B8). So, we use principal component analysis to create a measure of tacit knowledge using the primary component among analyzing data, thinking creatively, interpreting information, communicating inside the organization, and making decisions. The created principal component measures have variance 3.71 and 3.42, explaining 74% and 68% of the total variance in the Comtrade-UNIDO and GTAP datasets, respectively.

4.3 An alternative complexity measure

As an alternative for complexity we employ the PRODY index by Hausmann, et al. (2007) which measures the relative sophistication of products traded globally in that sector. The assumption behind this measure is that if a large share of products in a particular sector is exported by high income countries then that sector produces more sophisticated products. To construct the PRODY index we use the trade data from Comtrade and GTAP for the respective datasets. Denoting total exports of country j as E_j,$E_j = \sum\limits_{s} e_{js}$, $PRODY$ of sector s is defined as:

$$PRODY_s = \sum_{j} \frac{e_{js}/E_j}{\sum\limits_{j} e_{js}/E_j} Y_j \tag{32}$$

where e_{js}/E_j is the sector s share in the total value of exports of country j, which is set in relation to the aggregate of these shares across countries that are exporting in this sector. This revealed comparative advantage measure of country j in sector s is then weighted by the income levels of the countries j, Y_j. The sum of weighted comparative advantages across countries is then a measure of the sophistication of exports of sector s. For income data we use GDP per capita from the World Bank World Development Indicators. We deflate the measure by the average income level. An advantage of this measure is that it varies over time, allowing us to drop our strict assumption that tacit knowledge intensity doesn't change or at least changes proportionally in all sectors. PRODY correlates highly with the different O*NET tacit knowledge measures, typically more than 0.5 (see table B13). The rankings of sectors according to PRODY index are given in tables B11 and B12.

4.4 Skill intensity data

We follow Ciccone and Papaioannou (2009) and construct a schooling intensity measure for different sectors using data from Integrated Public Use Microdata Series (IPUMS) USA (Ruggles, et al. (2015)). We extract data on educational attainment and employment status for 1960 to 2000. The data are reported in the 1990 Census Bureau industrial classification which we match to ISIC rev. 3 two digit codes. Using survey data methods we estimate the counts of employees by educational attainment and sector, $emp_{edu,s}$, and by sector, emp_s. Then the schooling intensity measure in each sector is obtained by multiplying the share of employees in each educational attainment group by 0, 1, 6, 10, 12, 14, 16, and 18, respectively:

$$Schooling_s = \sum_{edu} \frac{emp_{edu,s}}{emp_s} * edu$$

Thus the schooling intensity measure calculates the average number of years of schooling of an employee of a particular sector. Tables B14 and B15 show summary statistics of schooling intensity by decade and correlation coefficients with the complexity measures, respectively. The tables show that the average years of schooling have been steadily growing while the variation across sectors has been decreasing. As expected, schooling intensity is highly correlated with the complexity of a sector. In figure C8 one can see that the differences in schooling across sectors become smaller over the decades but the pattern remains similar.

The GTAP data on high and low skilled labor usage are available for all reported countries.

However, the skill composition data are extrapolated from a subset of European countries and six non-European countries (United States, Canada, Australia, Japan, Taiwan, and South Korea).[10] Thus, through all of our analysis we use high skill intensity averages across countries where high skill intensity is measured as a share of value added paid to high skilled workers.

In GTAP 9 the method of collecting and imputing the labor compensation data changed.[11] GTAP 9 contains 5 aggregate occupational categories.[12] After aggregating the high skill categories, the summary statistics and correlations are reported together with the data for previous years in Tables B16 and B17. The change in the method is noticeable in the summary statistics table where reported high skill intensity is much higher in 2011 than in previous year. Also the correlation of the high skill intensity measure in 2011 with the measures for earlier years is less than 70% , while the measures for earlier years exhibit a correlation of at least 98%.

5 Estimation Results

In this section we present our estimation results. We start with the relation between tacit knowledge and the speed of convergence. Then we check if this relation is different between manufacturing and service sectors employing GTAP data. We repeat these steps with the complexity measure PRODY and test if the relation between high skill intensity and the speed of convergence is similar. Next we examine whether there is a relation between the speed of convergence of sectors and their income elasticities. Finally, we move on to the robustness checks.

The baseline convergence regressions can be found in the online appendix. The results using the Comtrade-UNIDO dataset (Table C1) are very similar to the ones in Levchenko and Zhang (2016). Like them we find that the speed of convergence, in other words how much of the initial difference between productivities is expected to disappear in the course of the decade, slows down over time with 28% in 1960s-1970s and 16% in 1990s-2000s. For the whole period the average speed of convergence is 19% per decade. Using GTAP data we find a convergence of 6% per year (table C2), which is larger than the Barro and Sala-i-Martin (1992) 2% rate of convergence.[13] In the regressions covering shorter periods we find a convergence of 3-6% per

[10] See www.gtap.agecon.purdue.edu/resources/download/7046.pdf

[11] See www.gtap.agecon.purdue.edu/resources/download/7812.pdf

[12] ILO categories: Officials and managers, Technicians, Service/Shop workers, Agricultural and Unskilled labor.

[13] A larger convergence rate than traditionally estimated seems to be due to incidental parameters problem discussed in Barro (2015). Convergence regressions using panels that are small in time dimension and including country fixed effects tend to overestimate convergence.

year, except in the period between 2001 and 2004 where the estimated speed of convergence is strikingly high and reaches 17% per year. There is no obvious difference in speed of convergence between manufacturing and service sectors.

5.1 Tacit knowledge, speed of convergence and income levels

For the sake of brevity we report only the results using the first principal component of the complexity variables. The estimation results with each complexity variable separately can be found in the online appendix.

Table 2 reports the results using the Comtrade-UNIDO dataset. The first 3 columns report the results from long-run convergence, where the change in productivity is over several decades, i.e. from 1960s to 2000s, from 1960s to 1980s, and from 1980s to 2000s. In the following four columns the results are from decade-by-decade, 1960s-1970s, 1970s-1980s and so on, regressions. As in the baseline convergence regressions in all specifications we find negative and strongly statistically significant coefficients on β, indicating convergence: the more backward sectors in a country, and the more backward countries within a specific sector catch up the fastest.

The coefficients on γ are positive and statistically significant in the first three columns of table 2, supporting the hypothesis that catch-up is slower in tacit knowledge intensive sectors. The speed of convergence between the most and least tacit knowledge intensive sectors differs by 12-14 percentage points. E.g., between 1960s and 2000s the speed of convergence is 15% per decade for the most complex sector and 29% per decade for the least complex sector, while the average complex sector exhibits a convergence rate of 23% per decade. The difference in the speed of convergence between the most and least complex sectors is smaller in decade-by-decade regressions, ranging from 5 to 12 percentage points. However, these results are not statistically significant, except for 1980s-1990s regression where γ is significant at the 10% level. The results from the decade-by-decade regressions seem to be more sensitive to business cycles, resulting in statistically non-significant coefficients.

Table 3 reports the results using GTAP data for the periods between 1997 and 2011, 1997-2004, and 2004-2011. The first three columns of Table 3 report the results from the pooled sample, columns 4-6 report the results for manufacturing sectors only, and the results for services are in columns 7-9. The estimates of β remain negative and strongly significant in all specifications. These convergence regressions cover a little more or less than a decade and, thus statistically non-significant estimates of γ are not surprising in the pooled sample.

Table 2: The effect of tacit knowledge on the speed of convergence in different time periods

	(1) 1960s-2000s	(2) 1960s-1980s	(3) 1980s-2000s	(4) 1960s-1970s	(5) 1970s-1980s	(6) 1980s-1990s	(7) 1990s-2000s
$log(z_{Initial})$	-0.604***	-0.459***	-0.353***	-0.266***	-0.222***	-0.252***	-0.164***
	(-12.07)	(-9.45)	(-6.30)	(-7.60)	(-5.73)	(-6.27)	(-4.40)
$log(z_{Initial}) * PC1_{complex}$	0.0340**	0.0206*	0.0263**	0.0108	0.00587	0.0138	0.00725
	(3.08)	(2.53)	(2.77)	(1.57)	(0.85)	(1.92)	(1.09)
Constant	5.226***	4.555***	-2.814**	4.894***	-1.722***	-3.284***	2.845***
	(14.40)	(11.60)	(-3.40)	(14.64)	(-6.72)	(-6.67)	(12.36)
Observations	640	672	895	688	847	911	1039
Adjusted R^2	0.905	0.806	0.893	0.844	0.837	0.866	0.905
SoC in averagely complex sector	0.232	0.307	0.218	0.309	0.251	0.290	0.180
SoC in least complex sector	0.290	0.355	0.270	0.345	0.269	0.336	0.201
SoC in most complex sector	0.153	0.231	0.138	0.248	0.219	0.215	0.143

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The dependent variable is the growth of estimated TFP in respective time periods. All estimations include country, and sector dummies. Standard errors clustered at the country level. The speed of convergence, per decade, is reported for least, averagely, and most complex sectors.

Table 3: The effect of tacit knowledge on the speed of convergence in different time periods using GTAP data

	All sectors			Manufacturing sectors			Service sectors		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	1997-2011	1997-2004	2004-2011	1997-2011	1997-2004	2004-2011	1997-2011	1997-2004	2004-2011
$log(z_{Initial})$	-0.547***	-0.461***	-0.229***	-0.555***	-0.466***	-0.225***	-0.565***	-0.483***	-0.241***
	(-13.98)	(-14.23)	(-9.41)	(-12.24)	(-11.89)	(-6.21)	(-10.21)	(-11.48)	(-7.60)
$log(z_{Initial}) * PC1_{complex}$	0.000834	-0.000739	-0.000864	-0.0184*	-0.0151*	-0.0108	0.0122*	0.00801	0.00667*
	(0.19)	(-0.22)	(-0.32)	(-2.17)	(-2.44)	(-1.98)	(2.13)	(1.87)	(2.38)
Constant	19.58***	17.09***	8.221***	18.49***	17.91***	10.58***	22.11***	20.44***	14.21***
	(47.79)	(47.03)	(11.28)	(13.71)	(15.56)	(10.08)	(15.31)	(18.88)	(13.63)
Observations	1848	1848	2996	990	990	1605	792	792	1284
Adjusted R^2	0.934	0.947	0.812	0.946	0.966	0.798	0.925	0.931	0.867
SoC in averagely complex sector	0.057	0.088	0.037	0.058	0.090	0.036	0.059	0.094	0.039
SoC in least complex sector	0.057	0.088	0.037	0.050	0.079	0.031	0.065	0.100	0.043
SoC in most complex sector	0.056	0.089	0.038	0.073	0.109	0.046	0.051	0.085	0.034

t statistics in parentheses

The dependent variable is the growth of estimated TFP in respective time periods. All estimations include a constant, country, and sector dummies. Standard errors clustered at the country level. The speed of convergence, per year, is reported for least, averagely, and most complex sectors.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

When splitting the sample into manufacturing sectors only and services only we find strikingly different results. It appears that since late 1990s our hypothesis, that catch up is slower in more complex sectors, holds only within services sectors. The speed of convergence in the most complex service sector is 3-8% per year while in the least complex sector it is 4-10% per year. We find opposite results in the specifications with manufacturing sectors only: γ changes sign and remains statistically significant. These results indicate that within the manufacturing sectors the speed of convergence is faster in more tacit knowledge intensive sectors. The most complex manufacturing sector converge at a rate of 5-11% per year while the least complex one at a rate of 3-8% per year.

Table 4: Summary statistics of log(TFP) in most and least tacit knowledge intensive sectors by income groups

	Low income			Medium income			High income		
Decade	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**
	Most tacit knowledge intensive sectors								
1960s	2.104	3.577	16	3.411	4.013	68	6.350	3.536	88
1980s	4.529	3.837	36	4.021	3.876	107	7.660	3.026	92
2000s	3.578	3.599	32	4.415	3.653	139	9.273	3.168	96
	Least tacit knowledge intensive sectors								
1960s	4.109	2.147	16	4.880	2.555	68	6.161	1.928	88
1980s	6.283	2.328	36	5.455	2.305	108	7.405	1.773	92
2000s	5.002	1.929	32	4.450	2.176	140	7.747	1.686	96

World Bank grouping of countries by income. The data is from 2005 where low income countries were with GNI per capita smaller or equal to \$875; middle income economies were with GNI per capita of \$876-\$10,725; and high income economies were those with GNI per capita larger than \$10,725.
The intensity of tacit knowledge is measured by the first principal component of the complexity variables. The most and least tacit knowledge intensive sectors are the first and last 25% of sectors ranked by the first principal component. The most tacit knowledge intensive sectors: Publishing, printing and reproduction of recorded media, Medical, precision and optical instruments, Machinery and computing machinery, Electrical machinery, radio, tv and communication equipment. The least tacit knowledge intensive sectors: Wood and wood products, Food, beverages and tobacco, Textiles, Other non-metallic mineral products.

The difference in convergence between manufacturing and services for the GTAP data is illustrated in Figure C7. There is a clear pattern of convergence for services, while in the manufacturing sectors divergence is visible. [14] Summary statistics on the relation between productivity and tacit knowledge support our analysis. Tables 4 and 5 show that the productivity levels of tacit knowledge intensive sectors in low income countries are much lower than in sectors with low levels of tacit knowledge. Also the difference in productivity between low and high

[14] β coefficient is indeed positive in the regressions excluding sector fixed effects for all manufacturing sectors and only low and medium complex manufacturing sectors indicating divergence between sectors.

income countries is larger in tacit knowledge intensive sectors. In the 1960s and 2000s high income countries display productivity levels in tacit knowledge intensive sectors three times higher than low income countries, while in non-complex sectors the difference is only 50%. These tables suggest that the difference in productivity remains high in the complex sectors, thus supporting the results from the formal analysis that there is less convergence in complex sectors. When looking at the later years in the GTAP data we see similar patterns although differences are much smaller. High income countries were more productive by 40-50% in tacit knowledge intensive sectors and 20-30% in non-complex sectors. The bigger differences between countries in highly complex sectors can be also observed in figures C5, C6 and C7, where the initial productivity levels and TFP growth are much more dispersed in highly complex sectors than in less complex sectors.

Table 5: Summary statistics of log(TFP) in most and least tacit knowledge intensive sectors by income groups from GTAP dataset

	Low income			Medium income			High income		
Year	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**
	Most tacit knowledge intensive sectors								
1997	21.588	8.837	42	24.699	8.81	182	31.008	7.158	238
2004	21.664	6.053	84	25.453	6.592	378	31.839	6.767	287
2011	23.639	5.719	119	28.237	6.222	399	32.358	6.407	301
	Least tacit knowledge intensive sectors								
1997	27.713	3.743	42	29.492	4.19	182	34.189	3.649	238
2004	27.096	4.827	84	30.593	4.78	378	36.049	4.491	287
2011	27.803	4.586	119	32.115	4.552	399	35.568	4.934	301

World Bank grouping of countries by income. The data is from 2010 where low income countries were with GNI per capita smaller or equal to $1,005; middle income economies were with GNI per capita of $1,006-$12,275; and high income economies were those with GNI per capita larger than $12,275.
The intensity of tacit knowledge is measured by the first principal component of the complexity variables. The most and least tacit knowledge intensive sectors are the first and last 25% of sectors ranked by the first principal component. The most tacit knowledge intensive sectors: Insurance, Other financial intermediation, Electronic equipment, Other business services, Communications, Other transport equipment, Paper & paper products. The least tacit knowledge intensive sectors: Agriculture, forestry and fisheries, Processed foods, Other transport, Lumber, Textiles, Trade, Non-metallic minerals.

In the online appendix we examine whether convergence is faster in sectors where routine, manual tasks are important. In these sectors knowledge is easily codified and thus the knowledge can be relatively quickly transferred across companies and countries. As we have shown above complex and manual tasks exhibit a negative correlation. In line with this negative correlation we find faster convergence in sectors with a high degree of routine tasks with the UNIDO data (Table C3). With the GTAP data we find in line with previous results faster convergence in services sectors where routine tasks score high and slower convergence in manufacturing sectors with a high routine task intensity (Table C4).

5.2 The speed of convergence and complexity measured by sophistication of products exported by a sector

Next, we employ the PRODY measure to proxy the complexity of a sector. The advantage of this measure is that it varies over time. As we have shown above this measure correlates highly with the O*NET measures of tacit knowledge intensity. As seen in tables 6 and 7 the results of the convergence regressions are also similar to the ones with O*NET tasks. More complex manufacturing sectors in the Comtrade-UNIDO dataset and services in the GTAP dataset, measured by the PRODY measure, exhibit smaller convergence rates. The estimated speed of convergence in the most and least complex sector is very close to the ones estimated with O*NET tasks. These results are statistically significant at least at a 5% level, except for the 1960s-2000s regression. The results for the manufacturing sectors in GTAP are statistically non-significant.

Table 6: The effect of complexity measured by PRODY on the speed of convergence in different time periods

	(1) 1960s-2000s	(2) 1960s-1980s	(3) 1980s-2000s
$log(z_{Initial})$	-0.613***	-0.587***	-0.476***
	(-8.67)	(-8.63)	(-5.40)
$log(z_{Initial}) * PRODY$	0.0473	0.0948**	0.104**
	(1.36)	(2.97)	(2.94)
Constant	4.899***	2.313***	-3.000***
	(18.61)	(16.10)	(-5.28)
Observations	640	672	895
Adjusted R^2	0.904	0.807	0.895
SoC in averagely complex sectors	0.198	0.304	0.210
SoC in least complex sectors	0.219	0.374	0.270
SoC in most complex sectors	0.173	0.220	0.163

t statistics in parentheses
The dependent variable is the growth of estimated TFP in respective time periods. In each regression the PRODY measure is from the same year as initial TFP. All estimations include country, and sector dummies. Standard errors clustered at the country level. The speed of convergence, per decade, is reported for least, averagely, and most complex sectors.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: The effect of complexity measured by PRODY on the speed of convergence in different time periods using GTAP data

	All sectors			Manufacturing sectors			Service sectors		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	1997-2011	1997-2004	2004-2011	1997-2011	1997-2004	2004-2011	1997-2011	1997-2004	2004-2011
$log(z_{Initial})$	-0.522***	-0.428***	-0.255***	-0.499***	-0.432***	-0.176***	-0.656***	-0.603***	-0.284***
	(-11.45)	(-10.66)	(-8.67)	(-6.16)	(-6.52)	(-3.48)	(-9.84)	(-9.60)	(-7.56)
$log(z_{Initial}) * PRODY$	-0.0211	-0.0311	0.0178*	-0.0464	-0.0291	-0.0379	0.111*	0.129**	0.0388***
	(-1.15)	(-1.54)	(2.07)	(-1.19)	(-0.85)	(-1.67)	(2.39)	(2.76)	(3.93)
Constant	20.42***	19.37***	15.11***	21.10***	19.16***	6.669***	25.70***	18.85***	7.222***
	(17.82)	(17.85)	(20.38)	(13.95)	(14.39)	(5.68)	(11.54)	(10.04)	(13.83)
Observations	1848	1848	2996	990	990	1605	792	792	1284
Adjusted R^2	0.934	0.947	0.812	0.945	0.966	0.798	0.925	0.932	0.869
SoC in averagely complex sectors	0.056	0.088	0.038	0.057	0.089	0.035	0.055	0.090	0.039
SoC in least complex sectors	0.054	0.083	0.041	0.052	0.084	0.030	0.067	0.113	0.045
SoC in most complex sectors	0.058	0.093	0.032	0.061	0.093	0.050	0.047	0.073	0.025

t statistics in parentheses

The dependent variable is the growth of estimated TFP in respective time periods. In each regression the PRODY measure is from the same year as initial TFP.All estimations include a constant, country, and sector dummies. Standard errors clustered at the country level. The speed of convergence, per year, is reported for least, averagely, and most complex sectors.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.3 High-skill intensity and catch-up

Complex tasks are mostly performed by high-skilled labor, thus we expect that high-skill intensive sectors would exhibit slower convergence rates. The results testing this hypothesis are presented in table 8 using the Comtrade-UNIDO dataset and in table 9 using GTAP data. The results in table 8 support our hypothesis, the estimated coefficients on interaction terms with schooling intensity have positive signs and are statistically significant at 5 % or 10 % level.

Table 8: The effect of schooling intensity on the speed of convergence in different time periods

	(1) 1960s-2000s	(2) 1960s-1980s	(3) 1980s-2000s
$log(z_{Initial})$	-1.147***	-0.785***	-0.916**
	(-5.17)	(-3.61)	(-3.43)
$log(z\_Initial) * Schooling$	0.0592*	0.0354	0.0508*
	(2.70)	(1.72)	(2.45)
Constant	5.786***	4.642***	-2.982***
	(18.75)	(16.51)	(-4.61)
Observations	640	672	895
Adjusted R^2	0.905	0.805	0.892
SoC in averagely schooling int. sectors	0.213	0.291	0.198
SoC in least schooling int. sectors	0.290	0.356	0.258
SoC in most schooling int. sectors	0.170	0.250	0.157

t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
The dependent variable is the growth of estimated TFP in respective time periods. In each regression the schooling intensity measure is from the same year as initial TFP. All estimations include country, and sector dummies. Standard errors clustered at the country level. The speed of convergence, per decade, is reported for least, averagely, and most schooling intensive sectors sectors.

Using GTAP data as before in columns 1-3 of table 9 with all sectors included into the regressions we do not find any significant relation between the speed of convergence and the high skill intensity of a sector. However, once we divide the sample into manufacturing sectors and services the interaction terms between the high skill intensity and the initial TFP level become statistically significant at the 5% level, with an exception of column 9 where the coefficient is statistically significant at the 10% level. Again, we get results opposite to what is expected for the manufacturing sectors in columns 4-6. The least high-skill intensive sector exhibits a speed of convergence of 4% per year while the most high-skill intense sector converges at 11% per year. In columns 7-9 the results from the sample of services are in line with the hypothesis that the speed of convergence is slower in highly skilled labor abundant sectors. The most high skill intensive services sector displays a convergence rate that is 2 percentage points lower than the least high skill intensive services sector, 5% vs 7% per year, respectively.

Table 9: The relation of high skill intensity and the speed of convergence in different time periods using GTAP data

	All sectors			Manufacturing sectors			Service sectors		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	1997-2011	1997-2004	2004-2011	1997-2011	1997-2004	2004-2011	1997-2011	1997-2004	2004-2011
$log(z_{Initial})$	-0.542***	-0.473***	-0.202***	-0.383***	-0.368***	-0.118*	-0.634***	-0.547***	-0.273***
	(-10.49)	(-11.75)	(-6.86)	(-5.25)	(-6.12)	(-2.37)	(-8.48)	(-9.79)	(-6.57)
$log(z_{Initial})$∗Avg. high skill intens.	-0.0167	0.0569	-0.181	-1.364**	-0.791*	-1.045**	0.481*	0.409*	0.251
	(-0.10)	(0.45)	(-1.56)	(-3.14)	(-2.43)	(-3.18)	(2.25)	(2.58)	(1.85)
Constant	19.66***	16.93***	7.863***	14.25***	11.34***	10.12***	30.01***	25.63***	14.29***
	(41.39)	(40.55)	(15.11)	(8.46)	(7.91)	(8.28)	(11.51)	(12.87)	(13.15)
Observations	1848	1848	2996	990	990	1605	792	792	1284
Adjusted R^2	0.934	0.947	0.812	0.946	0.966	0.799	0.925	0.932	0.867
SoC in averagely high skill intense sectors	0.056	0.090	0.036	0.059	0.091	0.039	0.061	0.097	0.040
SoC in least high skill intense sectors	0.056	0.091	0.033	0.037	0.068	0.020	0.070	0.111	0.045
SoC in most high skill intense sectors	0.057	0.087	0.040	0.107	0.129	0.067	0.049	0.080	0.034

t statistics in parentheses

The dependent variable is the growth of estimated TFP in respective time periods. In each regression the high skill intensity measure is from the same year as initial TFP. All estimations include a constant, country, and sector dummies. Standard errors clustered at the country level. The speed of convergence, per year, is reported for least, averagely, and most complex sectors.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: The relation of income elasticity and the speed of convergence in different time periods using GTAP data

	All sectors			Manufacturing sectors			Service sectors		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	1997-2011	1997-2004	2004-2011	1997-2011	1997-2004	2004-2011	1997-2011	1997-2004	2004-2011
$log(z_{Initial})$	-0.312***	-0.264***	-0.0997*	0.0383	0.0634	-0.162**	-0.331***	-0.307***	-0.0966
	(-4.62)	(-3.74)	(-2.02)	(0.32)	(0.61)	(-3.01)	(-3.83)	(-3.54)	(-1.30)
$log(z_{Initial})$*Income elast.	-0.176**	-0.150**	-0.108*	-0.542***	-0.481***	-0.0663	-0.150*	-0.115	-0.0988
	(-3.29)	(-2.87)	(-2.62)	(-5.21)	(-5.56)	(-1.19)	(-2.33)	(-1.90)	(-1.66)
Income elast.	6.033	3.574	-1.025	1.874	3.685	-1.166	5.973	1.366	-2.874
	(0.94)	(0.62)	(-0.34)	(0.46)	(1.07)	(-0.37)	(0.68)	(0.16)	(-0.58)
Constant	1.391	6.349	6.918**	20.30***	16.06***	7.111**	0.759	10.72	14.47
	(0.09)	(0.47)	(3.38)	(3.93)	(3.76)	(3.15)	(0.04)	(0.54)	(1.27)
Observations	1848	1848	2996	990	990	1605	792	792	1284
Adjusted R^2	0.936	0.948	0.814	0.948	0.968	0.797	0.927	0.932	0.868
SoC in sectors with average income elasticity	0.049	0.078	0.034	0.054	0.084	0.037	0.048	0.080	0.032
SoC in sectors with low income elasticity	0.037	0.061	0.024	0.021	0.032	0.031	0.038	0.066	0.023
SoC in sectors with high income elasticity	0.095	0.140	0.060	.	.	0.053	0.084	0.125	0.055

t statistics in parentheses

The dependent variable is the growth rate of estimated TFP in respective time periods. In each regression the income elasticity measure is from the same year as initial TFP. All estimations include a constant, country, and sector dummies. Standard errors clustered at the country level. The speed of convergence, per year, is reported for least, averagely, and most income elastic sectors.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.4 Income elasticity and speed of convergence

In Table *10* we analyse the difference in speed of convergence across sectors in relation to the income elasticity of the products exported by the sector. The table shows that for most specifications the technological catchup is faster in sectors with higher income elasticity. Initial productivity exerts a stronger negative impact on productivity growth in more income elastic sectors, such that countries catch up more in these sectors. This finding is contrary to our hypothesis 4a based on the home market effect, arguing that rich countries would keep their comparative advantage more in income elastic goods with large home demand. However, the findings are consistent with our hypothesis 4b which states that an export-oriented strategy as that pursued by post-WWII Southeast and East Asian economies to direct their exports mostly to high income markets would explain the fact that catching up in high income elastic products as exports are concerned might indeed be higher than in low income elastic products. These findings suggest that emerging countries do a good job in catching up also in the sectors with rising demand in rich countries. The results are more significant for the combined sample of manufacturing goods and services, for manufacturing separately and for the larger period based on a smaller sample of countries. However, although the coefficients sometimes become insignificant, they never change sign.

5.5 Discussion of results

The results of the convergence regressions with different interacting variables convey a fairly consistent message. Employing task complexity to proxy for the importance of tacit knowledge, export sophistication, or skill intensity, we find for all these specifications by and large the same results: (i) Technological catchup is slower in task complex, sophisticated, and skill intensive sectors based on manufacturing trade and production data from COMTRADE and UNIDO for 1960 until 2000. (ii) However, when we examine the more recent period, we find that technological catchup is faster in task complex, sophisticated, and skill intensive manufacturing sectors based on GTAP data. (iii) Technological catchup is slower in task complex, sophisticated, and skill intensive service sectors based on GTAP data. (iv) Technological catchup is faster in income elastic sectors based on GTAP data, both for manufacturing and services.

Hence, the scope for catchup has changed over time for the manufacturing sectors. Whereas in earlier periods we find less catchup in task complex manufacturing sectors, in later periods we find more catchup in these sectors. To explain this change we refer to the increased integration of the world economy since the 1990s. In particular two phenomena are important. First, there has been a strong increase in foreign direct investment (FDI) from developed to emerging countries. This FDI has enabled emerging countries to increasingly employ technology transferred by multinationals from developed countries. Our data suggest that this process has in particular taken place in manufacturing sectors with high task complexity thus generating stronger catchup. Second, the revolution in information and communications technology (ICT) has made it easier to transfer knowledge across countries. Furthermore, there was increased mobility by students and trainees from developing countries and evidence of return migration for people that gained work experience in advanced economies. This enabled firms from emerging economies to acquire knowledge from rich countries, in particular in complex sectors where it was difficult for them to compete before. These processes have not fostered catching up in the more complex services sectors, because the relevance of tacit knowledge is more prevalent in those sectors. The ICT-revolution has not helped emerging countries to catch up in the sectors where tacit knowledge is particularly important (think of financial and business services), since knowledge important in those sectors can not be easily transferred through ICT but continuous to require close person-to-person interaction.

To test the FDI explanation in this subsection as well as the role that outsourcing of production stages in less complex manufacturing sectors plays we have to do more research. In particular we should examine the FDI patterns from developed to emerging countries to see whether there has been an acceleration in the 1990s and whether this has been concentrated in complex manufacturing sectors. Furthermore, a more detailed analysis of outsourcing pattern as well as product quality gaps could allow us to understand the continued gaps in industries that have initially been characterized by low high-skill intensity in advanced economies.

6 Concluding Remarks

We have analyzed the relationship between the speed of convergence and the importance of tacit knowledge across sectors. Employing methods from the recent trade literature, we inferred sectoral productivity from trade and production data from two data sources and for two separate periods, UNIDO and Comtrade data from 1960 until 2000 for manufacturing goods and GTAP data between 1997 and 2011 for both manufacturing goods and services. Using the early data on manufacturing we found that the speed of convergence is slower in more tacit knowledge intensive sectors, more skill intensive sectors and sectors with a higher degree of export sophistication. With the more recent data we found that the effect of tacit knowledge intensity on the speed of convergence is reversed within manufacturing sectors, but still holds for services, suggesting that the catch-up of developing countries is more difficult in complex service sectors such as business services. With the more recent GTAP data we found faster catch-up in income elastic sectors, both for manufacturing and for services. We discussed explanations for the changing relation between catch-up and tacit knowledge intensity over time, in particular the increase in foreign direct investment to emerging countries and the ICT-revolution, both fostering the transfer of knowledge to the catching-up countries.

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Appendix A Estimating technology parameters

The data on imports are collected from the COMTRADE database at 4 digit SITC rev. 1 level an converted to 2 digit ISIC rev. 3 classification employing a concordance developed by the authors. We create a country specific concordance using a HS1996 crosswalk between SITC and ISIC. We employ total exports from the imports data in HS1996 to generate the shares of ISIC sectors in SITC sectors for those cases where SITC sectors match more than one ISIC sector. Then we take the mean of shares over the years and assign the SITC sector to a particular ISIC sector only if the share is larger or equal to 0.5. [15]

To get domestic spending on domestically produced goods we subtract the country j's exports from it's output gathered from 2014 UNIDO Industrial Statistics Database. The UNIDO data is reported at 2 digit ISIC rev. 3 level with some countries reporting the data as aggregates of combinations of several sectors for certain time periods. Such observations are, where possible, disaggregated based on the shares of sectors in these combinations in earlier or later years. We discard the countries with a short span of the data, with available data ending before 1996, with combined sectors that could not be disaggregated, or with data of poor quality. After cleaning the data there are still about 6 % of year-country-sector observations where exports are larger than output (5.4 %), or output data was missing. We impute those observations with Amelia II [16], before logarithmically transforming the difference between output and exports to make sure that in the imputed observations output would never be smaller than exports. We conduct multiple imputations based on trends specific to each sector, leads and lags, and export values.

[15] We exclude sector 23 (Manufacture of coke, refined petroleum products and nuclear fuel) from our analysis because it cannot be properly separated from sector 11 (Extraction of crude petroleum and natural gas).

[16] A package in R for imputing the missing data, created by J. Honaker, G. King, and M. Blackwell.

Appendix B Summary statistics and correlation tables

Table B1: Countries in the sample

Country	Period	Country	Period
Argentina	1980s-2000s	Japan	1960s-2000s
Australia	1960s-2000s	Jordan	1960s-2000s
Austria	1960s-2000s	Kazakhstan	1990s-2000s
Bangladesh	1970s-2000s	Kenya	1970s-2000s
Belgium-Luxembourg	1960s-2000s	Malaysia	1960s-2000s
Bolivia	1970s-2000s	Mauritius	1970s-2000s
Brazil	1990s-2000s	Mexico	1980s-2000s
Bulgaria	1990s-2000s	Morocco	1970s-2000s
Cameroon	1970s-2000s	New Zealand	1960s-2000s
Canada	1960s-2000s	Nigeria	1960s-1990s
Chile	1960s-2000s	Norway	1960s-2000s
China	1980s-2000s	Pakistan	1960s-2000s
Colombia	1960s-2000s	Peru	1980s-2000s
Costa Rica	1960s-2000s	Philippines	1960s-2000s
Czech Republic	1990s-2000s	Poland	1990s-2000s
Denmark	1960s-2000s	Portugal	1960s-2000s
Ecuador	1960s-2000s	Rep. of Korea	1960s-2000s
Egypt	1960s-2000s	Romania	1980s-2000s
Ethiopia	1970s-2000s	Russian Federation	1990s-2000s
Fiji	1960s-2000s	Senegal	1970s-2000s
Finland	1960s-2000s	Slovenia	1990s-2000s
France	1960s-2000s	South Africa	1970s-2000s
Germany	1960s-2000s	Spain	1960s-2000s
Ghana	1960s-2000s	Sri Lanka	1960s-2000s
Greece	1960s-2000s	Sweden	1960s-2000s
Guatemala	1960s-1990s	Tanzania	1970s-2000s
Honduras	1970s-1990s	Thailand	1960s-2000s
Hungary	1990s-2000s	Trinidad and Tobago	1960s-2000s
Iceland	1960s-2000s	Tunisia	1960s-2000s
India	1960s-2000s	Turkey	1960s-2000s
Indonesia	1970s-2000s	Ukraine	1990s-2000s
Iran	1960s-2000s,	United Kingdom	1960s-2000s
Ireland	1960s-2000s	United States	1960s-2000s
Israel	1960s-2000s	Uruguay	1970s-2000s
Italy	1960s-2000s		

Table B2: Countries in the sample of GTAP dataset

Country	Period	Country	Period
Albania	1997-2011	Lithuania	1997-2011
Argentina	1997-2011	Luxembourg	1997-2011
Armenia	2004-2011	Madagascar	2001-2011
Australia	1997-2011	Malawi	1997-2011
Austria	1997-2011	Malaysia	1997-2011
Azerbaijan	2004-2011	Malta	1997-2011
Bahrain	2004-2011	Mauritius	2001-2011
Bangladesh	1997-2011	Mexico	1997-2011
Belarus	2004-2011	Mongolia	2004-2011
Belgium	1997-2011	Morocco	1997-2011
Bolivia	2001-2011	Mozambique	1997-2011
Botswana	1997-2011	Namibia	2004-2011
Brazil	1997-2011	Nepal	2004-2011
Bulgaria	1997-2011	Netherlands	1997-2011
Cambodia	2004-2011	New Zealand	1997-2011
Cameroon	2004-2011	Nigeria	2001-2011
Canada	1997-2011	Norway	2004-2011
Chile	1997-2011	Oman	2004-2011
China	1997-2011	Pakistan	2001-2011
Colombia	1997-2011	Panama	2004-2011
Costa Rica	2004-2011	Paraguay	2004-2011
Croatia	1997-2011	Peru	1997-2011
Cyprus	1997-2011	Philippines	1997-2011
Czech Republic	1997-2011	Poland	1997-2011
Cote d'Ivoire	2004-2011	Portugal	1997-2011
Denmark	1997-2011	Qatar	2004-2011
Ecuador	2001-2011	Rep. of Korea	1997-2011
Egypt	2004-2011	Romania	1997-2011
El Salvador	2004-2011	Russian Federation	1997-2011
Estonia	1997-2011	Saudi Arabia	2004-2011
Ethiopia	2004-2011	Senegal	2004-2011
Finland	1997-2011	Singapore	1997-2011
France	1997-2011	Slovakia	1997-2011
Georgia	2004-2011	Slovenia	1997-2011
Germany	1997-2011	South Africa	2001-2011
Ghana	2004-2011	Spain	1997-2011
Greece	1997-2011	Sri Lanka	1997-2011
Guatemala	2004-2011	Sweden	1997-2011
Honduras	2004-2011	Switzerland	1997-2011
Hong Kong	1997-2011	Taiwan	1997-2011
Hungary	1997-2011	Tanzania	1997-2011
India	1997-2011	Thailand	1997-2011
Indonesia	1997-2011	Tunisia	2001-2011
Iran	2001-2011	Turkey	1997-2011
Ireland	1997-2011	Uganda	1997-2011
Israel	2004-2011	United States	1997-2011
Italy	1997-2011	Ukraine	2004-2011
Japan	1997-2011	United Kingdom	1997-2011
Kazakhstan	2004-2011	Uruguay	1997-2011
Kenya	2004-2011	Venezuela	1997-2011
Kuwait	2004-2011	Viet Nam	1997-2011
Kyrgyzstan	2004-2011	Zambia	1997-2011
Lao People's Dem. Rep.	2004-2011	Zimbabwe	1997-2011
Latvia	1997-2011		

Table B3: List of sectors

ISIC code	Sector name
15t16	Food, beverages and tabacco
17	Textiles
18t19	Wearing apparel, Leather and Footwear
20	Wood products, except furniture
21	Paper and paper products
22	Publishing, printing
24	Chemicals and chemical products
25	Rubber and plastics
26	Other non-metallic mineral products
27	Basic metals
28	Fabricated metal products
29t30	Office, accounting, computing, and other machinery
31t32	Electrical machinery, Communication equipment
33	Medical, precision and optical instruments
34t35	Transport equipment
36	Furniture, manufacturing n.e.c

Table B4: List of sectors in GTAP dataset

GTAP code	Sector name
aff	Agriculture, Forestry, Fisheries
	Manufacturing sectors
b_t	Beverages and Tobacco products
crp	Chemical Rubber Products
ele	Electronic Equipment
fmp	Fabricated Metal Products
lea	Leather
lum	Lumber
mvh	Motor Motor vehicles and parts
nmm	Non-Metallic Minerals
ome	Other Machinery & Equipment
omf	Other Manufacturing: includes recycling
otn	Other Transport Equipment
ppp	Paper & Paper Products
prf	Processed foods
tex	Textiles
wap	Wearing Apparel
	Services
atp	Air transport
cmn	Communications
cns	Construction
ely	Electricity
gdt	Gas Distribution
isr	Insurance
obs	Other Business Services
ofi	Other Financial Intermediation
otp	Other Transport
trd	Trade
wtp	Water transport
wtr	Water

Table B5: Summary statistics of log(TFP) by income groups from GTAP dataset

	Low income			Medium income			High income		
Year	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**
				All sectors					
1997	26.528	6.857	168	28.805	6.936	728	33.535	6.131	952
2001	26.550	6.471	196	29.076	6.357	952	33.991	5.883	952
2004	25.44	6.285	336	28.687	6.452	1512	33.971	6.271	1148
2007	25.664	6.107	336	29.636	6.211	1512	34.06	6.233	1148
2011	26.708	6.011	476	30.663	6.187	1596	33.931	6.385	1204
				Manufacturing sectors					
1997	29.23	4.417	90	31.642	4.287	390	35.69	4.578	510
2001	29.332	4.631	105	31.922	4.036	510	36.298	4.386	510
2004	27.098	5.642	180	30.143	5.922	810	34.902	6.365	615
2007	27.186	5.346	180	30.961	5.613	810	35.139	5.942	615
2011	27.586	5.597	255	31.436	5.652	855	34.613	6.097	645
				Service sectors					
1997	23.435	8.123	72	25.62	8.181	312	31.158	6.956	408
2001	23.375	7.054	84	25.902	7.17	408	31.404	6.471	408
2004	24.016	6.474	144	27.425	6.673	648	33.268	6.024	492
2007	24.377	6.498	144	28.489	6.583	648	33.159	6.419	492
2011	26.203	6.301	204	30.218	6.682	684	33.555	6.671	516

World Bank grouping of countries by income. The data is from 2010 where low income countries were with GNI per capita smaller or equal to $1,005; middle income economies were with GNI per capita of $1,006-$12,275; and high income economies were those with GNI per capita larger than $12,275.

Tables B6 and B7 display summary statistics and Table B8 shows the pairwise correlations of task variables. The manual tasks exhibit a negative correlation with the analytical tasks, indicating that more complex sectors perform less routine tasks and vice versa. The task intensity levels for each sector are depicted in figures C3 and C4 for Comtrade-UNIDO and GTAP datasets, respectively.

Table B6: Summary statistics of O*NET tasks

	Comtrade-UNIDO				GTAP			
Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
AnalyzeData	2.49	0.16	2.23	2.77	2.49	0.25	1.91	3.06
ThinkCrea	2.44	0.16	2.23	2.88	2.46	0.15	2.21	2.79
InterprInfo	2.3	0.11	2.11	2.57	2.36	0.2	2.1	2.91
CommInOrg	3.57	0.07	3.47	3.74	3.56	0.11	3.25	3.78
MakeDec	3.27	0.09	3.1	3.43	3.27	0.11	3.1	3.54
ContrMachines	2.85	0.31	2.2	3.22	2.47	0.59	1.07	3.23
OperVehicles	2.06	0.35	1.44	2.7	2	0.59	0.64	3.21
PhysActiv	2.77	0.35	2.07	3.2	2.55	0.58	1.04	3.31
HandlObj	2.93	0.36	2.25	3.35	2.64	0.6	1.12	3.36
N		1135				3276		

Table B7: Summary statistics of O*NET tasks for manufacturing sectors and services separately

	Manufacturing sectors				Service sectors				Business services			
Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
AnalyzeData	2.48	0.17	2.21	2.84	2.56	0.28	2.17	3.06	2.885	0.145	2.717	3.064
ThinkCrea	2.44	0.16	2.23	2.79	2.49	0.12	2.21	2.67	2.601	0.06	2.536	2.671
InterprInfo	2.3	0.11	2.11	2.51	2.45	0.24	2.18	2.91	2.725	0.17	2.551	2.909
CommInOrg	3.58	0.06	3.47	3.69	3.56	0.13	3.39	3.78	3.71	0.067	3.604	3.779
MakeDec	3.26	0.1	3.1	3.47	3.3	0.12	3.13	3.54	3.431	0.096	3.335	3.537
ContrMachines	2.84	0.31	2.24	3.23	1.95	0.47	1.07	2.54	1.36	0.262	1.072	1.661
OperVehicles	2.02	0.33	1.4	2.7	1.88	0.75	0.64	3.21	1.046	0.404	0.643	1.598
PhysActiv	2.78	0.34	2.12	3.2	2.19	0.63	1.04	3.03	1.469	0.422	1.041	1.95
HandlObj	2.94	0.35	2.25	3.36	2.22	0.6	1.12	3.07	1.545	0.386	1.123	2.002
N	1755				1404				428			

Notes: summary statistics from GTAP dataset. Business services include Communications, Insurance, Other business services, Other financial intermediation.

Table B8: O*NET tasks cross-correlation table

Variables	AnData	ThCrea	InInfo	CoInOrg	MaDec	CoMach	OpVeh	PhActiv	HaObj
AnalyzeData	1.000								
ThinkCrea	0.643 (0.495)	1.000							
InterprInfo	0.722 (0.890)	0.796 (0.512)	1.000						
CommInOrg	0.375 (0.615)	0.760 (0.213)	0.713 (0.534)	1.000					
MakeDec	0.745 (0.805)	0.781 (0.625)	0.697 (0.806)	0.494 (0.387)	1.000				
ContrMachines	-0.805 (-0.718)	-0.859 (-0.487)	-0.886 (-0.847)	-0.672 (-0.390)	-0.704 (-0.635)	1.000			
OperVehicles	-0.554 (-0.776)	-0.688 (-0.403)	-0.642 (-0.777)	-0.809 (-0.742)	-0.596 (-0.647)	0.655 (0.626)	1.000		
PhysActiv	-0.844 (-0.874)	-0.895 (-0.556)	-0.898 (-0.948)	-0.707 (-0.511)	-0.831 (-0.772)	0.935 (0.914)	0.797 (0.795)	1.000	
HandlObj	-0.890 (-0.845)	-0.869 (-0.557)	-0.893 (-0.930)	-0.658 (-0.434)	-0.806 (-0.750)	0.958 (0.943)	0.725 (0.721)	0.986 (0.988)	1.000

Notes: values in parentheses from GTAP dataset.

Tables B9 and B10 display summary statistics of PRODY measures for whole sample in both datasets, and also separately for manufacturing sectors and services in GTAP dataset. Correlations coefficients of PRODY with O*NET measures are given in table B13.

Table B9: Summary statistics of PRODY measures

	Comtrade-UNIDO				GTAP			
Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
PRODY(1960s/1997)	1.385	0.542	0.635	2.429	1.049	0.328	0.426	1.58
PRODY(1970s/2001)	1.283	0.444	0.645	2.049	1.099	0.418	0.366	2.081
PRODY(1980s/2004)	1.278	0.454	0.572	1.903	1.102	0.61	0.306	3.165
PRODY(1990s/2007)	1.25	0.481	0.409	1.947	1.079	0.576	0.308	3.153
PRODY(2000s/2011)	1.125	0.415	0.457	1.731	1.058	0.554	0.314	3.059
N		1135				3276		

Table B10: Summary statistics of PRODY for manufacturing sectors and services separately

	Manufacturing sectors				Service sectors			
Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
PRODY(1997)	1.125	0.357	0.45	1.58	1.007	0.225	0.618	1.432
PRODY(2001)	1.094	0.414	0.366	1.592	1.161	0.39	0.506	2.081
PRODY(2004)	1.079	0.442	0.306	1.64	1.196	0.753	0.355	3.165
PRODY(2007)	1.024	0.406	0.308	1.51	1.209	0.71	0.415	3.153
PRODY(2011)	0.989	0.375	0.314	1.479	1.202	0.688	0.445	3.059
N		1755				1404		

Notes: summary statistics from GTAP dataset. Restricting the sample to countries available in all years in the estimation of PRODY does not reduce the Std. Dev. in 2004 and later.

Table B11: Sector ranking by PRODY

ISIC code	**Sector name**	**PRODY score**
20	Wood products, except furniture	0.564
17	Textiles	0.624
18t19	Wearing apparel, Leather and Footwear	0.651
15t16	Food, beverages and tabacco	0.662
27	Basic metals	0.942
26	Other non-metallic mineral products	1.169
36	Furniture, manufacturing n.e.c	1.247
22	Publishing, printing	1.337
25	Rubber and plastics	1.383
31t32	Electrical machinery, Communication equipment	1.403
24	Chemicals and chemical products	1.468
28	Fabricated metal products	1.492
34t35	Transport equipment	1.579
33	Medical, precision and optical instruments	1.835
29t30	Office, accounting, computing, and other machinery	1.928
21	Paper and paper products	1.948

PRODY average across decades.

Table B12: Sector ranking by PRODY (GTAP dataset)

GTAP code	Sector name	PRODY score
aff	Agriculture, Forestry, Fisheries	0.383
	Manufacturing sectors	
wap	Wearing Apparel	0.349
lea	Leather	0.489
tex	Textiles	0.533
prf	Processed foods	0.744
lum	Lumber	0.832
nmm	Non-Metallic Minerals	0.931
omf	Other Manufacturing: includes recycling	1.018
b_t	Beverages and Tobacco products	1.063
ele	Electronic Equipment	1.232
fmp	Fabricated Metal Products	1.295
crp	Chemical Rubber Products	1.438
otn	Other Transport Equipment	1.441
mvh	Motor Motor vehicles and parts	1.505
ppp	Paper & Paper Products	1.505
ome	Other Machinery & Equipment	1.553
	Services	
ely	Electricity	0.491
gdt	Gas Distribution	0.713
wtr	Water	0.725
otp	Other Transport	0.789
atp	Air transport	0.936
cmn	Communications	0.975
wtp	Water transport	1.023
cns	Construction	1.162
trd	Trade	1.418
obs	Other Business Services	1.451
isr	Insurance	1.617
ofi	Other Financial Intermediation	2.557

PRODY average across years.

Table B13: Correlation table of PRODY and tacit knowledge measures

Variables	AnalyzeData	ThinkCrea	InterprInfo	CommInOrg	MakeDec
PRODY(1960s/1997)	0.682 (0.483)	0.384 (0.351)	0.463 (0.330)	0.080 (0.366)	0.541 (0.429)
PRODY(1970s/2001)	0.773 (0.592)	0.425 (0.391)	0.558 (0.549)	0.132 (0.434)	0.639 (0.578)
PRODY(1980s/2004)	0.690 (0.616)	0.473 (0.348)	0.590 (0.639)	0.200 (0.558)	0.617 (0.645)
PRODY(1990s/2007)	0.724 (0.649)	0.590 (0.374)	0.678 (0.690)	0.374 (0.544)	0.647 (0.677)
PRODY(2000s/2011)	0.849 (0.623)	0.554 (0.353)	0.752 (0.678)	0.396 (0.544)	0.682 (0.652)

Notes: values in parentheses from GTAP dataset.

Table B14: Summary statistics of schooling intensity measures

Variable	Mean	Std. Dev.	Min.	Max.
Schooling (1960)	9.693	0.959	7.786	11.047
Schooling (1970)	10.615	0.848	9.193	11.977
Schooling (1980)	11.597	0.786	10.103	12.721
Schooling (1990)	12.843	0.546	11.908	13.709
Schooling (2000)	12.943	0.636	11.989	14.144
N		1135		

The schooling intensity measure is the average years of employee schooling.

Table B15: Cross-correlation table of schooling intensity and tacit knowledge measures

Variables	AnData	ThCrea	InInfo	CoInOrg	MaDec	SI1960	SI1970	SI1980	SI1990	SI2000
Schooling (1960)	0.857	0.646	0.871	0.532	0.718	1.000				
Schooling (1970)	0.895	0.616	0.836	0.436	0.723	0.988	1.000			
Schooling (1980)	0.904	0.705	0.854	0.430	0.726	0.935	0.960	1.000		
Schooling (1990)	0.939	0.709	0.835	0.448	0.732	0.924	0.950	0.983	1.000	
Schooling (2000)	0.952	0.686	0.800	0.425	0.722	0.908	0.939	0.958	0.988	1.000

Table B16: Summary statistics of high skill intensity measures using GTAP data

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
	All sectors				
High skill int.(1997)	0.13	0.051	0.016	0.287	1848
High skill int.(2001)	0.126	0.052	0.015	0.276	2100
High skill int.(2004)	0.115	0.047	0.012	0.244	2996
High skill int.(2007)	0.116	0.048	0.012	0.247	2996
High skill int.(2011)	0.222	0.061	0.064	0.365	2996
	Manufacturing sectors				
High skill int.(1997)	0.115	0.025	0.073	0.165	990
High skill int.(2001)	0.109	0.023	0.067	0.156	1125
High skill int.(2004)	0.097	0.019	0.064	0.136	1605
High skill int.(2007)	0.099	0.019	0.065	0.138	1605
High skill int.(2011)	0.214	0.024	0.163	0.245	1605
	Service sectors				
High skill int.(1997)	0.159	0.056	0.104	0.287	792
High skill int.(2001)	0.157	0.056	0.107	0.276	900
High skill int.(2004)	0.145	0.05	0.091	0.244	1284
High skill int.(2007)	0.147	0.051	0.093	0.247	1284
High skill int.(2011)	0.246	0.073	0.155	0.365	1284

The high skill intensity measure is the share of value added paid to the high skilled workers averaged across countries. Using t test we find that the average high skill intensity is significantly larger in services compared to manufacturing sectors.

Table B17: Cross-correlation table of high skill intensity and tacit knowledge measures

Variables	AnData	ThCrea	InInfo	CoInOrg	MaDec	HS97	HS01	HS04	HS07	HS11
High skill int.(1997)	0.873	0.392	0.876	0.649	0.713	1.000				
High skill int.(2001)	0.856	0.380	0.883	0.637	0.704	0.994	1.000			
High skill int.(2004)	0.839	0.336	0.880	0.584	0.670	0.980	0.989	1.000		
High skill int.(2007)	0.843	0.337	0.881	0.578	0.672	0.981	0.989	1.000	1.000	
High skill int.(2011)	0.527	-0.058	0.504	0.615	0.377	0.663	0.686	0.699	0.697	1.000

The high skill intensity measure is the share of value added paid to the high skilled workers averaged across countries.

Table B18: Summary statistics of income elasticity measures (η_{js})

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
			All sectors		
Income elast.(1997)	1.053	0.277	0.545	2.405	1848
Income elast.(2001)	1.054	0.297	0.512	2.56	2100
Income elast.(2004)	1.032	0.258	0.515	2.268	2996
Income elast.(2007)	1.03	0.265	0.518	2.335	2996
Income elast.(2011)	1.006	0.234	0.538	2.113	2996
			Manufacturing sectors		
Income elast.(1997)	1.004	0.172	0.545	1.353	990
Income elast.(2001)	1.002	0.17	0.512	1.354	1125
Income elast.(2004)	0.965	0.165	0.515	1.336	1605
Income elast.(2007)	0.97	0.166	0.518	1.339	1605
Income elast.(2011)	0.943	0.142	0.538	1.238	1605
			Service sectors		
Income elast.(1997)	1.147	0.344	0.851	2.405	792
Income elast.(2001)	1.152	0.378	0.809	2.56	900
Income elast.(2004)	1.151	0.294	0.79	2.268	1284
Income elast.(2007)	1.142	0.309	0.796	2.335	1284
Income elast.(2011)	1.119	0.266	0.844	2.113	1284

Using t test we find that the average income elasticity is significantly larger in services compared to manufacturing sectors.

Table B19: Cross-correlation table of income elasticity and tacit knowledge measures

Variables	AnData	ThCrea	InInfo	CoInOrg	MaDec
Income elast.(1997)	0.370	0.244	0.320	0.087	0.439
Income elast.(2001)	0.305	0.216	0.261	0.067	0.379
Income elast.(2004)	0.450	0.340	0.456	0.279	0.470
Income elast.(2007)	0.454	0.304	0.440	0.286	0.460
Income elast.(2011)	0.445	0.253	0.446	0.270	0.435

Table B20: Cross-correlation table

Variables	$PC1_{complex}$	$PC1_{manual}$	PRODY(2004)	Inc. elast.(2004)	High skill int.(2004)
			All sectors		
$PC1_{complex}$	1.000				
$PC1_{manual}$	-0.895	1.000			
PRODY(2004)	0.685	-0.605	1.000		
Income elast.(2004)	0.490	-0.503	0.281	1.000	
High skill int.(2004)	0.820	-0.909	0.593	0.488	1.000
			Manufacturing sectors		
$PC1_{complex}$	1.000				
$PC1_{manual}$	-0.961	1.000			
PRODY(2004)	0.724	-0.580	1.000		
Income elast.(2004)	0.687	-0.570	0.715	1.000	
High skill int.(2004)	0.737	-0.633	0.665	0.619	1.000
			Service sectors		
$PC1_{complex}$	1.000				
$PC1_{manual}$	-0.943	1.000			
PRODY(2004)	0.630	-0.651	1.000		
Income elast.(2004)	0.266	-0.240	-0.009	1.000	
High skill int.(2004)	0.910	-0.939	0.604	0.178	1.000

$PC1_{complex}$ and $PC1_{manual}$ are primary components among the complex and manual tasks, respectively. The former one explains 68 % of total variance and the latter one - 88 %.

Appendix C Additional regression results

Appendix C.1 Robustness

We check the robustness of the findings in the main text by employing manual tasks as an opposite measure to the complexity variable. These manual tasks can be easily codified, and thus the knowledge can be relatively quickly transfered across companies and countries. As we have shown above complex and manual tasks exhibit a negative correlation. Thus, the more important are complex tasks the less manual tasks are performed in a sector. This implies that sectors intense in manual tasks should converge faster. The results with manual tasks are presented in table C3 for the Comtrade-UNIDO dataset and in table C4 for the GTAP dataset. As expected, the interaction terms with manual tasks have an opposite sign compared to the interactions terms with complex tasks in the previous tables. In the Comtrade-UNIDO dataset the sector most intensive in manual tasks has a rate of convergence more than 10 percentage points higher than the least manual sector. The interaction terms are statistically significant at 5% level in the estimations for 1960s-2000s and 1980s-2000s, and at 10% level for 1960s-1980s (except the interaction term with Controlling Machines). Also, it seems that manual tasks are picking up part of the convergence: when including the interaction term with manual tasks the estimates of β become statistically non-significant. The more intensive in manual tasks is the sector and the more backward it was the faster it's productivity has grown.

Again the results on manufacturing sectors in the GTAP dataset are contradicting the ones from Comtrade-UNIDO data. Here the more intensive in manual tasks a sector is the slower it converges; however, these results are statistically significant only with "Operating Vehicles" but not with the other three manual tasks. In services we get statistically significant results for the tasks "Controlling Machines" and "Operating Vehicles". Those service sectors that are more intensive in manual tasks converge faster, the speed of convergence in the most manual service sector is around 2 percentage points higher than in the least manual service sector.

Table C1: Convergence regressions for different periods

	(1) 1960s-2000s	(2) 1980s-2000s	(3) 1960s-1970s	(4) 1970s-1980s	(5) 1980s-1990s	(6) 1990s-2000s
$log(z_{Initial})$	-0.526***	-0.304***	-0.242***	-0.208***	-0.227***	-0.150***
	(-9.78)	(-6.15)	(-6.49)	(-6.17)	(-6.16)	(-4.21)
Constant	3.729***	-2.759***	3.754***	-2.418***	-2.877*	3.556***
	(15.50)	(-4.05)	(32.69)	(-11.77)	(-10.58)	(15.25)
Observations	640	895	688	847	911	1039
Adjusted R^2	0.903	0.891	0.843	0.837	0.866	0.904
Speed of Convergence, per decade	0.187	0.181	0.277	0.233	0.257	0.162

t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
The dependent variable is the growth of estimated TFP in respective time periods. All estimations include country, and sector dummies. Standard errors clustered at the country level.

Table C2: Convergence regressions for different time periods using GTAP data

	1997-2011 (1)	2004-2011 (2)	1997-2001 (3)	2001-2004 (4)	2004-2007 (5)	2007-2011 (6)
Panel A: All sectors						
$log(z_{Initial})$	-0.545***	-0.231***	-0.152***	-0.399***	-0.0851***	-0.192***
	(-15.33)	(-9.65)	(-6.34)	(-12.32)	(-4.95)	(-7.01)
Constant	19.63***	13.16***	9.866***	11.86***	5.332***	10.08***
	(49.15)	(17.18)	(35.95)	(29.54)	(9.59)	(10.75)
Observations	1848	2996	1848	2100	2996	2996
Adjusted R^2	0.934	0.812	0.840	0.934	0.823	0.777
Speed of Convergence, per year	0.056	0.037	0.041	0.170	0.030	0.053
Panel B: Manufacturing sectors						
$log(z_{Initial})$	-0.565***	-0.225***	-0.192***	-0.335***	-0.0341*	-0.251***
	(-12.46)	(-6.25)	(-8.39)	(-5.67)	(-2.51)	(-5.38)
Constant	14.46***	6.680***	8.121***	14.77***	1.578***	5.988***
	(14.44)	(18.64)	(17.28)	(5.54)	(11.01)	(11.28)
Observations	990	1605	990	1125	1605	1605
Adjusted R^2	0.945	0.797	0.941	0.955	0.861	0.791
Speed of Convergence, per year	0.059	0.036	0.053	0.136	0.012	0.072
Panel C: Service sectors						
$log(z_{Initial})$	-0.537***	-0.227***	-0.139***	-0.428***	-0.0802***	-0.189***
	(-11.18)	(-7.66)	(-4.17)	(-11.81)	(-3.73)	(-6.56)
Constant	28.20***	13.52***	6.395***	17.48***	5.372***	3.459***
	(12.70)	(14.62)	(4.17)	(16.94)	(7.94)	(8.37)
Observations	792	1284	792	900	1284	1284
Adjusted R^2	0.924	0.867	0.791	0.900	0.856	0.817
Speed of Convergence, per year	0.055	0.037	0.037	0.186	0.028	0.052

t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
The dependent variable is the growth of estimated TFP in different time periods. All estimations include country, and sector dummies. Standard errors clustered at the country level.

Table C3: The effect of routine task intensity on the speed of convergence in different time periods

Tasks:	ContrMachines	OperVehicles	PhysActiv	HandlObj
	(1)	(2)	(3)	(4)
		Panel A: 1960s-2000s		
$log(z_{Initial})$	0.0164	-0.239	-0.0616	-0.0673
	(0.09)	(-1.77)	(-0.36)	(-0.40)
$log(z_{Initial}) * Task$	-0.217**	-0.164*	-0.197**	-0.183**
	(-3.40)	(-2.62)	(-3.09)	(-3.11)
Observations	640	640	640	640
Adjusted R^2	0.906	0.905	0.906	0.905
SoC in averagely manual sector	0.230	0.214	0.234	0.231
SoC in least manual sector	0.154	0.161	0.159	0.163
SoC in most manual sector	0.287	0.285	0.294	0.285
		Panel B: 1960s-1980s		
$log(z_{Initial})$	-0.209	-0.267**	-0.132	-0.168
	(-1.41)	(-2.77)	(-1.05)	(-1.24)
$log(z_{Initial}) * Task$	-0.0815	-0.0838	-0.118*	-0.0971
	(-1.44)	(-1.74)	(-2.45)	(-1.94)
Observations	672	672	672	672
Adjusted R^2	0.805	0.805	0.806	0.805
SoC in averagely manual sector	0.291	0.290	0.308	0.301
SoC in least manual sector	0.246	0.245	0.237	0.244
SoC in most manual sector	0.319	0.340	0.358	0.340
		Panel C: 1980s-2000s		
$log(z_{Initial})$	0.129	-0.112	0.0441	0.0640
	(0.91)	(-1.00)	(0.34)	(0.50)
$log(z_{Initial}) * Task$	-0.167**	-0.108	-0.143*	-0.142**
	(-2.90)	(-1.82)	(-2.60)	(-2.74)
Observations	895	895	895	895
Adjusted R^2	0.893	0.892	0.893	0.893
SoC in averagely manual sector	0.214	0.203	0.218	0.216
SoC in least manual sector	0.137	0.155	0.146	0.147
SoC in most manual sector	0.264	0.257	0.268	0.265

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The dependent variable is the growth of estimated TFP in respective time periods. All estimations include a constant, country, and sector dummies. Standard errors clustered at the country level. The speed of convergence, per decade, is reported for least, averagely, and most routine sectors.

Table C4: The effect of routine task intensity on the speed of convergence in different time periods using GTAP data

	Manufacturing sectors				Service sectors			
Tasks:	ContrMachines (1)	OperVehicles (2)	PhysActiv (3)	HandlObj (4)	ContrMachines (5)	OperVehicles (6)	PhysActiv (7)	HandlObj (8)
Panel A: 1997-2011								
$log(z_{Initial})$	-0.585***	-0.756***	-0.685***	-0.684***	-0.437***	-0.460***	-0.473***	-0.480***
	(-5.16)	(-7.17)	(-6.86)	(-6.64)	(-8.24)	(-10.31)	(-9.90)	(-9.84)
$log(z_{Initial}) * Task$	0.00734	0.0920*	0.0456	0.0425	-0.0630*	-0.0592**	-0.0383	-0.0335
	(0.19)	(2.36)	(1.34)	(1.29)	(-2.02)	(-3.28)	(-2.00)	(-1.78)
Observations	990	990	990	990	792	792	792	792
Adjusted R^2	0.945	0.946	0.945	0.945	0.925	0.926	0.925	0.925
SoC in averagely complex sectors	0.060	0.061	0.060	0.060	0.064	0.062	0.060	0.060
SoC in least complex sectors	0.062	0.085	0.073	0.072	0.050	0.049	0.051	0.052
SoC in most complex sectors	0.059	0.044	0.055	0.056	0.073	0.075	0.065	0.064
Panel B: 1997-2004								
$log(z_{Initial})$	-0.485***	-0.625***	-0.550***	-0.546***	-0.387***	-0.398***	-0.413***	-0.417***
	(-5.67)	(-8.06)	(-7.46)	(-7.05)	(-9.43)	(-11.23)	(-11.19)	(-11.00)
$log(z_{Initial}) * Task$	0.00430	0.0728*	0.0292	0.0260	-0.0486*	-0.0509***	-0.0308*	-0.0277
	(0.15)	(2.43)	(1.14)	(1.04)	(-2.16)	(-3.79)	(-2.28)	(-1.99)
Observations	990	990	990	990	792	792	792	792
Adjusted R^2	0.966	0.966	0.966	0.966	0.932	0.932	0.932	0.931
SoC in averagely complex sectors	0.092	0.093	0.092	0.093	0.101	0.099	0.097	0.096
SoC in least complex sectors	0.094	0.123	0.105	0.104	0.083	0.081	0.084	0.085
SoC in most complex sectors	0.091	0.071	0.086	0.088	0.112	0.118	0.103	0.102
Panel C: 2004-2011								
$log(z_{Initial})$	-0.268***	-0.346***	-0.333***	-0.327***	-0.175***	-0.194***	-0.204***	-0.211***
	(-3.78)	(-5.27)	(-5.51)	(-5.03)	(-4.99)	(-6.45)	(-6.18)	(-6.20)
$log(z_{Initial}) * Task$	0.0153	0.0561*	0.0397	0.0355	-0.0321*	-0.0258**	-0.0138	-0.00911
	(0.59)	(2.56)	(1.85)	(1.60)	(-2.17)	(-2.64)	(-1.35)	(-0.88)
Observations	1605	1605	1605	1605	1284	1284	1284	1284
Adjusted R^2	0.797	0.798	0.798	0.798	0.867	0.868	0.867	0.867
SoC in averagely complex sectors	0.037	0.038	0.038	0.038	0.042	0.040	0.039	0.038
SoC in least complex sectors	0.041	0.053	0.049	0.048	0.034	0.034	0.035	0.036
SoC in most complex sectors	0.035	0.026	0.032	0.033	0.047	0.046	0.041	0.040

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
The dependent variable is the growth of estimated TFP in respective time periods. All estimations include a constant, country, and sector dummies. Standard errors clustered at the country level. The speed of convergence, per year, is reported for least, averagely, and most manual sectors.

Table C5: The effect of tacit knowledge on the speed of convergence in different time periods

Tasks:	AnalyzeData	ThinkCrea	InterprInfo	CommInOrg	MakeDec
	(1)	(2)	(3)	(4)	(5)
			Panel A: 1960s-2000s		
$log(z_{Initial})$	-1.317***	-1.554***	-1.809***	-3.872**	-2.532**
	(-4.17)	(-4.79)	(-4.88)	(-3.39)	(-2.81)
$log(z_{Initial}) * Task$	0.299*	0.386**	0.531**	0.920**	0.594*
	(2.45)	(3.09)	(3.41)	(2.90)	(2.19)
Observations	640	640	640	640	640
Adjusted R^2	0.904	0.905	0.905	0.905	0.905
SoC in averagely complex sectors	0.211	0.229	0.220	0.219	0.221
SoC in least complex sectors	0.263	0.286	0.291	0.284	0.295
SoC in most complex sectors	0.168	0.141	0.146	0.141	0.170
			Panel B: 1960s-1980s		
$log(z_{Initial})$	-1.018**	-1.028***	-0.984***	-1.700*	-2.280**
	(-3.22)	(-4.89)	(-3.58)	(-2.35)	(-3.45)
$log(z_{Initial}) * Task$	0.229	0.234**	0.226*	0.354	0.553**
	(1.90)	(3.06)	(2.11)	(1.79)	(2.81)
Observations	672	672	672	672	672
Adjusted R^2	0.806	0.806	0.805	0.804	0.807
SoC in averagely complex sectors	0.296	0.304	0.289	0.286	0.315
SoC in least complex sectors	0.355	0.352	0.332	0.320	0.417
SoC in most complex sectors	0.243	0.218	0.235	0.236	0.239
			Panel C: 1980s-2000s		
$log(z_{Initial})$	-1.039***	-1.084***	-1.250***	-3.252**	-1.596*
	(-3.61)	(-3.48)	(-3.55)	(-3.20)	(-2.28)
$log(z_{Initial}) * Task$	0.282**	0.301*	0.397**	0.813**	0.383
	(2.68)	(2.66)	(2.87)	(2.94)	(1.88)
Observations	895	895	895	895	895
Adjusted R^2	0.893	0.893	0.893	0.893	0.892
SoC in averagely complex sectors	0.205	0.215	0.204	0.212	0.208
SoC in least complex sectors	0.265	0.268	0.265	0.281	0.263
SoC in most complex sectors	0.150	0.124	0.129	0.118	0.164

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The dependent variable is the growth of estimated TFP in respective time periods. All estimations include a constant, country, and sector dummies. Standard errors clustered at the country level. The speed of convergence, per decade, is reported for least, averagely, and most complex sectors.

Table C6: The effect of tacit knowledge on the speed of convergence in each decade

Tasks:	AnalyzeData	ThinkCrea	InterprInfo	CommInOrg	MakeDec
	(1)	(2)	(3)	(4)	(5)
			Panel A: 1960s-1970s		
$log(z_{Initial})$	-0.652**	-0.606**	-0.528*	-0.685	-1.067*
	(-2.83)	(-3.34)	(-2.04)	(-1.35)	(-2.15)
$log(z_{Initial}) * Task$	0.155	0.139	0.119	0.122	0.245
	(1.70)	(1.90)	(1.06)	(0.88)	(1.62)
Observations	688	688	688	688	688
Adjusted R^2	0.844	0.844	0.843	0.843	0.844
SoC in averagely complex sectors	0.307	0.310	0.294	0.287	0.309
SoC in least complex sectors	0.365	0.352	0.325	0.304	0.370
SoC in most complex sectors	0.251	0.231	0.252	0.260	0.258
			Panel B: 1970s-1980s		
$log(z_{Initial})$	-0.310	-0.336	-0.311	-0.634	-1.105*
	(-1.29)	(-1.54)	(-1.45)	(-1.04)	(-2.13)
$log(z_{Initial}) * Task$	0.0384	0.0485	0.0426	0.117	0.265
	(0.44)	(0.61)	(0.50)	(0.70)	(1.74)
Observations	847	847	847	847	847
Adjusted R^2	0.837	0.837	0.837	0.837	0.838
SoC in averagely complex sectors	0.241	0.245	0.239	0.242	0.270
SoC in least complex sectors	0.254	0.259	0.250	0.258	0.333
SoC in most complex sectors	0.228	0.219	0.225	0.218	0.216
			Panel B: 1980s-1990s		
$log(z_{Initial})$	-0.852***	-0.601**	-0.517	-1.390*	-1.055
	(-3.61)	(-2.89)	(-1.78)	(-2.36)	(-1.90)
$log(z_{Initial}) * Task$	0.239**	0.145	0.122	0.321	0.246
	(2.74)	(1.90)	(1.02)	(1.98)	(1.50)
Observations	911	911	911	911	911
Adjusted R^2	0.868	0.866	0.866	0.866	0.866
SoC in averagely complex sectors	0.294	0.285	0.269	0.278	0.288
SoC in least complex sectors	0.384	0.328	0.301	0.323	0.348
SoC in most complex sectors	0.210	0.205	0.227	0.209	0.237
			Panel B: 1990s-2000s		
$log(z_{Initial})$	-0.271	-0.331	-0.440	-1.151*	-0.586
	(-1.30)	(-1.61)	(-1.83)	(-2.05)	(-1.24)
$log(z_{Initial}) * Task$	0.0464	0.0695	0.122	0.275	0.130
	(0.59)	(0.90)	(1.21)	(1.78)	(0.92)
Observations	1039	1039	1039	1039	1039
Adjusted R^2	0.904	0.904	0.905	0.905	0.905
SoC in averagely complex sectors	0.169	0.176	0.175	0.183	0.176
SoC in least complex sectors	0.184	0.194	0.203	0.218	0.204
SoC in most complex sectors	0.154	0.141	0.136	0.129	0.152

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The dependent variable is the growth of estimated TFP in respective decade. All estimations include a constant, country, and sector dummies. Standard errors clustered at the country level. The speed of convergence, per decade, is reported for least, averagely, and most complex sectors.

Table C7: The effect of tacit knowledge on the speed of convergence in different time periods using GTAP data

Tasks:	AnalyzeData (1)	ThinkCrea (2)	InterprInfo (3)	CommInOrg (4)	MakeDec (5)
			Panel A: 1997-2011		
$log(z_{Initial})$	-0.449***	-1.022***	-0.622***	-0.685*	-0.346
	(-5.04)	(-5.81)	(-4.99)	(-2.12)	(-1.33)
$log(z_{Initial}) * Task$	-0.0355	0.187**	0.0293	0.0385	-0.0591
	(-1.31)	(2.88)	(0.69)	(0.46)	(-0.80)
Observations	1848	1848	1848	1848	1848
Adjusted R^2	0.934	0.935	0.934	0.934	0.934
SoC in averagely complex sectors	0.055	0.059	0.057	0.057	0.055
SoC in least complex sectors	0.052	0.067	0.059	0.059	0.054
SoC in most complex sectors	0.058	0.049	0.055	0.055	0.058
			Panel B: 1997-2004		
$log(z_{Initial})$	-0.355***	-0.882***	-0.540***	-0.345	-0.158
	(-5.35)	(-5.57)	(-5.72)	(-1.55)	(-0.85)
$log(z_{Initial}) * Task$	-0.0395	0.165*	0.0297	-0.0325	-0.0901
	(-1.90)	(2.61)	(0.88)	(-0.58)	(-1.67)
Observations	1848	1848	1848	1848	1848
Adjusted R^2	0.947	0.947	0.947	0.947	0.947
SoC in averagely complex sectors	0.086	0.092	0.091	0.088	0.086
SoC in least complex sectors	0.080	0.104	0.093	0.086	0.082
SoC in most complex sectors	0.092	0.078	0.086	0.090	0.093
			Panel C: 2004-2011		
$log(z_{Initial})$	-0.170**	-0.220	-0.160*	-0.592***	-0.167
	(-3.34)	(-1.58)	(-2.08)	(-5.72)	(-1.02)
$log(z_{Initial}) * Task$	-0.0231	-0.00426	-0.0278	0.101***	-0.0190
	(-1.34)	(-0.08)	(-0.96)	(3.72)	(-0.40)
Observations	2996	2996	2996	2996	2996
Adjusted R^2	0.812	0.812	0.812	0.812	0.812
SoC in averagely complex sectors	0.037	0.037	0.037	0.038	0.037
SoC in least complex sectors	0.034	0.037	0.035	0.044	0.037
SoC in most complex sectors	0.039	0.038	0.039	0.034	0.038

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The dependent variable is the growth of estimated TFP in respective time periods. All estimations include a constant, country, and sector dummies. Standard errors clustered at the country level. The speed of convergence, per year, is reported for least, averagely, and most complex sectors.

Table C8: The effect of tacit knowledge on the speed of convergence in different time periods using GTAP data

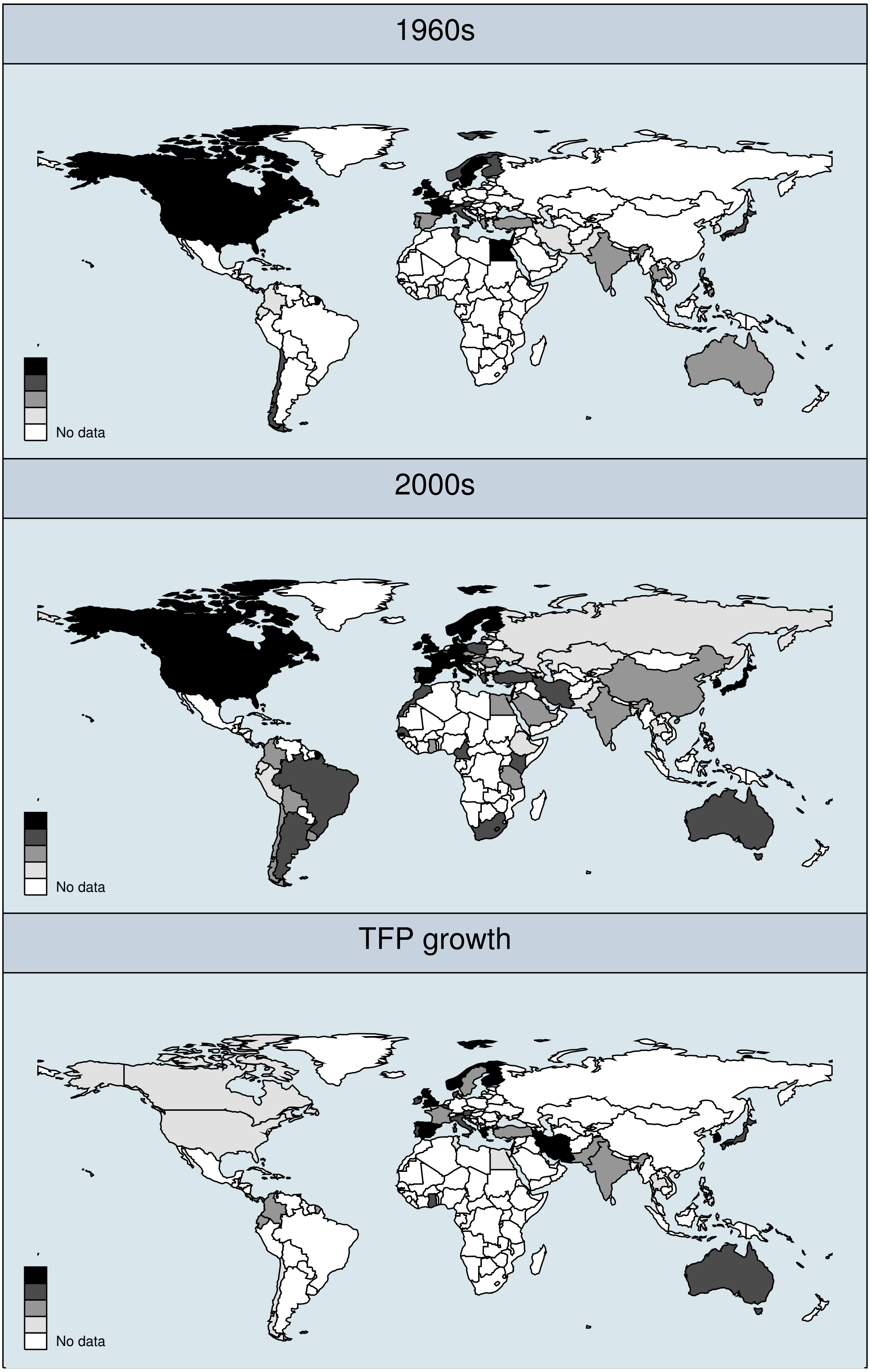
	Manufacturing sectors					Service sectors				
Tasks:	AnalyzeData (1)	ThinkCrea (2)	InterprInfo (3)	CommInOrg (4)	MakeDec (5)	AnalyzeData (6)	ThinkCrea (7)	InterprInfo (8)	CommInOrg (9)	MakeDec (10)
Panel A: 1997-2011										
$log(z_{Initial})$	-0.0244	-0.635***	-0.322	0.639	0.911	-0.713***	-1.363***	-0.830***	-1.719**	-0.837**
	(-0.12)	(-4.15)	(-1.61)	(1.05)	(1.86)	(-5.65)	(-5.22)	(-5.11)	(-3.35)	(-2.68)
$log(z_{Initial}) * Task$	-0.212**	0.0280	-0.103	-0.335	-0.445**	0.0634	0.324***	0.110*	0.325*	0.0884
	(-2.76)	(0.50)	(-1.32)	(-1.94)	(-3.02)	(1.72)	(3.52)	(2.14)	(2.44)	(1.03)
Observations	990	990	990	990	990	792	792	792	792	792
Adjusted R^2	0.946	0.945	0.945	0.945	0.946	0.925	0.925	0.925	0.926	0.924
SoC in averagely complex sectors	0.058	0.060	0.059	0.057	0.056	0.058	0.059	0.060	0.059	0.057
SoC in least complex sectors	0.040	0.061	0.055	0.043	0.045	0.064	0.074	0.065	0.078	0.059
SoC in most complex sectors	0.080	0.058	0.069	0.070	0.077	0.052	0.044	0.051	0.048	0.053
Panel B: 1997-2004										
$log(z_{Initial})$	-0.0472	-0.561***	-0.380*	0.118	1.037**	-0.600***	-1.019***	-0.666***	-1.258***	-0.563*
	(-0.32)	(-4.18)	(-2.03)	(0.24)	(3.01)	(-6.28)	(-4.29)	(-5.87)	(-3.46)	(-2.48)
$log(z_{Initial}) * Task$	-0.168**	0.0347	-0.0396	-0.165	-0.455***	0.0485	0.218*	0.0756*	0.218*	0.0292
	(-2.97)	(0.70)	(-0.54)	(-1.20)	(-4.42)	(1.72)	(2.45)	(2.12)	(2.32)	(0.47)
Observations	990	990	990	990	990	792	792	792	792	792
Adjusted R^2	0.966	0.966	0.966	0.966	0.967	0.931	0.932	0.931	0.932	0.931
SoC in averagely complex sectors	0.089	0.092	0.092	0.090	0.086	0.093	0.094	0.096	0.094	0.090
SoC in least complex sectors	0.065	0.094	0.089	0.077	0.067	0.101	0.110	0.101	0.114	0.092
SoC in most complex sectors	0.117	0.089	0.098	0.100	0.122	0.086	0.076	0.084	0.081	0.088
Panel C: 2004-2011										
$log(z_{Initial})$	0.0787	-0.112	-0.0347	0.543	0.257	-0.275***	-0.656***	-0.348***	-0.901***	-0.548***
	(0.56)	(-0.84)	(-0.22)	(1.20)	(0.83)	(-4.22)	(-3.98)	(-4.36)	(-4.30)	(-3.61)
$log(z_{Initial}) * Task$	-0.122*	-0.0455	-0.0819	-0.215	-0.147	0.0174	0.168**	0.0460	0.185***	0.0953*
	(-2.30)	(-0.97)	(-1.37)	(-1.66)	(-1.59)	(0.85)	(2.79)	(1.76)	(3.39)	(2.25)
Observations	1605	1605	1605	1605	1605	1284	1284	1284	1284	1284
Adjusted R^2	0.799	0.797	0.797	0.798	0.798	0.867	0.868	0.867	0.868	0.867
SoC in averagely complex sectors	0.037	0.036	0.037	0.036	0.037	0.038	0.040	0.039	0.039	0.038
SoC in least complex sectors	0.024	0.034	0.033	0.024	0.032	0.040	0.048	0.041	0.051	0.042
SoC in most complex sectors	0.050	0.039	0.046	0.045	0.044	0.036	0.030	0.034	0.032	0.034

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

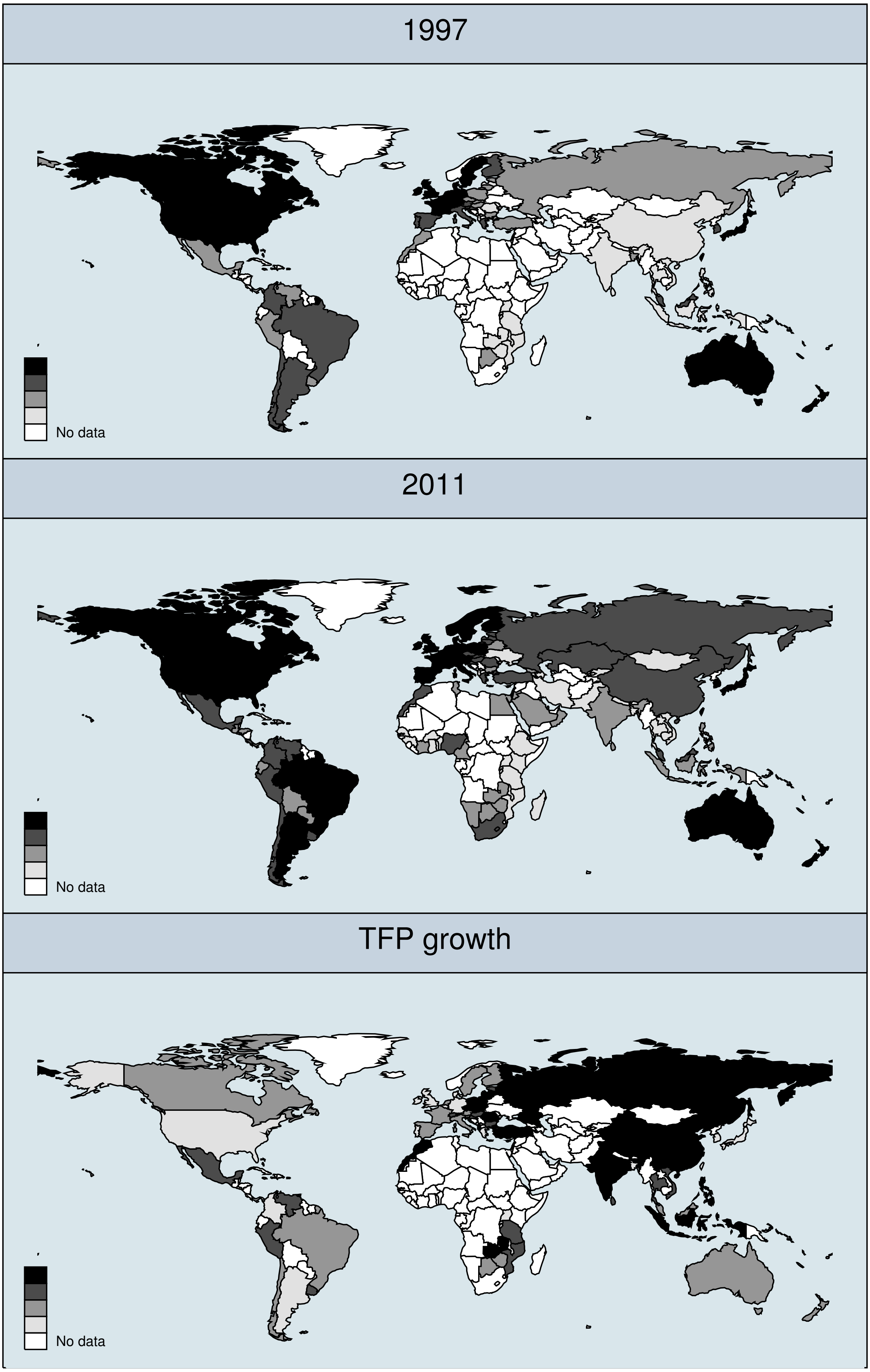
The dependent variable is the growth of estimated TFP in respective time periods. All estimations include a constant, country, and sector dummies. Standard errors clustered at the country level. The speed of convergence, per year, is reported for least, averagely, and most complex sectors.

Figure C1: Productivity using Comtrade-UNIDO data



Notes: The darker the color the higher the average TFP level or the TFP growth of a country.

Figure C2: Productivity using GTAP data



Notes: The darker the color the higher the average TFP level or the TFP growth of a country.

Figure C3: Complex and manual tasks in sectors of Comtrade-UNIDO dataset

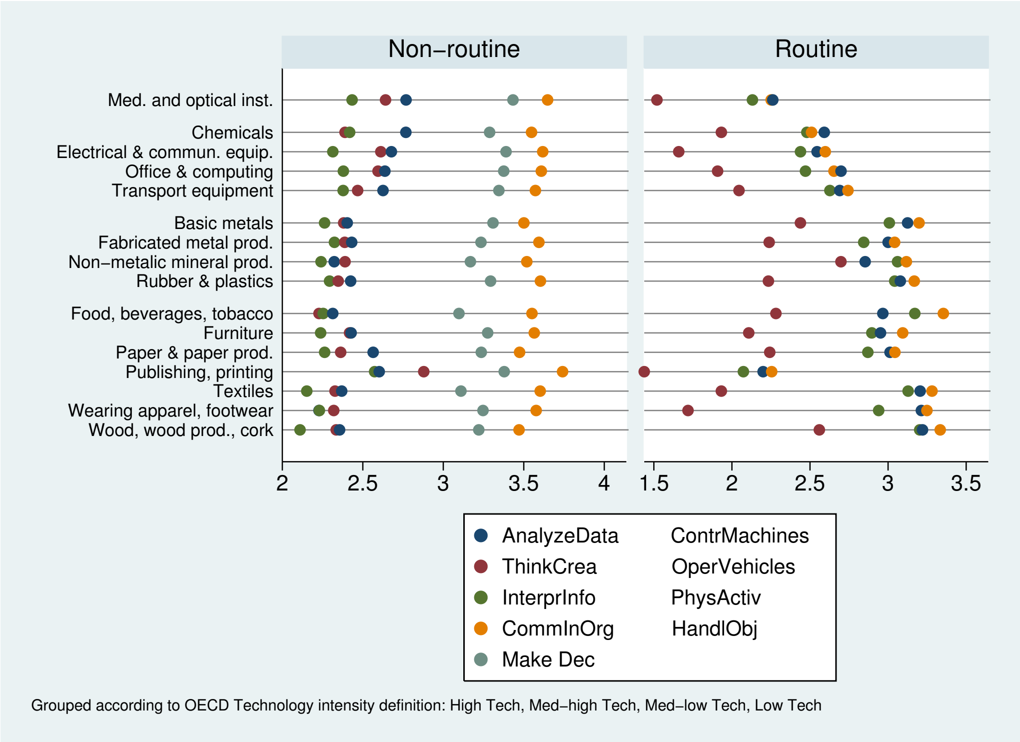


Figure C4: Complex and manual tasks in sectors of GTAP dataset

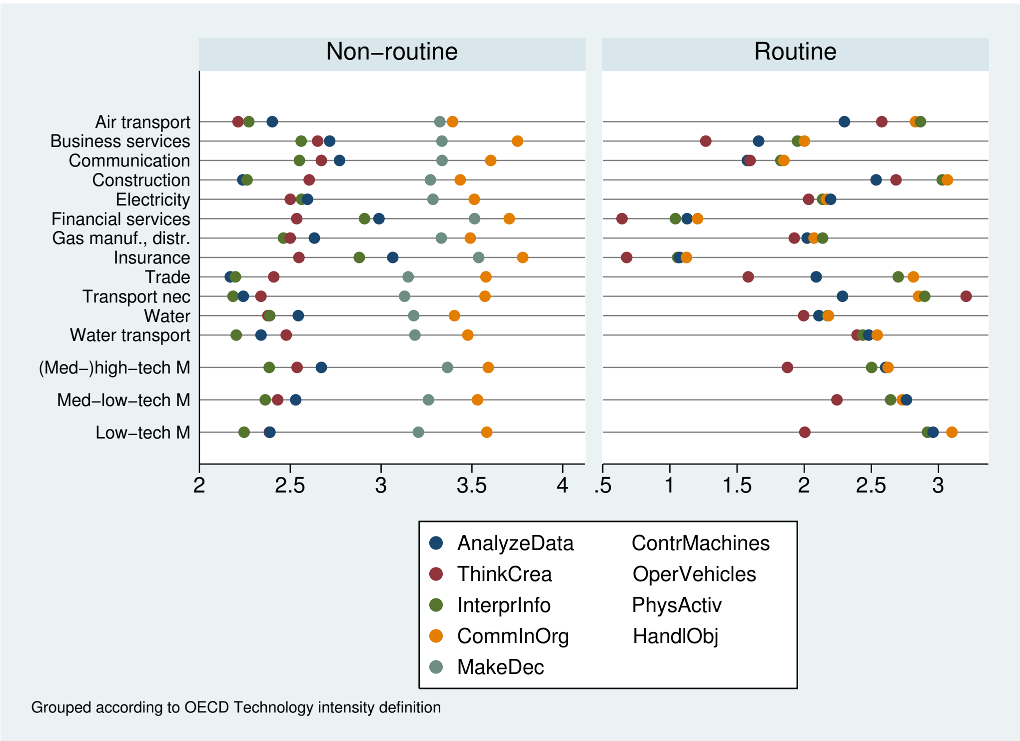
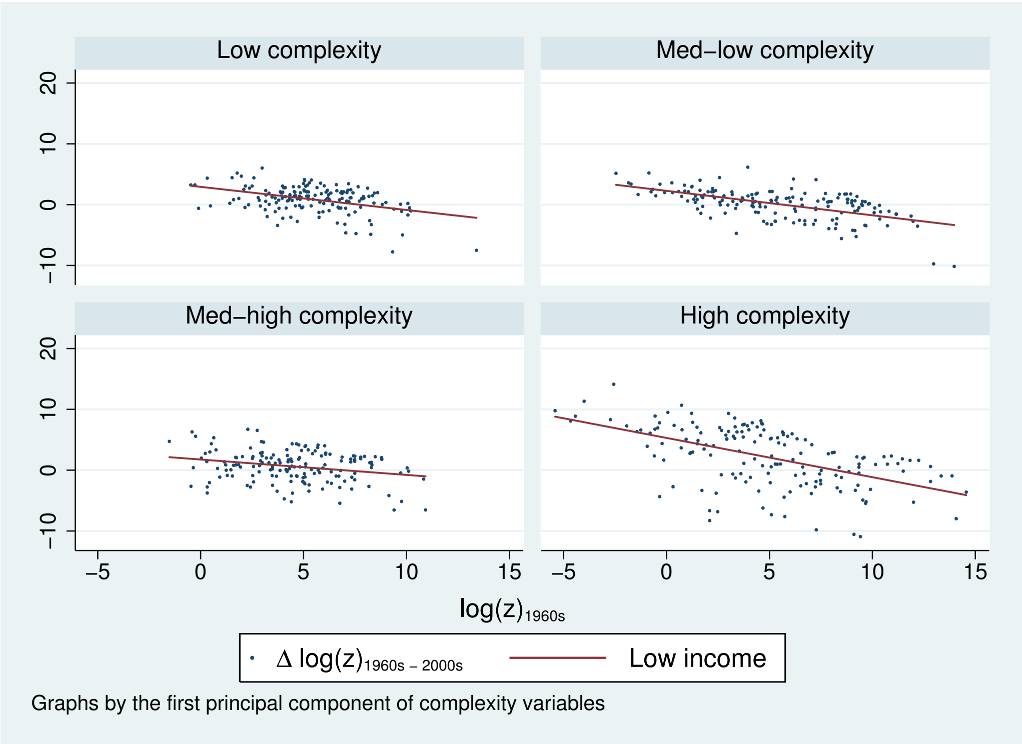
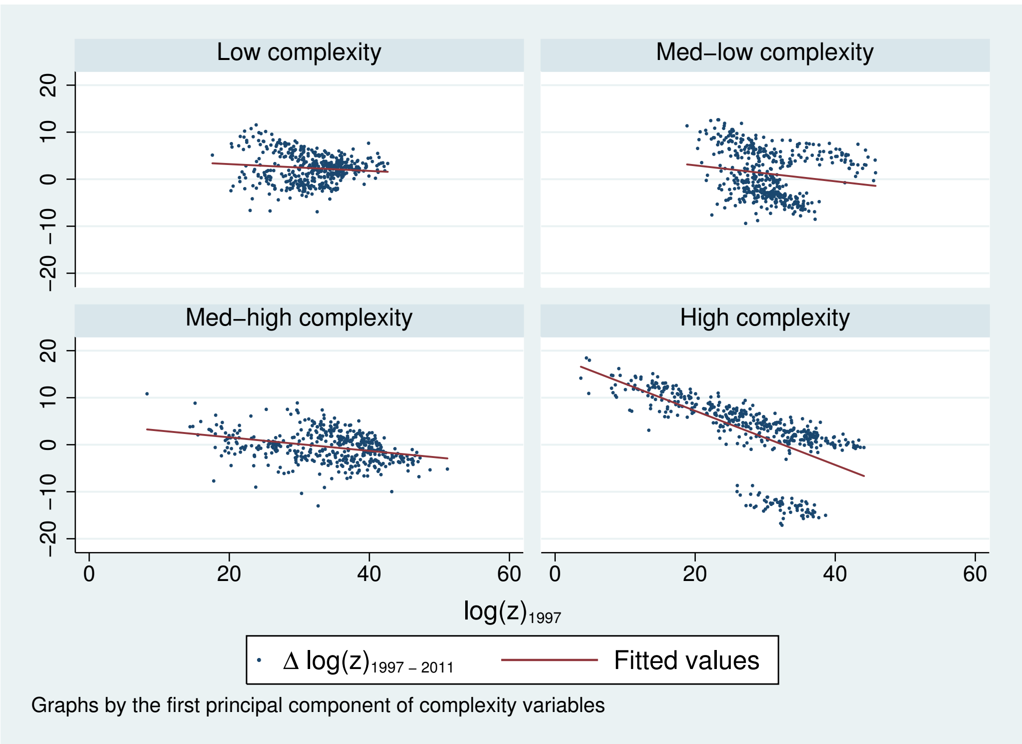


Figure C5: Convergence by level of complexity for different income groups, Comtrade-UNIDO dataset



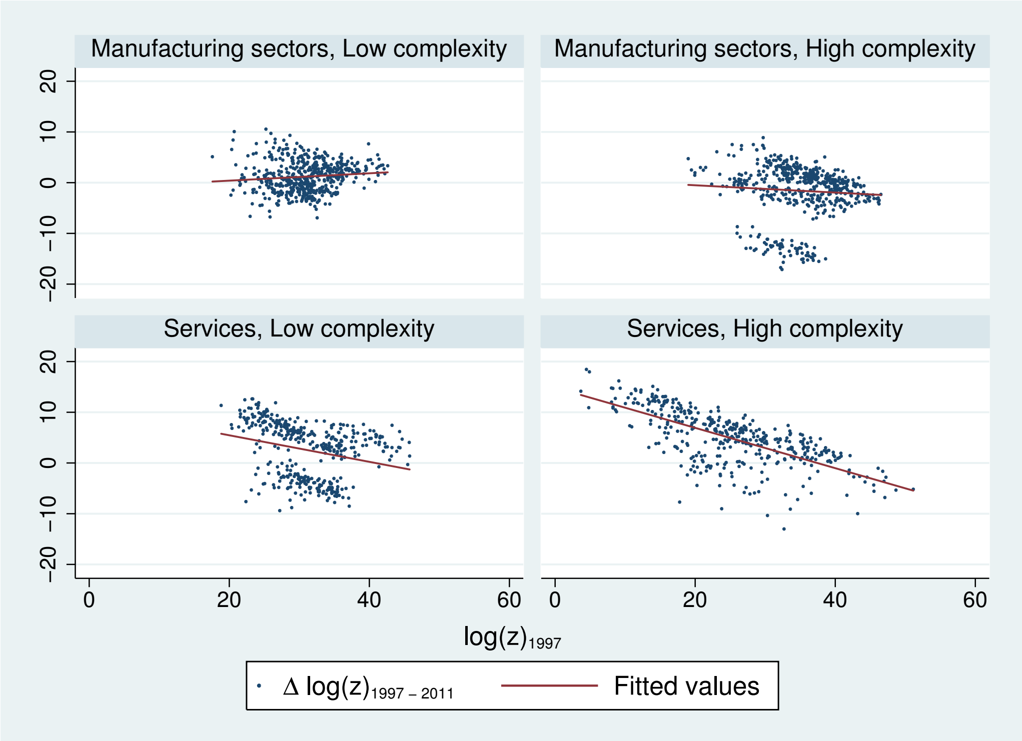
Notes: Low complexity sectors: 20, 15A, 17, 26; med-low complexity sectors: 18A, 21, 27, 36; med-high complexity sectors: 28, 25, 24, 34A; high complexity sectors: 31A, 29C, 33, 22.

Figure C6: Convergence by level of complexity for different income groups, GTAP dataset



Notes: Low complexity sectors: aff, prf, otp, lum, tex, trd, nmm; med-low complexity sectors: lea, atp, wtp, wap, wtr, cns, omf; med-high complexity sectors: b_t, fmp, mvh, crp, gdt, ely, ome; high complexity sectors: ppp, otn, cmn, obs, ele, ofi, isr.

Figure C7: Convergence by level of complexity for different income groups in manufacturing and services sectors separately, GTAP dataset



Notes: Low and med-low complexity manufacturing sectors: prf, lum, tex, nmm, lea, wap, omf; high and med-high complexity manufacturing sectors: b_t, fmp, mvh, crp, ome, ppp, otn, ele; low and med-low complexity service sectors: otp, trd, atp, wtp, wtr, cns; high and med-high complexity service sectors: gdt, ely, cmn, obs, ofi, isr.

Figure C8: Schooling intensity by industry in different decades

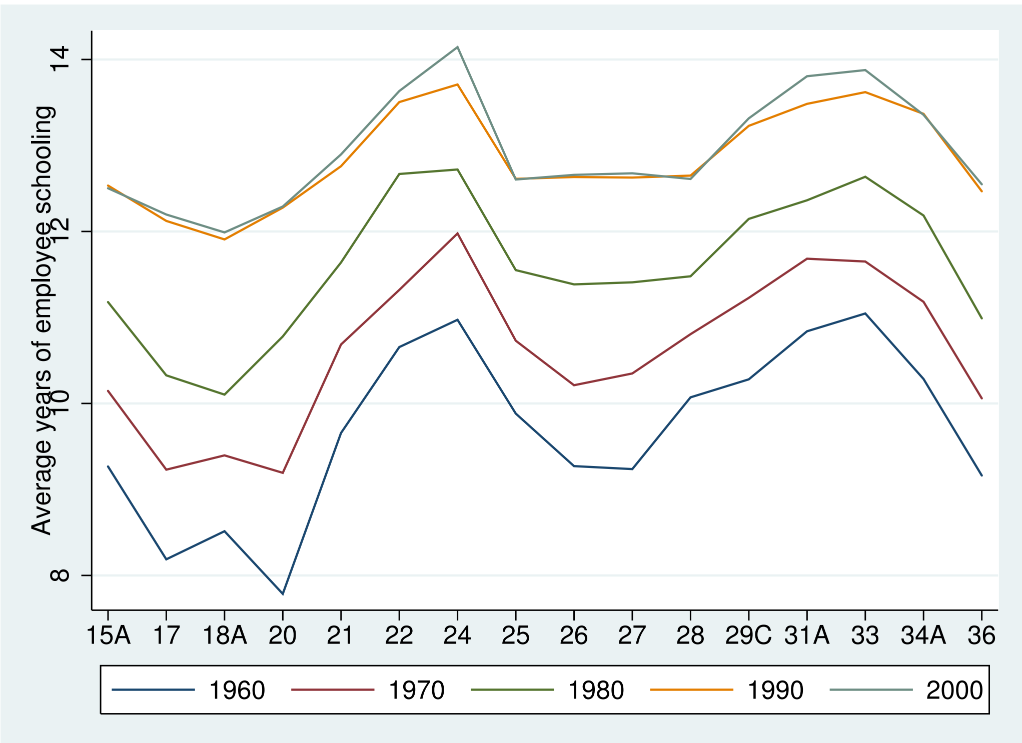


Figure C9: Convergence by level of income elasticity for all sectors, manufacturing and services sectors separately, GTAP dataset

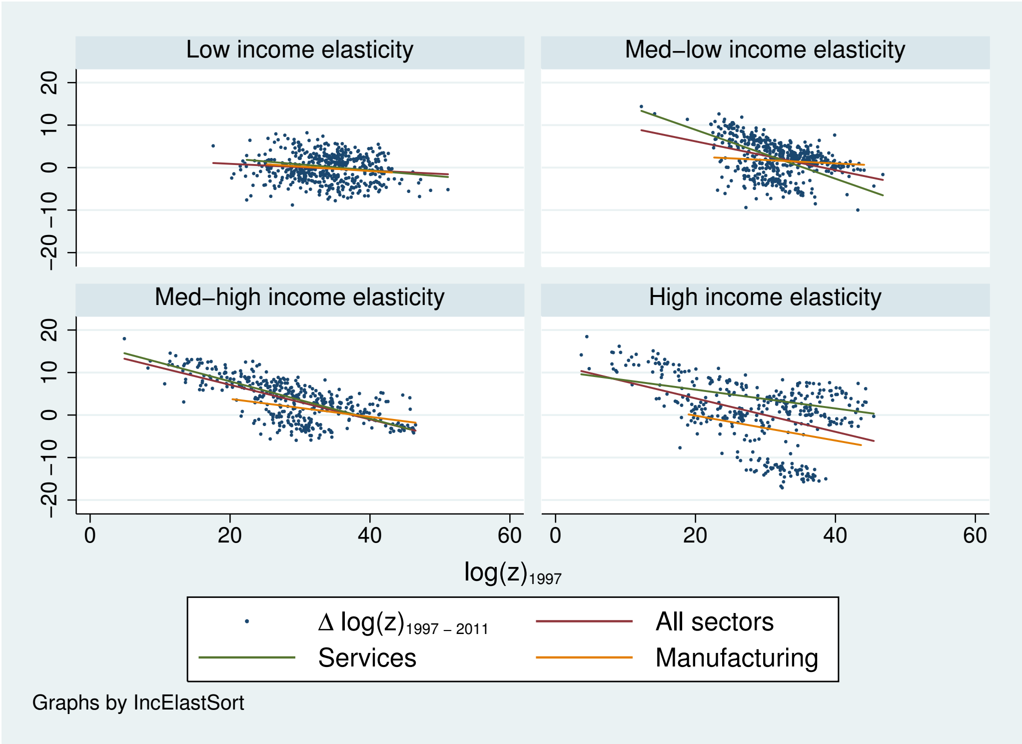
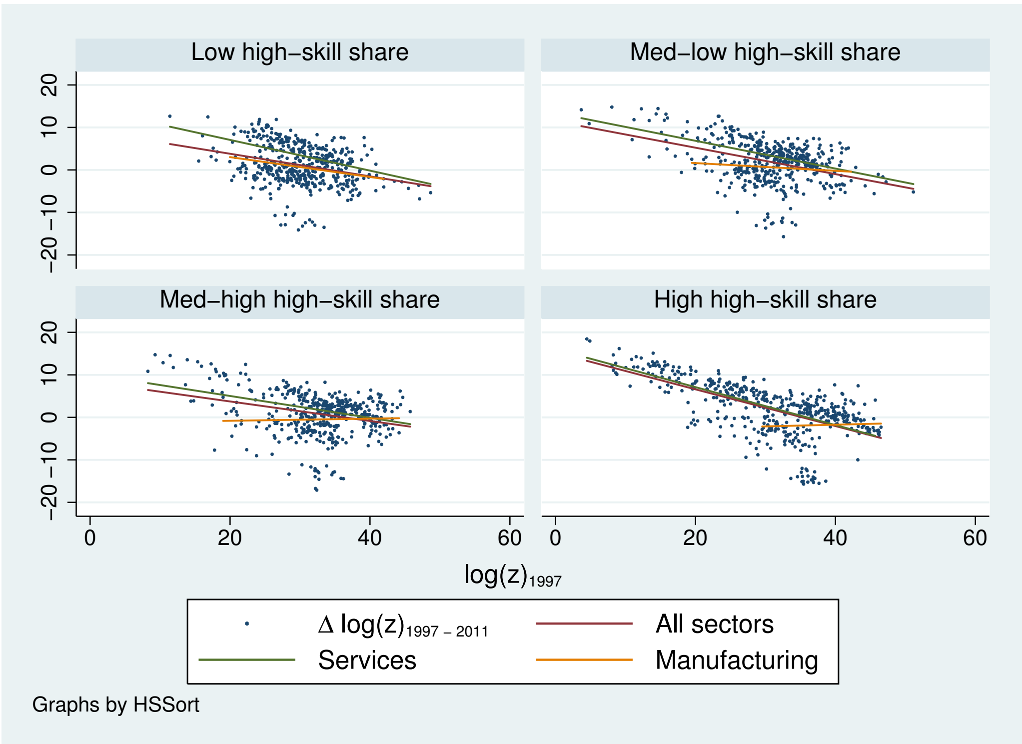


Figure C10: Convergence by level of skill intensity for all sectors, manufacturing and services sectors separately, GTAP dataset



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