UNIVERSITÄT DUISBURG ESSEN

Open-Minded

ifso institute for socio-economics

Claudius Gräbner
Philipp Heimberger
Jakob Kapeller

Do the "smart kids" catch up? Technological capabilities, globalisation and economic growth

uni-due.de/soziooekonomie/

ifso working paper *2020 no.9*

Do the "smart kids" catch up? Technological capabilities, globalisation and economic growth*

Claudius Gräbner[a,b,c] Philipp Heimberger[b,d] Jakob Kapeller[a,b]

[a] Institute for Socioeconomics, University of Duisburg-Essen, Germany
[b] Institute for the Comprehensive Analysis of the Economy (ICAE), Johannes Kepler University Linz, Austria
[c] ZOE. Institute for Future-Fit Economies, Bonn, Germany
[d] Vienna Institute for International Economic Studies (wiiw), Vienna, Austria

Emails for correspondence:
claudius@claudius-graebner.com (CG), heimberger@wiiw.ac.at (PH), jakob.kapeller@uni-due.de (JK)

Abstract

This paper analyses the impact of technological capabilities on convergence. While looking at the relevance of differences in technological capabilities has a long tradition in economics when it comes to explaining persistent deviations in income, we provide econometric tests on the role of technology in determining convergence outcomes in a growth regression framework. We exploit recent advances in measuring technological capabilities for a global country sample over the period 1985-2014. Our results show that convergence is conditional on technological capabilities. This finding is robust to controlling for economic globalisation, resource dependence, institutional quality and other confounding factors. The initial stock of accumulated technological capabilities is one essential factor that may allow poorer countries to convergence towards higher income levels in rich countries. A successful catching-up process cannot be expected for countries lacking a sufficient stock of previously accumulated technological capabilities.

Keywords: Economic complexity, technology, convergence, catch-up, globalisation, openness.

JEL classification code: E6, F4, O3.

* Supported by funds of the Oesterreichische Nationalbank (Austrian Central Bank, Anniversary Fund, project number: 18144). Data and code to replicate the findings of the paper are available via Github (https://github.com/graebnerc/technology-catchup).

1. Introduction

When Adam Smith wrote “The Wealth of Nations”, the richest country in the world – most likely the Netherlands – was about four times richer in terms of per capita income than the poorest country. Today, the richest country is about 250 times richer than the poorest country (Bolt et al. 2018; own calculations). Especially if we consider the more recent past, there are large differences in per capita incomes across countries. While selected developing countries – such as China and other East Asian countries – have achieved exceptional growth rates over recent decades, there is no systematic evidence that poor countries have grown significantly faster than rich countries (e.g. Rodrik 2011; Subramanian 2011). Whenever researchers have been able to find evidence for convergence, it is typically conditional on other factors – such as institutions, natural resource abundance, geography or economic openness (e.g. Ben-David and Loewy 1998; Neumayer 2004; Efendic et al. 2011).

The present paper contributes to this literature by analysing the relevance of another conditioning factor relevant for understanding convergence: the accumulated set of technological capabilities as measured by a country’s economic complexity (Hidalgo and Hausmann 2009; The Atlas of Economic Complexity 2019). Explaining persistent differences in income by looking at differentials in technological capabilities has a long tradition in economics. The importance of technology has been emphasised by various distinct strands of literature. First, evolutionary growth theory, in which economic development is driven by the diffusion of new technologies (Fagerberg and Verspagen 2002), has argued that technology plays a prime role in determining convergence outcomes (e.g. Amendola at al. 1993; Dosi and Nuvolari 2020). Second, the literature on Economic Complexity has more recently suggested that the stock of accumulated technological capabilities is a main determinant of economic growth and for the level of per capita incomes countries can achieve in the long run (e.g. Hidalgo et al. 2007; Hidalgo and Hausmann 2009; Mewes and Broekel 2020; Koch 2020). From this perspective, technological capabilities emerge as a major explanatory variable for why some countries and regions are rich and others remain poor. Finally, some contributions to the endogenous growth theory have stressed different levels of technological progress as a main explanatory factor for income inequality between countries (although this literature is not concerned with technological capabilities in particular): models in the spirit of Mukoyama (2004) highlight incomplete diffusion of technologies across the world as a reason for persistent global inequality. This lack of diffusion can have different sources: for Acemoglu and Zilibotti (2001) or Mukoyama (2004), the *inappropriateness* of technologies is key; for Acemoglu et al. (2002), problems of technology diffusion can be traced back to incomplete contract institutions.

Although the relevance of technology and technological capabilities has been stressed by numerous theories and the persistent lack of successful technology diffusion has been clearly documented (e.g. Fagerberg and Verspagen 2002, Comin and Mestieri 2018), the empirical literature has so far not offered extensive tests of the relevance of technological capabilities as a conditioning factor for economic convergence. The present papers builds upon recent advances in the literature on economic complexity that provides the data on the stock of technological capabilities accumulated by various countries. These data are inferred from what countries are exporting, and they are available for a global data sample over long time horizons (Hidalgo and Hausmann 2009; The Atlas of Economic Complexity 2019). We use them to test whether higher initial levels of accumulated technological capabilities represent an essential factor allowing poorer countries to converge faster towards richer countries.

To this end, we first explicate the theoretical background of the study in Section 2. Then we present our results in Section 3. Section 4 provides a discussion of the results and concludes the paper.

2. Economic complexity and convergence in the world economy

A large volume of empirical convergence studies has modelled economic growth as a function of initial income and other conditioning variables (e.g. Barro 1991; Mankiw et al. 1992; Abreu et al. 2005). The following cross-sectional model represents the key specification:

$$\ln y_i(t) - \ln y_i(0) = \alpha + \beta \ln y_i(0) + X_i + \varepsilon_i + \quad (1)$$

where $\ln y_i(t) - \ln y_i(0)$ denotes the growth rate of GDP per capita over the relevant growth period in country i, $\ln y_i(0)$ stands for the initial level of GDP per capita at the beginning of the growth period, X_i contains other control variables that could potentially affect growth, and ε_i represents the error term. The main parameter of interest in these studies is the estimated coefficient of the income level at the start of the relevant growth period (β): a negative estimated coefficient would indicate that initially poorer countries, on average, grew faster than initially richer countries. In other words: in equation (1), convergence in per capita income levels would require that – holding the term $\gamma' X_i$ constant – the coefficient of initial income is negative and significant.

In principle, inferences from a growth model as specified in equation (1) can be drawn without explicitly referring to a theoretical growth model (e.g. Kormendi and Meguire 1985;

Barro 1991). However, such data-driven approaches have been criticised on the ground that they provide hypothesis tests without prior theorising, so that the results so obtained provide restricted insights at best (e.g. Levine and Renelt 1992; Sala-i-Martin et al. 2004). In what follows, we explicate the theoretical background for specifying empirical convergence models by reviewing selected theoretical perspectives that focus on the role of technology for economic development and growth.

First, in traditional neoclassical approaches to empirical convergence both the initial level of technology and its subsequent growth rate are assumed to be constant and identical for all the countries in the sample, apart from random variation in initial technology, presuming that countries with initially access to identical technologies should converge over time to the same income per capita levels. Empirical evidence, however, contradicts the prediction of unconditional convergence: while some initially poorer countries – especially in East Asia – have managed to grow and converge quickly over the last decades, unconditional converge is not evident for the group of poorer countries as a whole (e.g. Subramanian 2011; Rodrik 2012). Therefore, the empirical literature has focused on conditional convergence, i.e. growth developments that depend on institutions, economic policies, geography and other circumstances that are country-specific.

If growth rates are conditional on country-specific factors, different economies will grow toward different levels of long-run income. Against the background of missing empirical evidence for unconditional convergence, neoclassical growth models have incorporated endogenous technological change. As a result, these models do not necessarily exhibit convergence (e.g. Durlauf et al. 2005; Acemoglu 2009). However, while endogenous growth theory also incorporates technology, its focus is not primarily directed at understanding catch-up dynamics in great detail.

Second, the relevance of technological capabilities for economic development and catch-up has been discussed extensively in the field of evolutionary political economy. Specifically, the literature on 'technology gaps' argues that technology plays the role of a "primus inter pares" (Dosi and Nuvolari 2020) when it comes to determinants of catch-up.

In this literature, economic development is considered to be a nonlinear process, driven by the diffusion of new technologies, constantly shaped by (and shaping) the institutional framework of the economy (Fagerberg and Verspagen 2002). As a theoretical implication and contrary to the neoclassical literature discussed above, the idea of a balanced growth path is rejected even as an as-if assumption. Key factors for the explanation of convergence and divergence in the world economy, like *innovation*, *diffusion* and *absorptive capacities*, clearly relate to technological aspects. Since these factors operate mainly on the firm level, firms usually receive particular attention in evolutionary accounts (e.g., Fagerberg et al. 2005; Cimoli et al. 2009), and the focus is on the accumulation of technological capabilities. – although there is also some work with regard to the accumulation of non-technological capabilities – with Abramovitz (1986) being the classical reference for social capabilities such as education, infrastructures, and financial institutions. Moreover, more recently, holistic accounts on these factors have been provided by the contributions concerned with 'national innovation systems' (e.g. Lundvall 1992; Castelacci and Natera 2013).

Compared to the neoclassical growth literature, the evolutionary literature puts less emphasis on comparative advantage and positive welfare implications of trade liberalisation. Rather, it suggests that a focus on trade liberalisation bears the danger of locking countries into undesirable specialisation patterns that are path-dependent and, hence, difficult to alter (e.g.

Dosi et al. 1990; Gala et al. 2018). In this respect, evolutionary accounts are in agreement with the literature on economic complexity, which stresses that "what you export matters" (Hausmann et al. 2007) and argues that advantageous specialisations – not the exploitation of comparative advantages – are at the root of successful economic development (e.g. Hidalgo et al. 2007; Gräbner et al. 2020b). By contrast, and consistent with more classical contributions to development (e.g. List 1856; Myrdal 1957), the necessity of industrial policy is frequently highlighted when it comes to breaking technological lock-ins in laggard regions (e.g. Reinert 2007; Dosi et al. 2019; Gräbner et al. 2020d). Not surprisingly, there are clear overlaps to the structuralist literature on global inequality, which emphasises that differences in (average) income tend to be persistent as they emerge from structural differences in production structures and power relations (e.g. Prebisch 1950; Hirschman 1958; Cimoli et al. 2009). In other words, the view that technological capabilities moderate economic growth and convergence patterns emerges as a common thread across different strands of the political economy literature.

Finally, there is a growing body of work on global divergence and catch-up dynamics using evolutionary macroeconomic agent-based models with endogenous technological change. For instance, Dosi et al. (2019) argue that global divergence is an endogenous phenomenon originating in national specialisation and trade patterns, driven by the dynamics of absolute technological advantages. The deeper origins of the latter are cumulative feedback mechanisms at the firm level, which then have self-reinforcing effects at the country level, so that "success breeds success and failure begets more failure" (Kaldor 1980, p. 88). Note that this setting does not build on the assumption of original differences in technological capabilities. It is the path dependent nature of technological capability accumulation that leads to divergence and prevents catch-up. Dosi et al. (2020) use an extended model to study the effectiveness of different catch-up policies. They find that market liberalisation remains ineffective, yet industrial policies are an effective tool to achieve convergence. Protectionism alone drives countries into a middle-income trap.

3. Econometric approach and data

We estimate the following main cross-sectional regression specification:

$$\overline{growth_{\iota,1985-2014}} = \beta_1 \ln GDPpc_{i,1985} + \beta_2 eci_{i,1985} + \beta_3 eci_{i,1985} \cdot GDPpc_{i,1985} + + \beta_2 eci_{i,1985} + \gamma' \overline{X_{\iota,1985-2014}} + \varepsilon_{i,1985-2014} \quad (2)$$

where the dependent variable $\overline{growth_{\iota,1985-2014}}$ denotes the average growth rate in GDP per capita (in chained PPPs) in country i over the time period 1985-2014. $GDPpc_{i,1985}$ stands for the logarithm of GDP per capita in country i in the year 1985, thereby representing a country's initial level of income in the time period considered. GDPpc is included as the "convergence term": if countries with an initially lower level of GDP per capita were to grow systematically faster than their peers, the coefficient of GDPpc would need to be negative and statistically significant. $eci_{i,1985}$ is the Economic Complexity Index (The Atlas of Economic Complexity 2019), which serves as a proxy for the knowledge intensity of, or, in other words, the level of technological capabilities accumulated by a given economy (Hidalgo and Hausmann 2009). The main idea behind the ECI is to infer the level of technological capabilities from the export baskets of a given country. In particular, the ECI is computed by means of a recursive algorithm that assesses the variety of the exports of a given country (diversification) as well as how many other countries are able to export certain types of products (specialisation). In the supplementary appendix, we provide a detailed explanation on how the economic complexity data used in this paper are constructed. Furthermore, we discuss advantages as well as potential shortcomings of using the complexity data to proxy for technological capabilities. Since the ECI is computed from trade data, it comes with excellent data coverage for a global country sample over a long time horizon.

We also include an interaction term of ECI and GDP per capita to test whether conditional convergence holds independently of the level of technological development, in which case we would expect the interaction term to be insignificant and close to zero. A negative interaction term, on the other hand, would imply that convergence runs faster for countries with high technological capabilities, while it may work much slower – or not at all – for countries where technological capabilities are low. With a positive coefficient, the interpretation would be the other way around, that is, convergence would be stronger for low-tech countries. Finally, $\overline{X_{\iota,t}}$ is a vector of additional controls (with average values for 1985-2014), which we use in some of the regression specifications. The list of additional controls includes the KOF economic globalisation index (Gygli et al. 2019), population growth, human capital, as well as variables that capture the quality of institutions and resource dependence. Table 1 summarises the variables used in the regression specifications and lists the data sources used in our analysis. Our data comprise a cross-section of 108 observations, including a mix of advanced and developing countries, with data availability being the main argument for the selection of countries. Although we use different model specifications, the underlying country sample always remains the same in all specifications (with minor exceptions when including additional controls in our robustness checks). This rules out the possibility that differences in the results across different specifications are driven by changes in the underlying country group. The supplementary appendix presents a table with descriptive statistics for all the variables used in the empirical analysis and provides a full list of all countries under study.

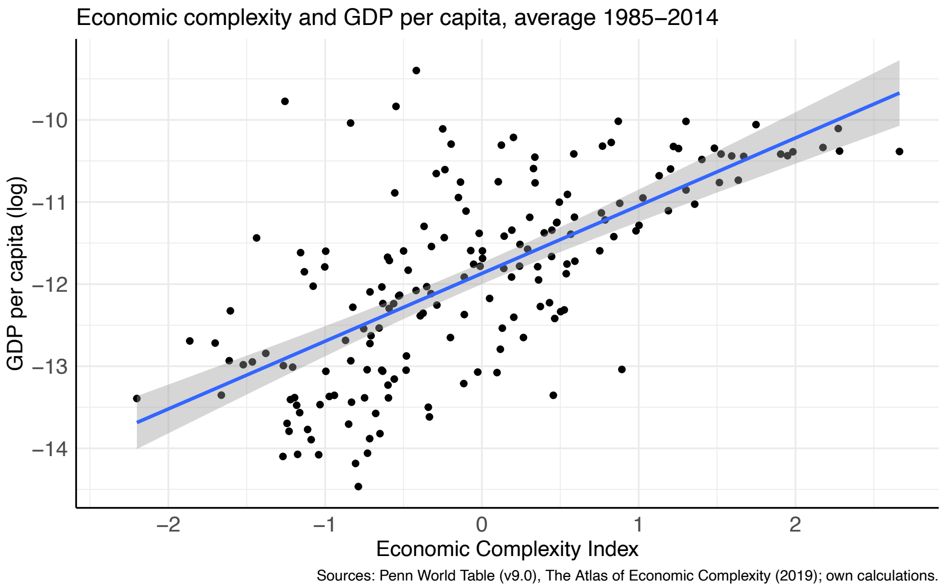
For illustration purposes, Figure 1 shows the positive correlation between average levels of economic complexity and GDP per capita covering the period 1985-2014.

Table 1: Variables and data sources

	Data description	Data sources
growth	Average growth of GDP per capita at chained PPPs (in %)	Penn World Table (v9.0); authors' calculations
log(GDPpc)	Logarithm of GDP per capita at chained PPPs in US$	Penn World Table (v9.0); authors' calculations
ECI	Economic Complexity Index	The Atlas of Economic Complexity
pop	Growth rate of total population (in%)	Penn World Table (v9.0); authors' calculations
global	KOF economic globalisation index	Gygli et al. (2019)
hc	Human capital index, based on years of schooling and returns to education	Penn World Table (v9.0)
oil	Share of oil exports in a given country's total exports (in %)	UN Commodity Trade Statistics; own calculations
coal	Share of coal and metal exports in a given country's total exports (in %)	UN Commodity Trade Statistics; own calculations
einst	Economic institutional quality (relative factor scores)	Kuncic (2014)
pinst	Political institutional quality (relative factor scores)	Kuncic (2014)
linst	Legal institutional quality (relative factor scores)	Kuncic (2014)
prights	Property rights index	2020 Index of Economic Freedom (Heritage Foundation)

Source: authors' illustration.

Figure 1: Economic complexity and GDP per capita



3.1 Baseline results

Table 2 shows the main empirical results obtained by a standard OLS regression. In the first column, we regress average GDP per capita growth over 1985-2014 on the initial level in GDP per capita without controlling for any other confounding factors. The coefficient of the GDPpc variable is negative but not statistically significant. In other words, we do not find significant evidence for the presence of unconditional convergence in our sample. In column (2), we control for economic complexity as a proxy for initial technological capabilities and also include an interaction term of ECI and GDPpc. This improves the fit of the regression considerably. More than 15% of the total variation in average economic growth over the time period 1985-2014 can be accounted for by simply controlling for initial values in economic complexity, income per capita and their interaction. The coefficients of the economic complexity variable and its interaction term with GDP per capita are individually and jointly significant. In other words: we find evidence that the impact of initial GDP levels on subsequent economic growth is conditional on the initial level of accumulated technological capabilities. Convergence runs faster among high-tech countries while it runs slower among low-tech countries. From another perspective, this result implies that the growth performance of poor countries will over-proportionally benefit from higher technological capabilities.

However, these preliminary results could be affected by omitted variable bias. Therefore, we continue by introducing additional control variables one at a time. This step-wise procedure allows us to test whether the choice of the set of further controls has an undue influence on the results for our main variables of interest, namely the proxy for technological capabilities and its interaction with the convergence term. Columns (3) to (5) of Table 2 include the KOF indicator for economic globalisation, population growth and human capital, respectively. All these additional control variables are statistically significant: higher levels of economic globalisation – used as a proxy for international market integration in trade and finance (Gygli et al. 2019; Gräbner et al. 2020c) – are associated with higher average growth. Population growth comes with lower GDP per capita growth over the period considered, while human capital shows a significant and positive relationship with growth. The main result, according to which countries with a better starting position in 1985 in terms of technological capabilities grew significantly faster over the period 1985-2014, is not affected by the introduction of these additional controls. Notably, both the linear coefficients of GDPpc and ECI as well as their interaction term remain statistically significant and signed as expected across all specifications. This result is confirmed in column (6), which reports results from estimating a model that simultaneously includes technological capabilities, economic globalisation, population growth and human capital as control variables. This is our preferred model specification. The supplementary appendix also reports plots of the residuals and tests for autocorrelation. The diagnostics do not provide evidence that the main OLS assumptions are violated.

We also test whether these results remain robust once we exploit the panel structure of the data. To this end, we estimate the following panel specification:

$$growth_{i,t_1 \dots t_2} = \beta_1 GDPpc_{i,(t_1-1)} + \beta_2 eci_{i,(t_1-1)} + \beta_3 eci_{i,(t_1-1)} * GDPpc_{i,(t_1-1)} + \gamma' X_{i,t_1 \dots t_2} + \varepsilon_{i,t_1 \dots t_2} \quad (3)$$

The variables are defined as before, but equation (3) uses the panel structure of the data, referring to country i in period $t_1 \dots t_2$. To smooth out cyclical variation in the data (especially in the growth variable) and to allow for more reliable long-term interpretations we split the panel data into six five-year periods (e.g. Arora and Vamvadikis 2005; Mullings and Mahabir 2018): 1985-1989, 1990-1994, …, 2010-2014. Equation (3) also includes a time lag for the variables GDPpc and ECI. By lagging the level of GDP per capita, this variable again serves as the "convergence term", i.e. it allows us to test whether countries that are initially poorer, on average, tend to grow faster (conditional on other confounding factors). The lag of the ECI variable is included since we are interested in the impact of initial levels of technological capabilities on growth. All the other control variables, summarised in **X**, enter equation (3) in contemporaneous levels.

Equation (7) in Table 2 summarises the panel regression results obtained from estimating equation (3) by using pooled OLS. The results confirm the main insights from the cross-sectional analysis, i.e. there is evidence for conditional convergence, and higher initial levels of economic complexity are a significant predictor for stronger growth over the period 1985-2014. The main difference in comparing the panel results to the cross-sectional findings is that the additional control variables economic globalisation and population growth no longer show a statistically significant coefficient. A potential point of criticism involves the role of unobserved country characteristics that may influence growth outcomes, which may also have an impact on the results obtained for the economic complexity variable. To address this point, column (8) of Table 2 introduces country-fixed effects to control for such unobservable, time-invariant and country-specific characteristics. This, again, confirms the main results obtained above.[1]

[1] We also estimated a specification including time-fixed effects, but they do not make a significant contribution to explaining growth outcomes.

Table 2: Main econometric results (1985-2014, 108 countries).

	(1) uncond. conv.	(2) ECI	(3) kofecon	(4) popgrowth	(5) humancapital	(6) all controls	(7) panel-pooled	(8) country-FE
log(GDPpc)	-0.06	-0.59^{***}	-0.91^{***}	-0.69^{***}	-1.36^{***}	-1.50^{***}	-1.04^{***}	-0.87^{**}
	(0.16)	(0.21)	(0.22)	(0.20)	(0.23)	(0.23)	(0.265)	(0.38)
ECI		5.33^{***}	5.55^{***}	5.02^{***}	6.03^{***}	5.82^{***}	5.89^{***}	7.94^{**}
		(1.75)	(1.61)	(1.76)	(1.44)	(1.43)	(1.59)	(3.26)
global			0.04^{***}			0.03^{**}	-0.001	-0.03
			(0.01)			(0.01)	(0.01)	(0.03)
pop				-0.64^{***}		-0.43^{*}	-0.22	-0.01
				(0.23)		(0.23)	(0.23)	(0.33)
hc					2.01^{***}	1.45^{***}	1.32^{**}	7.03^{***}
					(0.40)	(0.41)	(0.52)	(1.02)
log(GDPpc) · ECI		-0.51^{***}	-0.55^{***}	-0.52^{***}	-0.64^{***}	-0.64^{***}	-0.60^{**}	-0.78^{**}
		(0.18)	(0.17)	(0.18)	(0.15)	(0.15)	(0.16)	(0.36)
Constant	2.97^{**}	7.87^{***}	8.65^{***}	9.80^{***}	9.99^{***}	11.39^{***}	9.37^{***}	
	(1.43)	(1.94)	(1.87)	(1.87)	(1.69)	(1.73)	(1.83)	
Observations	108	108	108	108	108	108	754	754
R^2	0.001	0.18	0.22	0.25	0.31	0.36	0.06	0.12
Adjusted R^2	-0.01	0.16	0.19	0.22	0.29	0.32	0.05	-0.04

Note: *p<0.1; **p<0.05; ***p<0.01

Source: Authors' calculations. Column panel-pooled refers to estimation with pooled 5-year averages of the panel data; column country-FE to estimation with 5-year averages of the panel data controlling for country fixed-effects. log(GDPpc)… logarithm of GDP per capita; ECI… Economic Complexity Index; global… KOF economic globalisation index; pop… population growth; hc… human capital index. For more details on the variables see Table 1.

3.2 Robustness checks: Assessing alternative samples and specifications

In what follows, we take several steps to assess the robustness of the main results on how technological capabilities affect convergence. In particular, we vary the country sample and the time period covered, and we account for additional variables to control for resource dependence and institutional quality.

Our preferred cross-sectional model specification (6) in Table 2 serves as a point of reference for the robustness checks. To facilitate comparison, the baseline results are shown again in column (1) of Table 3. We first check whether these results hold when the country sample is restricted to developing countries as defined in the classification by the IMF (2018). The number of observations declines from 108 to 82, yet the results shown in column (2) of Table 3 are both quantitatively and qualitatively very similar to the baseline findings in column (1). This indicates that the impact of initial GDP levels on subsequent economic growth in the sample of developing countries is conditional on the initial level of accumulated technological capabilities. Second, the time period covered (1985-2014) was characterised by a substantial increase in economic openness compared to previous decades (e.g. Gygli et al. 2019; Gräbner et al. 2020c). In column (3) of Table 3, we instead consider the period between 1970 and 1984. We also find evidence for convergence in this earlier time span conditional on the set of control variables (see the negative and significant coefficient of GDPpc). However, while the signs of the main explanatory variables remain unchanged, we fail to find evidence for a significant interaction of economic complexity with the convergence term. In other words: over the period 1970-1984[2], the evidence that convergence runs faster for countries with high technological capabilities is much weaker than for the time period 1985-2014. This suggests that there is indeed something peculiar about the latter period, which was marked by a strong increase in international market integration (Jones and Romer 2010).

The third robustness check takes into account the role of resource dependence. A large empirical literature has been concerned with the existence of a 'natural resource curse', where an abundant availability of natural resources inhibits economic growth by negatively affecting the behaviour of market participants and political actors, and by influencing the terms-of-trade in the countries concerned (e.g. Williams 2011; Boschini et al. 2013; Havranek et al. 2016). To test whether and to what extent resource dependence impacts economic growth, we use two different proxies: first, the share of oil exports in a given country's total exports, which is highest for countries abundant in oil resources (e.g. Kuwait, Saudi Arabia); and, second, the share of coal and metal exports in a country's total exports, which is highest for developing countries such as Cote d'Ivoire, Mongolia or Peru, but also relatively high for resource-rich advanced countries such as Australia. The results in columns (4) and (5) of Table 3 suggest that neither of these two resource dependence proxies shows a statistically significant impact on growth, while our main finding – that convergence is conditional on the

[2] Due to data availability limitations, we cannot go further back in time than the year 1970.

initial level of technological capabilities – enjoys further confirmation. This suggests that, on average, technological capabilities are an important facilitating factor of convergence outcomes even when accounting for resource dependence in terms of a country's export structure. While the coefficient for the oil export share remains insignificant (p=0.14), it is, however, still sizeable: the parameter estimate implies that a ten percentage point increase in the share of oil exports is associated with an increase in GDP per capita growth by 1.9 percentage points. Furthermore, it should be noted that including the oil variable further improves the overall fit of the regression, as evidenced by the increase in the adjusted R^2 statistic. Hence, we would be hesitant to declare that the share of oil exports does not impact growth performance at all.

The fourth robustness check deals with the role of institutions, which, according to the existing literature on growth, are an important determinant of growth outcomes (e.g. Rodrik et al. 2004; Lee and Kim 2009; Efendic et al. 2011). Therefore, we test whether introducing institutional quality into our regression framework will affect our main findings and possibly absorb the impact of technology, as Rodrik et al. (2004) argue for geography and trade. To this end, we include three different indices for institutional quality, covering the economic, political and legal dimension, respectively (Kuncic et al 2014). The results in columns (6)-(8) of Table 3 again confirm the prime role of technological capabilities. On average, technological capabilities are a significant determinant of growth and a conditioning factor for convergence even after controlling for various proxies of institutional quality in the economic, political and legal dimension.[3] The quality of political institutions is even negatively related to economic growth (see column 7). If we use an index for the protection of property rights as an

[3] Note that we have to restrict the time period to 1990-2010 when we include measures for institutional quality because of limited data availability. The number of countries in the data set is also somewhat smaller, but remains above 91 in all models.

alternative measure for the quality of institutions, the correlation is positive but remains insignificant (see the supplementary appendix). One possible explanation is that the share of oil exports acts as an omitted variable in this context (as it is positively related to growth and negatively related to the quality of institutions; this can be verified by looking at the supplementary appendix, which shows pair-wise correlations of all variables). We inspect this more closely in our final specification (see column 9 in Table 3) and indeed find that the negative relationship between the quality of political institutions and growth is no longer significant once we also control for oil exports. However, it still seems that the net impact of political institutions on economic growth is somewhere between neutral and slightly detrimental, which raises the questions how our results can be aligned with past findings on how high institutional quality might boost economic growth (e.g. Efendic et al. 2011).

Another possible explanation for these findings refers to the strong correlation between *economic complexity* and the *quality of political institutions* (the correlation coefficient is 0.8; see the supplementary appendix for a full table on pair-wise correlations). Against this backdrop, our results suggest that those past studies that pointed to a strong impact of institutional quality on economic growth may confound the impact technological capabilities with that of political institutions. This would explain why our estimates documenting the prime role of technology for growth as well as convergence are so persistent, and why the standard results for institutional quality get inverted as soon as technological capabilities are adequately considered. Note that this argument does not preclude the possibility that 'good institutions' can be conducive to developing marketable technological skills as, eventually, theory construction trumps statistical precision when it comes to issues of interpretation. In such a narrative, 'good institutions' might still be *primus inter pares*, while technology is the core mediator. In any case, these results suggest that future investigations on the relationship between institutions, economic complexity and growth outcomes are necessary to shed light on the underlying causal mechanisms.

In sum, the robustness checks presented in Table 3 highlight the stability of our main results: there is only little variation in the size of the coefficients of the ECI variable and its interaction term with the initial GDP per capita level across different specifications, i.e. we find robust and statistically significant evidence for convergence outcomes that are conditional on technological capabilities.

Table 3: Robustness checks

	(1) baseline	(2) developing	(3) 1970-1984	(4) oil	(5) coal	(6) einst	(7) pinst	(8) linst	(9) pinst + oil
log(GDPpc)	-1.500^{***}	-1.510^{***}	-1.340^{**}	-1.846^{***}	-1.517^{***}	-1.216^{***}	-1.098^{**}	-1.167^{**}	-1.494^{***}
	(0.230)	(0.297)	(0.579)	(0.321)	(0.245)	(0.453)	(0.432)	(0.459)	(0.504)
ECI	5.825^{***}	6.163^{***}	4.077	5.684^{***}	5.835^{***}	6.173^{***}	5.947^{***}	5.871^{***}	6.642^{***}
	(1.427)	(2.252)	(2.715)	(1.436)	(1.426)	(1.875)	(1.937)	(2.022)	(2.170)
global	0.034^{**}	0.029	0.045^{*}	0.036^{***}	0.034^{**}	0.040	0.047^{**}	0.040^{*}	0.046^{*}
	(0.013)	(0.022)	(0.026)	(0.014)	(0.013)	(0.027)	(0.024)	(0.024)	(0.024)
pop	-0.433^{*}	-0.443	-0.655	-0.477^{**}	-0.429^{*}	-0.521	-0.585^{*}	-0.532	-0.626^{*}
	(0.229)	(0.308)	(0.527)	(0.224)	(0.232)	(0.325)	(0.334)	(0.336)	(0.334)
hc	1.446^{***}	1.600^{**}	0.971	1.562^{***}	1.483^{***}	1.394^{***}	1.784^{***}	1.472^{***}	1.747^{***}
	(0.406)	(0.638)	(0.892)	(0.430)	(0.441)	(0.487)	(0.510)	(0.473)	(0.523)
oil				0.019					0.020
				(0.013)					(0.012)
coal					-0.003				
					(0.012)				
einst						-0.132			
						(0.653)			
pinst							-0.931		-0.576
							(0.562)		(0.660)
linst								-0.326	
								(0.532)	
log(GDPpc) · ECI	-0.642^{***}	-0.692^{**}	-0.447	-0.594^{***}	-0.644^{***}	-0.697^{***}	-0.653^{***}	-0.659^{***}	-0.705^{***}
	(0.150)	(0.264)	(0.302)	(0.150)	(0.149)	(0.189)	(0.194)	(0.204)	(0.214)
Constant	11.391^{***}	11.400^{***}	10.875^{***}	13.728^{***}	11.470^{***}	9.437^{**}	7.316^{*}	8.789^{**}	10.699^{**}
	(1.734)	(2.396)	(3.850)	(2.183)	(1.774)	(4.140)	(3.869)	(4.129)	(4.607)
Observations	108	82	108	108	108	89	89	89	89
R^2	0.360	0.355	0.221	0.388	0.360	0.281	0.323	0.285	0.351

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Source: Authors' calculations. developing… developing countries only; 1970-1984… variation of the time period: 1970-1984 instead of 1985-2014; log(GDPpc)… logarithm of GDP per capita; ECI… Economic Complexity Index; global… KOF economic globalisation index; pop… population growth; hc… human capital index; oil… oil exports; coal… coal and metal exports; einst… economic institutional quality; pinst… political institutional quality; linst… legal institutional quality. For more details on the variables see Table 1.

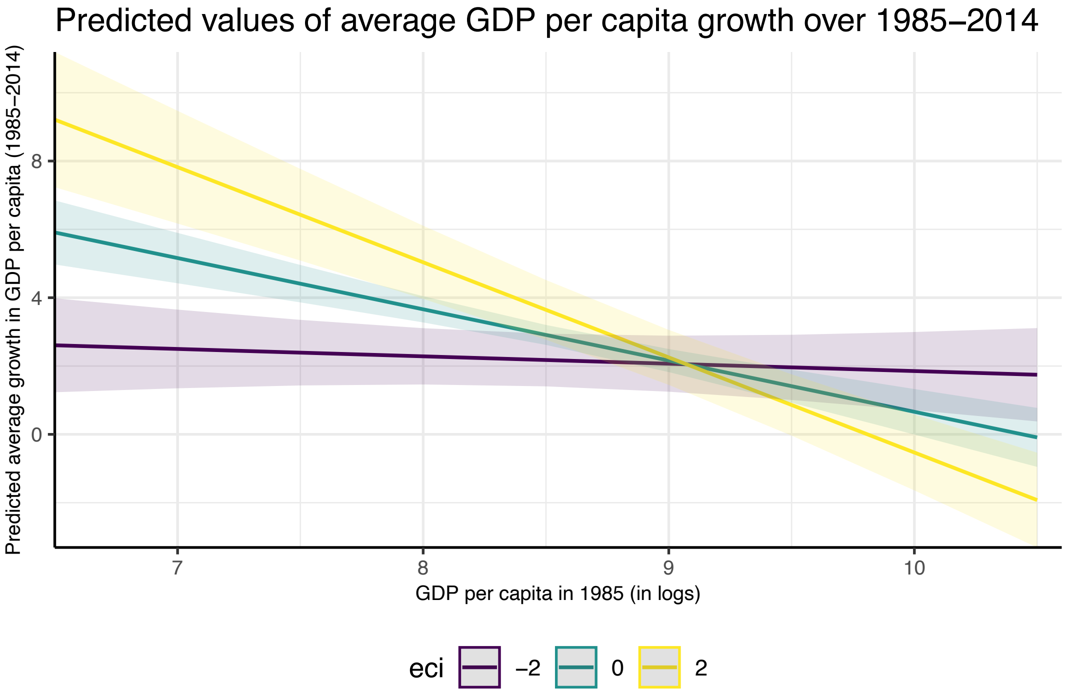
3.3 Convergence is conditional on technological capabilities

So far, the regression results were based on reporting the linear coefficient of the ECI index and its interaction with the initial level of GDP per capita separately. Now, we use our regression results to conduct a marginal effects analysis (e.g. Wooldridge 2010). To illustrate the conditionality of convergence on technological capabilities, Figure 2 shows the predicted values of average GDP per capita growth over the period 1985-2014 as a function of the 1985 level of GDP per capita and three different initial levels of economic complexity, where the predicted values are derived from our baseline model (including all the major additional control variables) as presented in the sixth column of Table 2 and the first column of Table 3. The marginal effects analysis suggests that convergence runs fast among high complexity countries, and slow among low complexity countries (see Figure 2). In fact, we even predict divergence for very low levels of economic complexity, i.e. those that are technologically not well equipped fall further behind those who are technologically more advanced. Furthermore, we find that the level of complexity does not make much of a difference for the prediction of GDP growth at high levels of initial GDP per capita – convergence patterns in the group of rich countries are not much affected by initial technological capabilities.

Notably, Figure 3 is based on the same model as Figure 2, but it offers a complementary perspective: it shows the predicted values of average GDP per capita growth as a function of the initial stock of technological capabilities at three different initial levels of per capita incomes. The marginal effects analysis suggests that the growth performance of initially poor countries will overproportionally benefit from higher technological capabilities, i.e. they converge faster. By contrast, convergence among initially rich countries is not predicted to be significantly stronger at high initial levels of economic complexity. In other words, Figure 3 suggests the insight that 'technology is key for catch-up' matters more for countries at the low end of the income-per-capita-scale. Conversely, Figure 2 implies that convergence will much more likely occur among technologically sophisticated nations than among technological laggards.

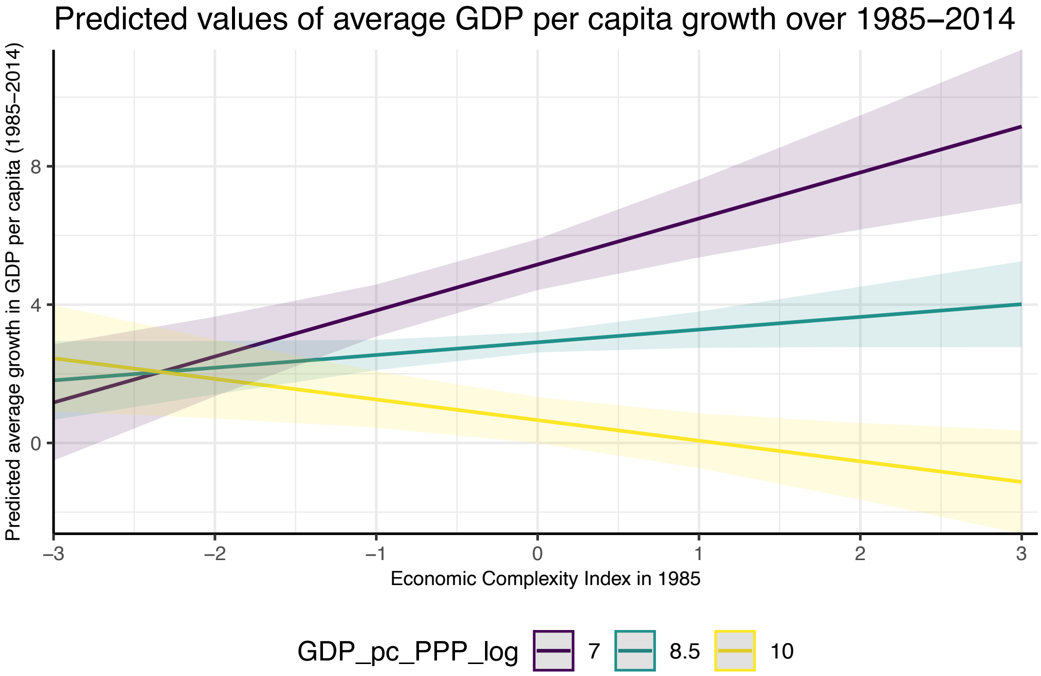
These findings underscore that for poorer countries, the initial stock of accumulated technological capabilities represents one essential factor that may allow for a convergence towards richer countries. Conversely, according to our model, we would not expect convergence for initially poor countries at the lowest level of economic complexity. This suggests that for countries that lack a sufficient stock of previously accumulated capabilities, catching-up is rather unlikely.

Figure 2: Marginal effects at different levels of initial technological capabilities



Note: The plot shows marginal effects at three different representative values of initial economic complexity (ECI). Results are based on model (6) in Table 2.

Figure 3: Marginal effects at different levels of initial GDP per capita



Note: The plot shows marginal effects at three different representative values of initial GDP per capita. Results are based on model (6) in Table 2.

4. Discussion and conclusions

This paper has analysed the impact of technological capabilities on convergence in a growth regression framework. By using data for a global country sample and by focusing on the period 1985-2014, we find evidence that the impact of initial GDP levels on subsequent economic growth depends on the initial stock of technological capabilities. In other words: convergence is conditional on technological capabilities. This main finding is confirmed by various robustness checks such as variations in the country sample, in the time period covered, as well as changes to the estimation technique. It is also robust to controlling for confounding factors such as economic globalisation, resource dependence and institutional quality.

The initial accumulated stock of technological capabilities is an important factor in promoting convergence of poorer countries towards higher income levels. The globalisation process of the last decades has been marked by a general increase in economic openness (e.g. Gräbner et al. 2020c), and our results suggest that developing countries with a more favourable starting position in the mid-1980s in terms of their accumulated stock of technological capabilities were, on average, much more successful in catching up to countries with higher incomes than their low-technology peers. This finding is broadly supportive of the evolutionary political economy literature, which argues that technology is an essential determinant of catch-up dynamics (e.g. Dosi et al. 2020). Moreover, our results suggest that – if the past is any guide to the future – successful convergence outcomes are unlikely to happen for developing countries that are not equipped with a relatively high amount of technological capabilities. Given that the accumulation of technological capabilities is a highly path dependent process, any form of successful catch-up cannot be expected to happen endogenously under the current set of global institutions. If one wished to address the resulting capabilities, one could either argue for targeted innovation policies in the currently poorer countries, or a reform of the global institutions governing the relationships between countries. While the latter requires coordination on a more global scale, such an approach would take into account barriers to catch-up that are not rooted in individual country characteristics, but in the interrelationships between countries. At least theoretically, such 'structuralist' barriers are likely to exist, so more empirical work in order to quantify their importance could offer guidance on the relative merit of a more global solution to the catch-up problem.

What are the implications for the original question of this paper, i.e. whether the "smart kids", i.e. the initially poor countries with relatively favourable starting positions in technological capabilities, catch up? While our findings highlight the importance of technology for convergence and point to an affirmative answer, the results should not be understood as a counter-argument against the relevance of other determinants for catch-up. In particular, while our findings suggest that convergence is conditional on technological capabilities after controlling for various proxies of institutional quality, these regressions were not at the centre of the present analysis. Future work could take the results on technological capabilities as a starting point and address potential endogeneity issues when it comes to the role of institutions. Such endeavour, aimed at illuminating the causal interrelationship between development, technological capabilities, and institutions, would be of considerable academic and societal relevance, and we hope that we have facilitated this task by the results provided in this paper.

References

Abramowitz, M. (1986): Catching up, forging ahead, and falling behind, *Journal of Economic History*, 46(2), 386-406.

Acemoglu, D., Zilibotti, F. (2001): Productivity differences, Quarterly Journal of Economics, 116(2), 563-606.

Acemoglu, D., Johnson, S., Robinson, J. (2002): Reversal of fortune: Geography and institutions in the making of the modern world income distribution, *Quarterly Journal of Economics*, 117(4), 1231-1294.

Acemoglu, D. (2009): Introduction to modern economic growth, Princeton, NJ: Princeton University Press.

Amendola, G., Dosi, G., Papagni, E. (1993): The dynamics of international competitiveness, *Weltwirtschaftliches Archiv*, 129(3), 451-471.

Arora, V., Vamvadikis, A. (2005): How much do trading partners matter for economic growth?, *IMF Staff Papers*, 52(1), 24-40.

Barro, R. (1991): Economic growth in a cross section of countries, Quarterly Journal of Economics, 106(2), 407-443.

Ben-David, D., Loewy, M. (1998): Free trade, growth, and convergence, *Journal of Economic Growth*, 3(2), 143-170.

Bolt, J., Inklaar, R., de Jong, H., van Zanden, J. L. (2018): Rebasing 'Maddison': new income comparisons and the shape of long-run economic development, *Maddison Project Working paper 10*.

Boschini, A., Pettersson, J., Roine, J. (2013): The resource curse and its potential reversal, *World Development*, 43, 19-41.

Castellaci, F., Natera, J. (2013): The dynamics of national innovation system: A panel cointegration analysis of the coevolution between innovative capability and absorptive capacity, *Research Policy*, 42(3), 579-594.

Cimoli, M., Dosi, G., Stiglitz, J. (2009): Institutions and policies shaping industrial development: an introductory note, in: Cimoli, M., Dosi, G., Stiglitz, J. (ed.): Industrial policy and development: the political economy of capabilities accumulation, Oxford: Oxford University Press.

Comin, D., Mestieri, M. (2018). If Technology Has Arrived Everywhere, Why Has Income Diverged? *American Economic Journal: Macroeconomics*, *10*(3), 137–178.

Dosi, G., Pavitt, K., Soete, L. (1990): The economics of technical change and international trade, Pisa: Sant'Anna School of Advanced Studies

Dosi, G., Roventini, A., Russo, E. (2019): Endogenous growth and global divergence in a multi-country agent-based model, Journal of Economic Dynamics and Control, 101(C), 101-129.

Dosi, G., Nuvolari, A. (2020): Introduction: Chris Freeman's "History, Co-Evolution and Economics Growth": an affectionate reappraisal, Industrial and Corporate Change, 29(4), 1021-1034.

Dosi, G., Roventini, A., Russo, E. (2020): Public policies and the art of catching up: matching the historical evidence with a multi-country agent-based model, LEM Papers Series 2020/10.

Durlauf, S., Johnson, P., Temple, J. (2005): Growth econometrics, in: Aghion, P., Temple, J. (2005): Handbook of Economic Growth, Amsterdam: North Holland, 555-677.

Efendic, A., Pugh, G., Adnett, N. (2011): Institutions and economic performance: A meta-regression analysis, European Journal of Political Economy, 27(3), 586-599.

Fagerberg, J., Verspagen, B. (2002): Technology-gaps, innovation-diffusion and transformation: an evolutionary interpretation, Research Policy, 31(8-9), 1291-1304.

Fagerberg, J., Mowery, D., Nelson, R. (2005): The Oxford handbook of innovation, Oxford: Oxford University Press.

Gala, P., Rocha, I., Magacho, G. (2018): The structuralist revenge: economic complexity as an important dimension to evaluate growth and development, *Brazilian Journal of Political Economy*, 38(2), 219-236.

Gräbner, C., Heimberger, P., Kapeller, J. (2020a): Code for replicating "Do the smart kids catch up? Technological capabilities, globalisation and economic growth", github, https://github.com/graebnerc/technology-catchup.

Gräbner, C., Heimberger, P., Kapeller, J., Schütz, B. (2020b): Is the Eurozone disintegrating? Macroeconomic divergence, structural polarisation, trade and fragility, *Cambridge Journal of Economics*, 44(3), 647-669.

Gräbner, C., Heimberger, P., Kapeller, J., Schütz, B. (2020c): Understanding economic openness: A review of existing measures, *Review of World Economics*, DOI: https://doi.org/10.1007/s10290-020-00391-1

Gräbner, C., Heimberger, P., Kapeller, J., Schütz, B. (2020d): Structural change in times of increasing openness: assessing path dependency in European economic integration, *Journal of Evolutionary Economics*, 30(5), 1467-1495.

Gygli, S., Haelg, F., Sturm, H. (2019): The KOF globalisation index – revisited, Review of International Organizations, 14(3), 543-574.

Hausmann, R., Hwang, J., Rodrik, D. (2007): What you export matters, Journal of Economic Growth, 12(1), 1-25.

Havranek, T., Horvath, R., Zeynalov, A. (2016): Natural resources and economic growth: a meta-analysis, *World Development*, 88, 134-151.

Hidalgo, C., Klinger, B., Barabasi, A., Hausmann, R. (2007): The product space conditions the development of nations, Science, 317(5837), 482-487.

Hidalgo, C., Hausmann, R. (2009): The building blocks of economic complexity, Proceedings of the National Academy of Sciences, 106(26), 10570-10575.

Hirschman, A. (1958): The strategy of economic development, New Haven: Yale University Press.

Jones, C., Romer, P. (2010): The New Kaldor Facts: Ideas, institutions, population, and human capital, *American Economic Journal: Macroeconomics*, 2(1), 224-245.

Kaldor, N. (1980): The foundations of free trade theory and their implications for the current world recession, in: Malinvaud, E., Fitoussi, J. (ed.): Unemployment in Western countries, 85-100, London: Palgrave Macmillan.

Koch, P. (2020): Economic complexity and growth: Can value-added exports better explain the link?, *Economics Letters*, forthcoming, doi: https://doi.org/10.1016/j.econlet.2020.109682

Kormendi, R., Meguire, P. (1985): Macroeconomic determinants of growth: Cross-country evidence, Journal of Monetary Economics, 16,(2), 141-163.

Kuncic, A. (2014): Institutional quality data set, Journal of Institutional Economics, 10(1), 135-161.

Lee, K., Kim, B. (2009): Both institutions and policies matter but differently for different income groups of countries: Determinants of long-run economic growth revisited, *World Development*, 37(3), 533-549.

Levine, R., Renelt, D. (1992): A sensitivity analysis of cross-country growth regressions, American Economic Review, 82(4), 942-963.

List, F. (1856): National system of political economy, Philadelphia: J.B. Lippincott & Co.

Lundvall, B. (1992): National systems of innovation: Towards a theory of innovation and interactive learning, London: Pinter Publishers.

Mankiw, G., Romer, D., Weil, D. (1992): A contribution to the empirics of economic growth, Quarterly Journal of Economics, 107(2), 407-437.

Mewes, L., Broekel, T. (2020): Technological complexity and economic growth of regions, *Research Policy*, forthcoming, doi: https://doi.org/10.1016/j.respol.2020.104156

Mullings, R., Mahabir, A. (2018): Growth by destination: the role of trade in Africa's recent growth episode, *World Development*, 102(C), 243-261.

Mukoyama, T. (2004): Diffusion and innovation of new technologies under skill heterogeneity, *Journal of Economic Growth*, 9(4), 451-479.

Myrdal, G. (1957): Economic theory and under-developed regions, London: Buckworth.

Neumayer, E. (2004): Does the resource curse hold for growth in genuine income as well?, *World Development*, 32(10), 1627-1640.

Prebisch, R. (1950): The economic development of Latin America and its principal problems, Economic Bulletin for Latin America, 7, 1-12.

Reinert, E. (2007): Globalization, economic development and inequality: an alternative perspective, Cheltenham: Edward Elgar.

Rodrik, D., Subramanian, A., Trebbi, F. (2004): Institutions rule: The primacy of institutions over geography and integration in economic development, *Journal of Economic Growth*, 9(2), 131-165.

Rodrik, D. (2011): The future of economic convergence, NBER Working Paper No. 17400.

Rodrik, D. (2012): Unconditional convergence in manufacturing, *Quarterly Journal of Economics*, 128(1), 165-204.

Sala-i-Martin, X., Doppelhofer, G., Miller, R. (2004): Determinants of long-term growth: A Bayesian averaging of classical estimates (BACE) approach, American Economic Review, 94(4), 813-835.

Subramanian, A. (2011): Eclipse: Living in the Shadow of China's Economic Dominance, Washington, DC: Peterson Institute for International Economics

The Atlas of Economic Complexity (2019): Center for International Development at Harvard University, http://www.atlas.cid.harvard.edu (accessed May 2019).

Williams, A. (2011): Shining a light on the resource curse: An empirical analysis of the relationship between natural resources, transparency, and economic growth, *World Development*, 39(4), 490-505.

Wooldridge, J. (2010): Econometric analysis of cross section and panel data, Cambridge, MA: MIT Press.

Do the "smart kids" catch up? Technological capabilities, globalisation and economic growth Supplementary appendix*

Abstract

First, the supplementary material introduces and discusses the index of economic complexity, which we use to proxy for technological capabilities. Second, we list the countries included in the country sample. Third, we present descriptive statistics. Fourth, we report additional regression results when using an alternative proxy for institutional quality. Fifth, we show residual plots and diagnostics for the main econometric models estimates in the paper. Finally, we show a matrix with pair-wise correlations of relevant variables.

*The authors gratefully acknowledge funding by the Oesterreichische Nationalbank (OeNB, Anniversary Fund, project number: 18144).

A. The economic complexity index

The index of economic complexity (ECI) was first introduced in Hidalgo et al (2007) and further explicated in Hidalgo and Hausmann (2009) and Hausmann et al (2013). For the underlying theory and a further interpretation, according to which the fundamental driving force for the development of nations is their ability to accumulate more and more information, see Simoes and Hidalgo (2011) and Hidalgo (2015).

The index can be understood as a measure of the knowledge intensity of an economy, or, in other words, the amount of technological capabilities present in this economy. Its prominence stems from the fact that it is an excellent predictor for future growth rates of national economies, indicating that "countries tend to approach the levels of income that correspond to their measured complexity" (Hidalgo and Hausmann, 2009, p. 10574). Here, we will briefly illustrate the way in which the indicator is constructed in the database we use (Simoes and Hidalgo, 2011). For a criticism of the computation method and an alternative see Cristelli et al (2013).

A.1. The computation of the index via the method of reflections

One first needs to compute the *revealed competitive advantage* (RCA) of each country c with regard to every product p. The RCA_{cp} is constructed by asking whether the share of a product in the export basket of a country is smaller or larger than the share of this product in the total exports of the world market as a whole. In other words, assuming that P is the set of all products and C the set of all countries, one relates the share of product $p \in P$ in the export basket of country $c \in C$, $\frac{X_{cp}}{\sum_{p' \in P} X_{cp'}}$, to the share of the product in total exports in the world, $\frac{\sum_{c' \in C} X_{c'p}}{\sum_{c' \in C} \sum_{p' \in P} X_{c'p'}}$. Thus, the RCA of country c in product p is given by:

$$RCA_{cp} = \frac{X_{cp} / \sum_{p' \in P} X_{cp'}}{\sum_{c' \in C} X_{c'p} / \sum_{c' \in C} \sum_{p' \in P} X_{c'p'}} \tag{1}$$

If $RCA_{cp} > 1$ one says that country c has a revealed comparative advantage in a product p.

Based on the RCA one can construct a bipartite network of countries and products in which a country c is connected to a product p if $RCA_{cp} > 1$. The resulting network can be represented by the adjacency matrix M_{cp}. For every single element $m_{cp} \in M_{cp}$ we have $m_{cp} = 1$ iff $RCA_{cp} > 1$ and zero otherwise. Consequently, the row sum of this matrix $\sum_p M_{cp}$ represents the diversity of a country's export basket, i.e. the number of different products the country exports with revealed competitive advantage, denoted by $k_{c,0}$. The column sums, $\sum_c M_{cp}$, then are the ubiquity of a product, i.e. the number of countries that export a given product with revealed competitive advantage, denoted by $\kappa_{p,0}$.

The intuition now is to say that the fact that a country exports a very ubiquitous product carries little information about the stock of technological capabilities of this country: if many other countries can produce this product as well, there cannot be anything special about it. To illustrate the basic intuition, Hidalgo and Hausmann (2009) use an analogy to Lego pieces: if a child shows you a very simplistic Lego building that could be built from almost any set of Lego pieces, it is hard to infer the stock of Lego pieces owned by that child. Yet, when a country exports a product that is only produced by few other countries, this seems to be something special. This corresponds to a child that provides you with a Lego building that requires very specific Lego pieces. After having seen the building, you can be very sure that the child possesses these specific pieces.

The same reasoning can be applied to the complexity of products : if a product is exported by almost all countries, the product is probably not very complex – it does not seem to require many capabilities. Yet, when there are only few countries exporting the product, then the product seems to be rather special. Or, in terms of the Lego analogy: if every child can build a certain building, it does not require particularly sophisticated pieces. Yet, if only very few children can make the building, the required pieces are probably rare and difficult to acquire.

This intuitive logic can be expressed in terms of M_{cp}. As indicated above

$$k_{c,0} = \sum_p M_{cp} = \text{Diversity of export basket} \tag{2}$$

$$\kappa_{p,0} = \sum_c M_{cp} = \text{Ubiquity of the product} \tag{3}$$

but this does not take into account the information that a less ubiquitous product carries more information about the capabilities of a country than an ubiquitous one. Similarly, we would like to consider the complexity of a country for the calculation of the complexity of a product. For example, for the complexity of countries we would like to take into account the average ubiquity of the products they export, but also the average diversity of the countries that export these products since this information is important to determine the general ubiquity of a product. It is easy to see that this gives rise to a recursion of the following form:

$$k_{c,N} = \frac{1}{k_{c,0}} \sum_p M_{cp} \kappa_{p,N-1} \tag{4}$$

$$\kappa_{p,N} = \frac{1}{\kappa_{p,0}} \sum_c M_{cp} k_{c,N-1} \tag{5}$$

Because $k_{c,N}$ and $\kappa_{p,N}$ are related to each other, the whole procedure has been termed 'method of reflections' (Hausmann et al, 2013). Since the following steps are equivalent for country and product complexity, we illustrate the procedure for country complexity only. First we insert the equation, resulting in:

$$k_{c,N} = \frac{1}{k_{c,0}} \sum_p M_{cp} \frac{1}{\kappa_{p,0}} \sum_{c'} M_{c'p} k_{c',N-2} \tag{6}$$

which can be simplified by rearranging the sum to:

$$k_{c,N} = \sum_{c'} k_{c',N-2} \sum \frac{M_{cp} M_{c'p}}{k_{c,0} \kappa_{p,0}}. \tag{7}$$

Setting $\tilde{M}_{cc'} = \sum_p \frac{M_{cp} M_{c'p}}{k_{c,0} \kappa_{p,0}}$ we get

$$k_{c,N} = \sum_{c'} k_{c',N-2} \tilde{M}_{cc'}. \tag{8}$$

The recursion (8) reaches an equilibrium whenever $k_{c,N} = k_{c,N-2} = 1$. Taking the eigenvector $\vec{K}$ that corresponds to the second-largest eigenvalue of $\tilde{M}_{cc'}$ in equilibrium yields the index of economic complexity ECI, which we first normalize by its mean and standard deviation:[1]

[1] Why not taking the eigenvector that corresponds to the largest eigenvalue of $\tilde{M}_{cc'}$ in equilibrium? It is easy to show that this eigenvector necessarily consists only of ones. Since we are interested in the differences among countries, it is the second-largest eigenvector that carries most of the relevant information.

$$ECI = \frac{\vec{K} - mean(\vec{K})}{sd(\vec{K})} \tag{9}$$

The product complexities PCI are obtained in exactly the same way. Assuming that $\vec{Q}$ is the product equivalent to $\vec{K}$ then PCI is obtained via:

$$PCI = \frac{\vec{Q} - mean(\vec{Q})}{sd(\vec{Q})} \tag{10}$$

Hence, PCI is a measure for the complexity of a product in the sense that complex products require many and very sophisticated capabilities to be produced, while simple products can be produced without such capabilities. ECI is a measure for the knowledge intensity of an economy, or the amount of available technological capabilities. The more complex a country, the more capabilities it has and the more complex products it can produce: just as one can infer the presence of particular Lego pieces by the buildings a child was able to built, one can infer the presence of particular capabilities by looking at the products a country is able to export (Hidalgo and Hausmann, 2009).

Empirically, we can observe that more complex countries have more diversified export baskets (they do not necessarily stop exporting simple products, see Tacchella et al, 2013), enjoy higher levels of income (Hidalgo and Hausmann, 2009) and lower levels of income inequality (Hartmann et al, 2017).

The method of reflections has been criticized by Tacchella et al (2013), who suggest an alternative computation method. The resulting ranking is slightly different, in particular for developing countries. See Tacchella et al (2012) and Tacchella et al (2013) for further details and a thorough comparison.

A.2. Strengths and weaknesses

Although we believe that the ECI is an excellent analytical tool to study economic development, there are a number of drawbacks that we wish to point out:

Ambiguity with regard to the concept of 'capabilities' Although this is not a particular weakness of the indicator as such, it should be mentioned that it does not contain any information on how capabilities have been acquired. Furthermore, there is no full-fledged theory of capabilities backing the indicator. It is clear that the capabilities include diverse aspects such as human and physical capital, national institutions, organizational capacities to coordinate diverse teams of people, and working practices and know-how on the firm level (e.g. Felipe et al, 2012, p. 37). Additionally, it is recognized that capabilities come in both embodied and disembodied form, in tacit and codified versions, and that they relate both to the creation and dissemination of knowledge (e.g. Archibugi and Coco, 2005, p. 177-178). Yet, there is no specific theory about how these capabilities yield overall prosperity, although Hidalgo (2015) sketches a theory based on "person bytes", which has, however, not (yet) been discussed widely in the scientific community.

No distinction between technological and productive capabilities A potential drawback of the ECI is that it does not distinguish between technological and productive capabilities as suggested in, among others, Archibugi et al (2009, p. 919). Such a distinction can be useful if one wishes to study how an increase of technological capabilities impacts on the productive capabilities of an economy. However, this distinction is often hard to make in practice since the production process itself usually impacts on technological capabilities (e.g. via *learning by doing*). Also, as argued in Hidalgo (2015), products can be seen as a 'crystalized' form of technological capabilities. As long as one is not concerned with very specific questions on the relationship between a country's ability to produce goods and its level of technological capabilities, the distinction does not seem to be decisive.

Measurement problems Since the indicator is built using trade data it inhabits all methodological and measurement problems associated with trade data. For example, the SITC codes used for long-term evolution of the ECI have problems in accommodating new products, such as smartphones. The more accurate harmonized system (HS) also experiences some problems: in 2007, for example, the new 2007 version of the HS system has been released. Some older categories still present in the 1992 version were dropped and integrated into other product codes. Some countries stopped reporting such products in the HS92 version of the system as well. This has lead to an apparent drop in the production of some products, and a corresponding rise in complexity for, e.g. tin products. The best way to avoid this problem is to use the most recent version of the HS system - yet this inevitably comes with a loss in data coverage.

Lack of services Another negative side-effect of the reliance on trade data is the lack of services: since trades in services do not pass custom offices, not all countries report service flows. Consequently, building the complexity index for services would necessarily yield results biased in favour of countries declaring services. Thus, a country's complexity takes into account only real products. This might be a problem for countries that rely heavily on services, or that have experienced strong de-industrialization.

Despite these drawbacks, we believe that the ECI is a very useful tool to study economic development. Among its many advantages we would like to stress the following:

Outcome-based measure The ECI is an outcome-based measure, i.e. it directly measures what countries make of their situation, rather than considering their institutional or geographical conditions with regard to their benefit for technological change. This facilitates cross-country comparisons compared to composite indicators based on institutional data: a law that works in one country does not necessarily work in another, which is why a comparison of countries in terms of their legal frameworks can be misleading if one is ultimately interested in their technological capabilities. Comparing the capabilities directly is probably a better choice.

Excellent coverage Since the ECI is calculated from trade data it is available for almost all UN countries from 1963. This exceeds the coverage of many alternatives by magnitudes and allows for promising long-run investigations.

Few degrees of freedom Many composite indicators aggregate the information from various sources. During the aggregation procedure, the various ingredients usually get weighted – a source of subjectivity and variation. For the ECI, on the other hand, there are not many ways to compute it. In fact, aside from the 'method of reflections' we are aware only of the alternative method of Tacchella et al (2013) to derive the index.

Intuitive interpretation and good predictor for economic growth The interpretation of the ECI is straightforward. Complex countries have many and sophisticated capabilities. They tend to be rich because they can transform inputs to outputs in fancy ways. Less complex products do not have these capabilities, which is why they are less developed. Also, the complexity and relatedness of products can be illustrated very nicely through the *product space* (Hidalgo et al, 2007).

A.3. Related literature

Here, we provide a very concise survey of the related literature and mention some related indices. The interested reader might refer to these sources for further information on the corresponding indices and concepts.

A.3.1. Theoretical accounts of technological capabilities

Although the ECI does not directly build upon a particular theory of capability accumulation, it suggests that the technological capabilities of a country are decisive for its future development. The idea that capabilities are at the heart of economic development and should be of prime interest for directed policy intervention dates back to at least Hirschman (1958), see also Lall (1992) or Bell and Pavitt (1995). Today, capabilities as determinants for economic development receive particular attention in the evolutionary literature on technological change (see e.g. Dosi et al, 2015) and in the area of evolutionary economic geography (e.g. Boschma, 2016).

More directly, the ECI builds upon the work of Hausmann et al (2007), who relate products to the level of income of the economies that export these products with a revealed competitive advantage. They already call it 'product complexity'. They also suggest a measure called 'export complexity', which is related to the average product complexity of a countries' export basket. Thus, the paper concludes that "what you export matters" for economic development (Hausmann et al, 2007, p. 1). This idea then was the basis for the 'product space' (Hidalgo et al, 2007). Here, the authors use export data to show that some products are important in the sense that they indicate the presence of capabilities that can be re-used in a variety of ways, while other products are associated with capabilities that are much less useful and only help to produce few peripheral products.

The idea that a country has to accumulate a complete set of capabilities before it can produce a certain product has similarities to the 'O-Ring' theory of development of Kremer (1993) He argues that the production of products involves different tasks, and once the knowledge has been required for one particular task, certain products cannot be produced at all. A similar argument is made by Sutton (2012), although from a firm perspective.

A.3.2. Related indices

There are some related indices that might be viable alternatives to the ECI in some instances. The most similar one is suggested by Tacchella et al (2012, 2013). From the underlying intuition, it is quasi-equivalent to the original ECI, yet the computation method is slightly different – and so is the resulting ranking. The differences are most pronounced for developing countries, see Cristelli et al (2013) for a more detailed comparison.

Furthermore, a number of other indicators for technological capabilities have been used in the literature, e.g. the Technology index of Furman et al (2002), which has been integrated to the WEF Global Competitive Report, the *AcCo Index* by Archibugi and Coco (2004), the *Science and Technology Capacity Index* of Wagner et al (2001), and the *innovation index* by Khayyat and Lee (2015).

Most of these measures are surveyed and compared in Archibugi and Coco (2005) and more recently in Archibugi et al (2009) and Felipe et al (2012). They are mainly composite indices that aggregate a number of different variables measuring the innovative capacities of economies such as *patents per million population*, *R&D expenditure*, *schooling* and *use of computers*. Thus, they are not directly output-oriented such as the ECI but rather concerned with the conditions necessary for positive technological change.[2] This way, they approach the problem of measuring

[2] A similar approach for the classification of products is undertaking by the complex products and system (CoPS) category of Hobday et al (2000). The latter, however, also takes a broader range of inputs into consideration.

technological capabilities in a different way than the ECI, which does not rely on any aggregation, but directly measures the outcome of technological capability building. Thus, they might be preferable if one seeks to study the conditions required for the accumulation of technological capabilities, but not so much the capabilities as such.

Finally, note that since the ECI is computed directly from import-export data, which is readily available for a vast majority of countries, its time and country coverage is much higher than that of the alternative indicators.

B. Data sample

The 108 countries included in the econometric analysis are: Albania, Argentina, Australia, Austria, Burundi, Belgium, Benin, Burkina Faso, Bulgaria, Bolivia, Brazil, Barbados, Central African Republic, Canada, Switzerland, Chile, China, Cote d'Ivoire, Cameroon, Congo, Colombia, Costa Rica, Cyprus, Germany, Denmark, Dominican Republic, Algeria, Ecuador, Egypt, Spain, Ethiopia, Finland, Fiji, France, Gabon, United Kingdom, Ghana, Gambia, Greece, Guatemala, Hong Kong SAR China, Honduras, Haiti, Hungary, Indonesia, India, Ireland, Iraq, Iceland, Israel, Italy, Jamaica, Jordan, Japan, Kenya, Cambodia, South Korea, Kuwait, Laos, Liberia, Morocco, Madagascar, Maldives, Mexico, Mali, Malta, Myanmar (Burma), Mongolia, Mauritania, Mauritius, Malawi, Malaysia, Niger, Nigeria, Nicaragua, Netherlands, Norway, Nepal, New Zealand, Pakistan, Panama, Peru, Philippines, Poland, Portugal, Paraguay, Rwanda, Saudi Arabia, Sudan, Senegal, Singapore, Sierra Leone, El Salvador, Sweden, Syria, Togo, Thailand, Trinidad and Tobago, Tunisia, Turkey, Tanzania, Uganda, Uruguay, United States of America, Venezuela, Vietnam, South Africa, Zambia.

C. Descriptive statistics

Here are the descriptive statistics for the variables used in the econometric analysis.

Table 1: Cross-sectional data (1985-2014)

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
eci	108	−0.007	1.035	−2.336	−0.758	0.596	2.410
GDP_pc_PPP_log	108	8.480	1.106	6.658	7.531	9.425	10.404
AdvancedCountry	108	0.241	0.430	0	0	0	1
popgrowth	108	1.687	1.014	−0.718	0.842	2.574	4.078
humancapital	108	2.242	0.670	1.089	1.656	2.759	3.565
primaryexports	108	0.248	0.194	0.007	0.090	0.391	0.859
oilexports	108	12.346	22.294	0.023	1.056	9.815	95.417
coalandmetalexports	108	7.397	11.432	0.116	1.602	8.854	69.771
avg_GDP_pc_PPP_growth	108	2.463	1.751	−1.950	1.320	3.426	7.187
kof_econ	108	52.274	15.616	21.917	40.612	63.068	91.224

Table 2: Cross-sectional data (1990-2010)

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
eci	89	0.050	1.096	−2.126	−0.578	0.836	2.639
GDP_pc_PPP_log	89	8.629	1.172	6.625	7.659	9.747	10.516
popgrowth	89	1.591	1.010	−0.869	0.777	2.533	3.568
humancapital	89	2.338	0.663	1.084	1.886	2.796	3.574
primaryexports	89	0.224	0.182	0.005	0.083	0.355	0.804
oilexports	89	12.559	22.339	0.030	1.158	11.203	91.644
coalandmetalexports	89	6.636	11.118	0.232	1.467	6.345	67.482
avg_GDP_pc_PPP_growth	89	2.856	1.935	−1.720	1.712	3.867	8.594
kof_econ	89	54.186	15.185	23.259	42.404	66.807	90.867
politicalquality	89	0.171	0.948	−1.848	−0.555	0.932	1.810
economicquality	89	−0.037	0.899	−2.145	−0.786	0.607	1.624
legalquality	89	0.017	0.908	−1.412	−0.682	0.659	1.708
propertyrights	89	54.671	22.226	10.000	37.500	70.000	90.667

Table 3: Cross-sectional data (1990-2010)

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
eci	756	−0.051	1.056	−2.773	−0.832	0.659	2.936
Penn_GDP_PPP_log	756	8.741	1.252	5.485	7.648	9.834	11.310
GDP_pc_growth	755	2.183	4.391	−17.202	0.066	4.733	22.401
kof_econ	756	51.577	17.038	14.720	39.037	62.971	93.187
popgrowth	756	1.712	1.208	−3.987	0.743	2.642	6.603
humancapital	756	2.216	0.695	1.022	1.630	2.727	3.723
OPECdummy	756	0.074	0.262	0	0	0	1

D. Additional regression results using an alternative proxy for institutional quality

Columns (1) and (2) of the table below show the same results as in columns (7) and (9) of Table 3 in the main paper, respectively. Columns (3) and (4) of the table below show additional regressions results when we use a property rights index to proxy for institutional quality.

Table 4:

	(1)	(2)	(3)	(4)
GDPpc (log)	-1.098^{**}	-1.494^{***}	-1.300^{***}	-1.854^{***}
	(0.432)	(0.504)	(0.460)	(0.447)
Globalization	0.047^{**}	0.046^{*}	0.032	0.032
	(0.024)	(0.024)	(0.022)	(0.021)
ECI	5.947^{***}	6.642^{***}	6.183^{***}	7.140^{***}
	(1.937)	(2.170)	(1.890)	(2.049)
Political inst	-0.931	-0.576		
	(0.562)	(0.660)		
Property rights			0.011	0.021
			(0.021)	(0.020)
Population growth	-0.585^{*}	-0.626^{*}	-0.568^{*}	-0.693^{**}
	(0.334)	(0.334)	(0.308)	(0.303)
Human capital	1.784^{***}	1.747^{***}	1.262^{**}	1.370^{***}
	(0.510)	(0.523)	(0.505)	(0.499)
Oil exports		0.020		0.028^{**}
		(0.012)		(0.011)
GDPpc (log) · ECI	-0.653^{***}	-0.705^{***}	-0.707^{***}	-0.772^{***}
	(0.194)	(0.214)	(0.192)	(0.204)
Constant	7.316^{*}	10.699^{**}	10.365^{***}	14.230^{***}
	(3.869)	(4.607)	(3.632)	(3.491)
Observations	89	89	89	89
R^2	0.323	0.351	0.284	0.351
Adjusted R^2	0.264	0.286	0.223	0.286
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

E. Residual plots and diagnostics

The following plots are based on model (6) in Table 1.

Figure 1: Residuals vs. fitted values

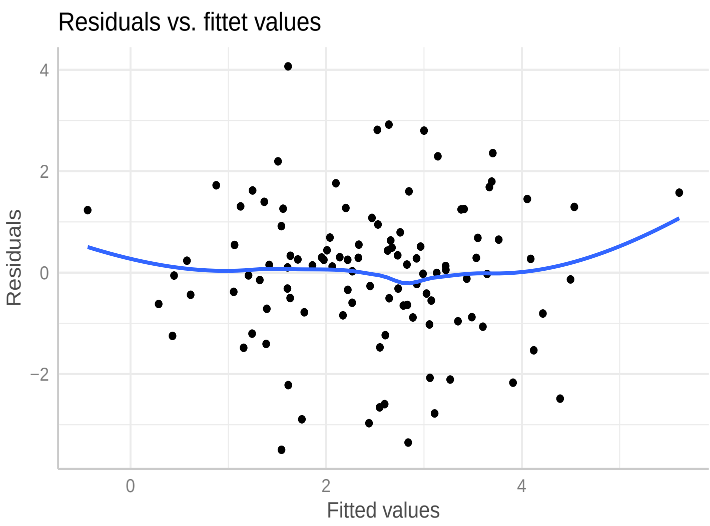
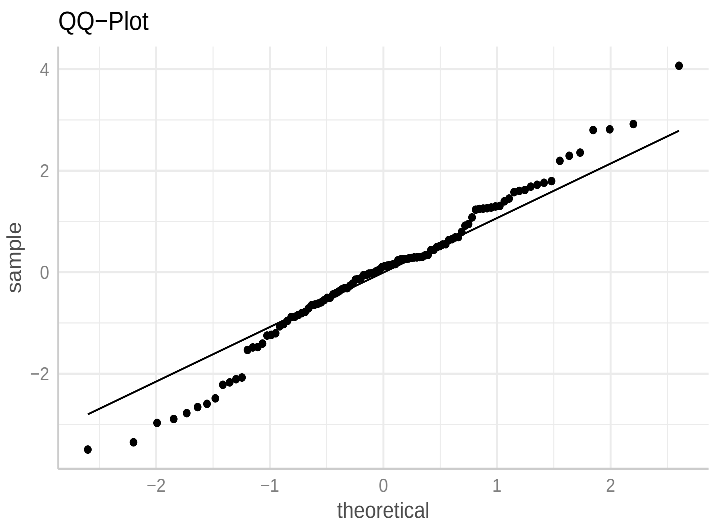


Figure 2: Quantile-Quantile plot



Here is the result from the Durbin-Watson test on autocorrelation:

```
Durbin-Watson test

data:  reg_predict_7
DW = 1.749, p-value = 0.09907
alternative hypothesis: true autocorrelation is greater than 0
```

F. Correlation matrix (Pearson correlation coefficients)

Here are the pairwise-correlations of the variables based on Pearson correlation coefficients for the cross-sectional data of the time period 1990-2010.

	ECI	GDPpc	growth	global	pop	hc	linst	pinst	einst	oil
ECI	1.00	0.78	0.05	0.67	-0.65	0.77	0.79	0.80	0.77	-0.33
GDPpc	0.78	1.00	0.01	0.77	-0.58	0.86	0.82	0.82	0.84	0.01
growth	0.05	0.01	1.00	0.09	-0.25	0.16	0.01	-0.01	0.08	0.07
global	0.67	0.77	0.09	1.00	-0.43	0.75	0.78	0.76	0.87	-0.08
pop	-0.65	-0.58	-0.25	-0.43	1.00	-0.67	-0.58	-0.62	-0.52	0.27
hc	0.77	0.86	0.16	0.75	-0.67	1.00	0.84	0.85	0.83	-0.15
linst	0.79	0.82	0.01	0.78	-0.58	0.84	1.00	0.97	0.90	-0.29
pinst	0.80	0.82	-0.01	0.76	-0.62	0.85	0.97	1.00	0.90	-0.32
einst	0.77	0.84	0.08	0.87	-0.52	0.83	0.90	0.90	1.00	-0.27
oil	-0.33	0.01	0.07	-0.08	0.27	-0.15	-0.29	-0.32	-0.27	1.00

References

Archibugi D, Coco A (2004) A New Indicator of Technological Capabilities for Developed and Developing Countries (ArCo). World Development 32(4):629–654

Archibugi D, Coco A (2005) Measuring technological capabilities at the country level: A survey and a menu for choice. Research Policy 34(2):175–194

Archibugi D, Denni M, Filippetti A (2009) The technological capabilities of nations: The state of the art of synthetic indicators. Technological Forecasting and Social Change 76(7):917–931

Bell M, Pavitt K (1995) The development of technological capabilities. In: Haque Iu (ed) Trade, Technology, and International Competitiveness, Washington, DC, pp 69–101

Boschma R (2016) Relatedness as driver of regional diversification: a research agenda. Regional Studies 51(3):351–364

Cristelli M, Gabrielli A, Tacchella A, Caldarelli G, Pietronero L (2013) Measuring the Intangibles: A Metrics for the Economic Complexity of Countries and Products. PLoS ONE 8(8):e70726

Dosi G, Grazzi M, Moschella D (2015) Technology and costs in international competitiveness: From countries and sectors to firms. Research Policy 44:1795–1814

Felipe J, Kumar U, Abdon A, Bacate M (2012) Product complexity and economic development. Structural Change and Economic Dynamics 23(1):36–68

Furman JL, Porter ME, Stern S (2002) The determinants of national innovative capacity. Research Policy 31(6):899–933

Hartmann D, Guevara MR, Jara-Figueroa C, Aristarán M, Hidalgo CA (2017) Linking Economic Complexity, Institutions, and Income Inequality. World Development 93:75–93

Hausmann R, Hwang J, Rodrik D (2007) What you export matters. Journal of Economic Growth 12(1):1–25

Hausmann R, Hidalgo CA, Bustos S, Coscia M, Simoes A, Yildirim MA (2013) The Atlas of Economic Complexity. Mapping Paths to Prosperity, The MIT Press, Cambridge, MA, and London, UK

Hidalgo CA (2015) Why Information Grows. The Evolution of Order, from Atoms to Economies, Basic Books, New York, NY

Hidalgo CA, Hausmann R (2009) The building blocks of economic complexity. Proceedings of the National Academy of Sciences 106(26):10570–10575

Hidalgo CA, Klinger B, Barabási AL, Hausmann R (2007) The Product Space Conditions the Development of Nations. Science 317(7):482–487

Hirschman AO (1958) The Strategy of Economic Development. Yale University Press, New Haven

Hobday M, Rush H, Tidd J (2000) Innovation in complex products and system. Research Policy 29(7-8):793–804

Khayyat NT, Lee JD (2015) A measure of technological capabilities for developing countries. Technological Forecasting and Social Change 92:210–223

Kremer M (1993) The O-Ring Theory of Economic Development. The Quarterly Journal of Economics 108(3):551–575

Lall S (1992) Technological capabilities and industrialization. World Development 20(2):165–186

Simoes AJG, Hidalgo CA (2011) The Economic Complexity Observatory: An Analytical Tool for Understanding the Dynamics of Economic Development

Sutton J (2012) Competing in Capabilities. Oxford University Press, Oxford, UK

Tacchella A, Cristelli M, Caldarelli G, Gabrielli A, Pietronero L (2012) A New Metrics for Countries' Fitness and Products' Complexity. Scientific Reports 2(723):1–7

Tacchella A, Cristelli M, Caldarelli G, Gabrielli A, Pietronero L (2013) Economic complexity: Conceptual grounding of a new metrics for global competitiveness. Journal of Economic Dynamics and Control 37(8):1683–1691

Wagner CS, Brahmakulam IT, Jackson BA, Wong A, Yoda T (2001) Science & Technology Collaboration: Building Capacity in Developing Countries? RAND Corporation, Santa Monica, CA

ifso working paper

ifso working papers are preliminary scholarly papers emerging from research at and around the Institute for Socio-Economics at the University of Duisburg-Essen.

All **ifso working papers** at uni-due.de/soziooekonomie/wp

ISSN 2699-7207

UNIVERSITÄT DUISBURG ESSEN

Open-Minded

ifso institute for socio-economics

Institute for Socio-Economics
University of Duisburg-Essen

Lotharstr. 65
47057 Duisburg
Germany

uni-due.de/soziooekonomie
wp.ifso@uni-due.de