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Guzmán Ourens

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*E-mail:guzman@decon.edu.uy. Department of Economics, Universidad de la República, Uruguay.

Abstract

Building upon an original and fruitful research line, a recent paper by Hidalgo and Hausmann (2009) proposed new indicators of product sophistication and economic complexity build solely upon international trade data, in their *Method of Reflections*. The authors find their indicators for economic complexity to be highly related to countries' income and show evidence supporting their use as predictors of future growth in the short and long run. This would make these indicators very appealing to empirical economists and policy-makers. This work tests these properties for the indicators constructing them upon a more disaggregated database and changing some other important methodological decisions. Results show that MR indicators are strongly related to income and they can be considered good predictors of long-term growth under certain conditions. Evidence supporting MR indicators as good predictors of short-term growth could not be found.

Keywords: Method of reflections, growth, specialization, economic complexity.

Resumen

Aportando a una línea de investigación original y fructífera, un reciente trabajo de Hidalgo y Hausmann (2009) propuso una serie de nuevos indicadores para medir sofisticación de productos y complejidad de la economía. Estos indicadores, agrupados en lo que se denominó el Método de los Reflejos, pueden construirse íntegramente utilizando solamente datos de comercio internacional. Los autores encuentran que sus indicadores de complejidad económica están altamente correlacionados con el ingreso per cápita de los países y presentan evidencia que sustenta la conclusión de que estos indicadores pueden contribuir en la predicción del crecimiento futuro en el corto y largo plazo. Esto volvería sus indicadores extremadamente atractivos para los hacedores de políticas económicas y los economistas empíricos. Este trabajo se propone testear dichas propiedades construyendo los indicadores sobre una base de datos diferente y alterando algunas otras decisiones metodológicas. Los resultados muestran que los indicadores están efectivamente altamente correlacionados con el nivel de riqueza de los países y pueden ser considerados buenos predictores del crecimiento en el largo plazo bajo ciertas condiciones. No se pudo encontrar evidencia que respalde su poder predictivo en el corto plazo.

Palabras clave: Método de los reflejos, especialización, crecimiento, complejidad económica.
JEL Classification numbers: O47, O33, F14.

1 Introduction

Should countries make a deliberate effort to change their specialization in order to enhance their growth possibilities? If the answer is yes, then in which direction should the changes be heading? These important questions are a matter of debate and are of key relevance to policy-makers, especially in poor countries.

Classic growth and trade models state that the kind of specialization a country has does not determine its future growth. Benchmark growth models like those in Ramsey (1928) or Solow (1956) are built upon one product economies so no importance is given to the difference in production between countries. In trade literature, models focusing on specialization are mostly based on the Heckscher-Ohlin model, which concludes that a country should specialize in activities that use intensively the resources that it has a relative advantage in (see Heckscher and Ohlin (1991)). But again the model is mute on whether the specialization in one kind of production yields higher growth than specialization in another.

Aside this tradition there are some early contributions paying attention to the fact that what a country produces is related to its growth possibilities. For Prebisch (1949), the process through which countries diverge in income levels is explained by their original specialization. While some countries initially specialized in high productivity activities, the rest specialized in a variety of activities with heterogeneous productivity levels which make this second group grow at a lower average rate over the long run. Closer to the mainstream, in Lewis (1954) it is possible to find one of the earliest models showing how growth processes imply structural changes in the long run. In his model of two sectors, capital accumulation in the high productivity sector induces growth but also determines the subtraction of labor from the low productivity sector. Growth is therefore causing a structural change and therefore it alters the specialization of the economy.

As time passed by, the empirical evidence that emerged strongly supported the idea that rich countries produce different products than poor countries (see for example Sachs and Warner (1995), Lall (2000), Hausmann, et al. (2007) or Ranjan Basu and Das (2011)). But even though this idea has been around for a while and empirical evidence supporting it is strong, there are still many works overlooking that fact.

Over the last few years new contributions have emerged on this debate. One particular research line that has received great attention from economic advisers and policy-makers around the world is that started by Hausmann and Rodrik (2003) and further developed by many works, the most recent being Hausmann and Hidalgo (2011). This line of works focused on the idea that the production of some products have a stronger impact on growth than the production of others. In Hausmann et al. (2007) there is a proposal to measure the contribution each product makes to the growth process and, building on that, they also presented a synthetic measure of the growth possibilities of nations according to what they are currently producing. The potential these tools have to be used for policy-making recommendation is huge and, as will be shown, did not go unnoticed been implemented in plenty of policy-oriented documents.

Hidalgo and Hausmann (2009) further developed these tools presenting the *Method of Reflections* (MR) which provides an original approach to the measure of *product sophistication* and *economic complexity*, based only on product's international trade data. The main argument is that the required capabilities for the production of one good can only be partially substituted by some others and so the set of capabilities in the economy determines what can be potentially produced in it. Sophisticated goods (i.e. those requiring a large set of diverse capabilities) will be produced only by complex economies (i.e. those having a large diversity of capabilities) which implies that the characteristics of a country's current production determine its growth possibilities. The authors claim that by looking at what a country is exporting with revealed comparative advantages their indicators are able to extract information about each countries' productive capabilities and provide a synthetic measure of economic complexity that is not only related to countries' current income but can predict future growth in the long and short run as well.

This work proposes to test the robustness of these properties by constructing MR indicators over a different dataset and by changing some important methodological decisions. The use of trade data in a six-digit aggregation level (opposed to the four-digit aggregation data used by the authors to support the properties) allows for a greater accuracy in the distinction of different products' capability requirements which makes it more suitable for the construction of the indicators. This work also presents results using different country samples, changing the revealed comparative advantage parameter in the construction of the indicators and including control variables in the analysis to see whether results are depending on these decisions or not. By performing these robustness checks for such a promising set of indicators this work aims to contribute to the debate on the influence specialization has on growth and, more particularly, aims at providing useful information to policy-makers concerned about structural change.

The organization of this work is as follows. Section 2 overviews the main works exploring the relationship between specialization and growth and identifies among them the main ideas that provide theoretical support for the use of complexity indicators like the ones proposed by Hidalgo and Hausmann (2009) to predict future growth. Section 3 explains the empirical strategy this work follows. Section 4 presents the database used and Section 5 present the MR indicators and their most important features. Section 6 introduces the filter applied by this work to select the different country samples used in income and growth regressions and Section 7 presents the main control variables to include. Results for the different exercises performed in this work are shown in Section 8. Finally Section 9 concludes.

2 Related literature

Many papers have underlined the strong relationship between specialization and growth. This section will not provide an exhaustive list of all of them since that escapes the objective of this work. Instead, the aim of the section is to briefly identify the main theoretical contributions explaining why this link exists.

The debate on which may be the driving forces behind the fact that specializing in some products yield higher growth than others can be organized differentiating two broad groups: first, the group of works arguing that the main difference comes from the international demand, and then a second group of works claiming that the reason relies within countries and is supply-based.

2.1 Demand-side arguments

From a Keynesian perspective some works argue that the relationship comes from the influence global demand has on growth possibilities. For example Thirlwall (1979) and Thirlwall and Hussain (1982) explain that demand for some products has lower income-elasticity than the demand of some others which implies that, for a poor country to converge to the rich countries (i.e. to outgrow the rest of the countries) it must specialize its production in the second group of goods. These contributions provided a very solid argument to explain why some natural-resource based economies, like those in Latin-America, were not growing as expected.

Deepening the demand side studies, Passinetti (1981) proposes a multi-sectoral model to analyse the changes of the productive structure of a country during the development process. His model includes different demand elasticities for each sector. This allowed him to conclude that transformations of the productive structure will impact directly upon the growth rate of a country.

More recently Araujo and Lima (2007) derived a growth rate consistent with balance of payments equilibrium in a multi-sectoral model, making a connection between Thirlwall's and Passineti's contributions. Their model has two countries with different income levels and each of them has a multiplicity of productive sectors. They find that a growth rate that is compatible with balance of payment stability of the poor country must be proportional to the growth rate of its exports. Moreover they find the proportionality factor to be affected positively by the income-elasticity of its export demands, and negatively by the income-elasticity of its import demands. Each of these income elasticities are weighted by coefficients that measure the share of each sector in the total volumes of exports and imports, which implies that a country can achieve a sustainable and converging growth rate, even with constant income-elasticities, if it manages to modify its productive structure appropriately.

2.2 Supply-side arguments

Arguments coming from the supply side are closer to the ideas behind the MR indicators. In this part of the literature the argument is mostly based upon the assumption that some sectors can absorb more technological advances than others and this implies that countries where those sectors are relatively more important have larger growth rates in the long term. One of the earliest examples of this literature is in Baumol (1967). The paper presents a model with two sectors, a progressive sector (that incorporates innovations at a high rate) and a stagnant sector (that does it at a lower rate), and shows that with such a setting the progressive sector will decrease its relative costs and prices as it incorporates technology and the stagnant sector will tend to vanish. Structural change will then take place as the economy develops. The author also explains that if the government were to make an effort in order for the stagnant sector to maintain its share in total output (e.g. through subsidies), then the economy will allocate an increasing part of its resources to this sector. Such an economy will have a lower growth rate than one where the stagnant sector decreases.

The endogenous growth literature also pointed to the fact that there are some productive processes that contribute more than others to growth. In Romer (1986), Aghion and Howitt (1992) and Grossman and Helpman (1991) the authors present models with technologically advanced sectors where structural change is the main driver of long term growth. In their models, structural change comes through the accumulation of new capital, the increase of labor division or greater quality goods. They all agree that structural change (i.e. changing what you are producing) influences growth through technological externalities, indivisibilities and complementarities in productive processes.

Within the endogenous growth literature Fagerberg (1994) provides a very clear exposition of the importance of abandoning the assumption of technology being a *free* good. The author explains how this assumption is behind the prediction of equal growth rates across countries in the neoclassical setting: if growth is mostly explained by technological progress and this is a shared good across nations, then every integrated economy will eventually grow at the same rate in the long run, and the only possibility for observing differences in growth rates is during transitional dynamics. By allowing technological progress not to be perfectly transferable, the possibility for everlasting heterogeneous growth rates arises.

There is also a vast literature showing how the development process implies to a great extent the diversification of the production. In Acemoglu and Zilibotti (1997) the authors argue that the earlier stage of development is characterized by countries having a limited amount of resources to dedicate to a multiplicity of imperfectly correlated investment projects. Having options implies that each economy's risk can be diversified. All projects are subject to significant indivisibilities and differ in their degree of uncertainty about their returns, but at the earliest stage of development relatively safe projects are scarce. This is why initially countries that have a poor resource endowment will try to diversify risks by choosing safe but less productive projects which will yield a slow initial growth rate. Additionally, by choosing between a smaller pool of options, the risk will end up being larger than in richer countries. The authors therefore arrive to an explanation to why poor countries face slower and more volatile growth processes than richer countries based on their different specialization.

The former contribution could be complemented with the works of Imbs and Wacziarg (2003), Klinger and Lederman (2004 and 2006) and Cadot et al. (2011) who provide empirical evidence showing the increasing diversification behind most countries' development process. All these works agree in that diversification is a common feature at early stages of development: poor countries grow by diversifying their production. They also point out that more advanced stages of development bring some degree of specialization.[2]

The MR indicators this work tests are one of the outcomes of a research line that can be considered to begin with Hausmann and Rodrik (2003). The authors underline that specializing on some products can bring higher growth than specializing in some others focusing on the concept of *cost discovery*: to undertake a new production within a country it is required that one pioneer firm takes the first step and discovers what the real costs of production are (i.e. invests in cost discovery). This pioneer has private losses if it fails but generates spills over for the entire economy if it succeeds as new information will be available to all firms. The resulting externality implies that the activity of cost discovery will be under-provided

[2]All works coincide in that the turning point where diversification stops and specialization begins is at a medium-to-high level of per capita GDP. Cadot et al. (2011, p. 594) conclude that "...*both the existence of a turning point in export concentration and its location around a GDP per capita of about $22,000 to $27,000 at PPP in constant 2005 international dollars —a very late point in the development process— are fairly robust*."

in decentralized economies (compared to the centralized economy solution) unless the state implements a policy to make firms internalize it. This is, according to the authors, behind the different development path between South-East Asian countries and Latin-American countries in the second part of the last century: while the first group had the state aiding the private sector in cost discovery activities the second group did not.

In Hausmann et al. (2007) the authors argue that some products have a higher level of associated productivity than others and therefore specializing in these products will bring higher growth. They associated this phenomenon with the existence of a high income-elasticity demand for these products (see Hausmann et al. (2007), p. 23) and thus they considered here a demand oriented explanation of their finding (although the paper tackles only marginally the analysis of its driving forces). This paper constituted a strong argument for state promoted structural change: if rich countries export rich country products then in order to become a rich country an effort should be made to reach production of such goods. In order to evaluate empirically which are those products that are related with higher income levels the authors proposed and indicator ($PRODY$) that assigns to each product the per capita GDP of countries that export it with revealed comparative advantages. Then they built another indicator that approaches an economy's wealth in sophistication by calculating the average $PRODY$ of each country's exports basket ($EXPY$), and showed that this indicator is a good predictor of future growth.

Going one step further, Hausmann and Klinger (2007) and Hidalgo et al. (2007) proposed an index of distance between any two products in terms of their production requirements. To construct this index (called *proximity*) they use trade data to measure how much exporting product a is contributing to the probability that product b is exported as well by a country. Notice how it is possible to find the notion of capabilities allowing different kind of productions already present in these works, which implies the authors shifted to a supply-side explanation of why some products contribute more to the growth process than others.

The matrix containing a measure of *proximity* for every pair of products constitutes what the authors called the *Product Space*. This matrix allows to compute the benefit of starting the production of some new good, not for the intrinsic value of doing so (which could be measured by $PRODY$), but for its strategic value, i.e. for how much the production of this good contributes to the probability of engaging the production of other new goods. In Hidalgo et al. (2007) the authors show that more densely connected products in the *Product Space* were also products having a greater valuation in terms of $PRODY$, so the conclusion was very clear: countries producing these goods are countries that have it easier to grow since not only their current production is correlated with high income levels but their diversifying options are correlated with high income as well.

In addition these works suggested a measure of distance between any non produced product and the current production of the economy which they called *density*. This measure, along with *PRODY*, has great potential for policy-making. After all, if it is possible to measure how easy it is for a country to produce a new good and also to establish how much each product contributes to per capita income, then it is possible to have a clear idea of which products should be stimulated and which prevented. The policy-recommendation quality of the indicators did not go unnoticed, many documents were written using them with that purpose (see for example Hausmann and Klinger (2006), Record and Nghardsaysone (2010), Abdon and Felipe (2011) or Jankowska et al. (2012)).

There are two main things these works provide to the foundation upon which MR indicators are constructed. First, these works underline the idea that the distance between any two goods' productive requirements is different for every pair. This idea is at odds with neoclassic literature which, by using a production function for all outputs, overlooks this fact. This notion constitutes the cornerstone of this research line and is of central importance for the construction of MR indicators. Second, the introduction of indicators that allow an empirical approximation to the concepts of product sophistication (*PRODY*) and economic complexity (*EXPY*) provided the basis for MR indicators.

Although *PRODY* and *EXPY* represented original contributions there were possibilities for their improvement. The fact that the indicators used per capita GDP in the valuation of products' sophistication meant that there was some degree of endogeneity embedded in the conclusion that rich countries were exporting rich country products. This motivated Hidalgo and Hausmann (2009) to present a new set of indicators, further developed in Hidalgo (2009) and Hidalgo and Hausmann (2010), in their *Method of Reflections*, which drops the use of per capita GDP to evaluate products' sophistication. Instead, the new proposal exploits to the fullest the information inside the global trade matrix: the authors claim to achieve measures of product sophistication and economic complexity by looking only at who is exporting what. As will be explained in Section 5 indicators are constructed following an iterative process that gathers more and more information with each iteration. At the first level economic complexity is measured only by the quantity of goods exported by each country, but then each successive iteration enriches the indicator adding information about how many countries are also exporting the same products, how many products are exported by those countries and so on. The iterative process goes on until iterations cease to add useful information.

In Hidalgo (2009) the author shows that MR indicators of product sophistication and economic complexity are highly correlated with *PRODY* and *EXPY* respectively, and in Hidalgo and Hausmann (2009) the authors present evidence supporting the properties this work tests , i.e. that MR complexity indicators are highly related to countries' income and help predict their future growth both in the long run and in the short run. Serving the same purposes than *PRODY* and *EXPY* but with less shortcomings this new set of indicators are even more appealing than those previously suggested by Hausmann et al. (2007). If properties assigned to these indicators are robust then not only can they help diagnosing a country's future growth perspectives (by measuring its economic complexity) but also they can provide a list of goods that enable the country improve its situation (evaluating their product sophistication). Using *density* to complement the analysis it would also be possible to obtain hints about which of these goods require a less number of new capabilities and therefore are easier to reach with the country's current productive structure. If this is so, these tools are likely to be used as an important information source for policy making throughout the world. This possibility provides enough justification to the task proposed in this work.

Finally Hausmann and Hidalgo (2011) present a model to formalize the theoretical ideas accompanying the indicators developments. They conclude that countries with fewer capabilities have lower incentives to accumulate new ones. This is because the pay-off they get from an extra capability is lower compared to the one that a country with many capabilities gets, as it will enable the production of a smaller number of new products. This is called by the authors the *quiescence trap* and implies a sort of increasing returns to diversification that helps explain the divergence in growth across countries.

2.3 A discussion on the main concepts stemming from the literature

The line of research started by Hausmann and Rodrik (2003) has so far refined both its methodological proposals and its theoretical framework. This section presents a more detailed discussion of the main concepts needed to explain why economic complexity can affect growth and relates these concepts to ideas from previously existing literature.

The concept of economic complexity is in Hidalgo and Hausmann (2009) related to the amount of technological capabilities a country has. Having many diverse capabilities implies having what it is required to produce many different products. Similarly, a product is considered sophisticated when it requires a great amount of different capabilities in its production process. In Hausmann and Hidalgo (2011) the authors show evidence suggesting that poor countries export a small quantity of products that many other countries export while rich countries export those products plus some others that are more rarely exported. This suggests, as the authors point out, that poor countries have accumulated fewer and more commonly spread capabilities than richer countries.

The authors do not provide a precise definition of *capabilities*, but if it includes anything that is fundamental for the production of at least one good, then it can be concluded that the concept is very broad. Tangible things like having certain natural resource or some machine are necessary for the production of some products, but also non-tangible things like having an innovative environment or solid institutions might be necessary for the development of some others. It can therefore be seen how this line of research is easily connected with about any of the different branches within the growth literature: geography, demography, institutions, learning by doing processes and a large etcetera.

Hidalgo and Hausmann (2009) explain that non-tradable capabilities are the ones responsible for a country's productivity. But, as will be clear in section 5, the capabilities measured by the MR need not be non-tradable. It is actually more suitable to include tradables into the concept as well since this would help explaining how some countries have acquired so many capabilities over time.

It is also important to notice that the MR approach implicitly points at the fact that some capabilities are more valuable than others. If the value of a given capability is the quantity of production processes in which it has a vital role, then a multi-purpose capability is going to be much more valuable than a very specific capability that only plays a role in a limited number of production processes.

The main theoretical ideas behind the Method of Reflections seem very much related to some of those previously underlined by the neo-schumpeterian or evolutionist literature on technology and innovation processes. In some of the most renown works related to this literature it is possible to find descriptions of the main characteristics behind the innovation process that are very close to what the authors this work follows are using. In Dosi (1982) for example, the author defines technology as the accumulated pieces of knowledge a country has and explains that these pieces of knowledge can be the result of a physical innovation or simply the outcome of learning. The author emphasises that the pieces of knowledge that form an economy's technology can be something already applied to production or not, so they determine current and also future production. It is easy to see the similarity between the concept of capability and these pieces of knowledge. Closing the link between the two approaches it can be said that what Hidalgo and Hausmann (2009) consider a complex economy could be considered as technologically rich by Dosi (1982).

Dosi (1982) also provides a characterization of the technological development process that resembles the approach MR authors give to the process of capabilities' accumulation and is also very similar to what endogenous growth authors have in mind. First, Dosi (1982, p. 154) explains that there are strong complementarities between different pieces of knowledge, which means that the accumulation or depletion of one of them can foster or hinder the accumulation of some other. Another characteristic is that the accumulation of knowledge is cumulative to some extent (i.e. a region incorporates knowledge upon what it already has) and this implies that technological trajectories with some degree of path dependence will emerge. Finally the author states that it is not possible to evaluate *ex ante* how fruitful any chosen technological trajectory will be, so any technological choice has some degree of uncertainty. It is noticeable how these ideas resemble those already mentioned by Hidalgo and Hausmann (2009), Hausmann et al. (2007) and Hausmann and Rodrik (2003).

Other contributions from the evolutionary theory can complete the characterization of the process through which economies build-up their complexity. Nelson and Winter (1982) for instance underline the concept of *routines*, which refers to the way firms do things (see Nelson and Winter (1982, p 14)), and is according to the authors a key element in the learning process. This helps understand the great importance that tacit knowledge (which seems to be one of the main things MR authors are including to in the concept of capabilities) has in that process. The authors also explain how the process of economic evolution is cumulative relating it with a Markov process: each industry, in each time period, bears the seeds of its condition in the next. In the type of technological process they describe, when a technological choice has to be taken, there is uncertainty regarding the final outcome of that decision and the choice actually made will determine the outcome of the economy. A wrong choice can lead to a situation of disadvantage in comparison to other countries or even to a technological dead-end given the discontinuities that exist in some technological branches. This can explain complexity and income divergence throughout the world.

3 Empirical strategy

The main objective of this work is to submit to different robustness test the propositions stating that MR indicators of economic complexity are strongly related to per capita income, and can function as predictors of future growth in the short and long run. In order to do so the first thing this work does is to compute MR indicators upon a different (and arguably more suitable) dataset. Section 4 will introduce the dataset chosen and explain the appealing features it has for this work.

Then it is useful to identify whatever arbitrary decision that may exist in the construction of the MR indicators, since these are potential sources of variations in the results. Section 5 presents the indicators and provides this information,, signalling the parameter that is subject to alterations in robustness checks performed in Section 8.

It is also helpful to identify the main features and vulnerabilities the indicators have, as done in Sections 5.2 and 5.3, to better interpret the results obtained.

Finally the results of the robustness checks are presented in Section 8, where each of the properties is treated independently. The first step is to present results obtained by computing the same regressions in Hidalgo and Hausmann (2009) upon the dataset proposed here and comparing these results with those from the authors. Then conditions that must be fulfilled in order to get significant results are explored. Finally modifications in the methodology are introduced to evaluate how much are results depending on them.

4 Data

This work's main source of information is export data from the *Base pour l'Analyse du Commerce International* (International Trade Database at the Product Level, BACI from here on), as reported by Gaulier and Zignago (2010) from CEPII. The BACI reports values and quantities of product exports from country i to country j in the first version of the Harmonized Commodity Description and Coding System (HS0) at a six-digit aggregation level for the period 1995-2007. This database uses UNCOMTRADE data and applies to it an harmonization method to match records declared by the exporter with those made by the importer as detailed in Gaulier and Zignago (2010).

UNCOMTRADE data does not include flows below 1,000 US dollars but accounts for more than 95% of total world trade. In order to have the same countries and products in every year, it is necessary to drop some observations[3]. The final sample used here is composed of 178 countries and 4948 products for each of the 13 years of the period. Table 1 resumes the most important descriptive statistics of the database.

The use of this database constitutes an important methodological departure from what is used in Hidalgo and Hausmann (2009) to test MR indicators' properties and is one of the main changes proposed here to test their robustness. Hidalgo and Hausmann (2009) uses as main source of information Feenstra et al. (2005) database which gathers UNCOMTRADE, Standard International Trade Classification (SITC), revision 4, data at a four-digit aggrega-

[3]Countries being-left out are the Vatican City, Serbia and Montenegro, San Marino and the Occidental Palestinian Territories which represent less than 0.09 % of total trade in the sample for each year considered here.

Table 1: Exports (in thousands of US dollars), descriptive statistics per year

Year	Obs	Mean	Std. Dev.	Min	Max
1995	335996	14400.75	191411.0	1	4.72e+07
1996	352013	14566.44	204919.1	1	5.51e+07
1997	359252	14735.86	201456.2	1	3.64e+07
1998	364275	14441.01	187488.4	1	3.19e+07
1999	368107	14815.93	215933.5	1	4.72e+07
2000	376855	16276.84	274366.7	1	8.16e+07
2001	376943	15750.66	252043.4	1	7.40e+07
2002	380339	16231.03	253714.0	1	6.95e+07
2003	385656	18602.92	287401.8	1	6.95e+07
2004	388272	22725.69	418400.8	1	1.63e+08
2005	398586	24910.17	452652.4	1	1.39e+08
2006	397596	28701.09	537532.7	1	1.64e+08
2007	398349	32955.9	620570.2	1	2.23e+08

Source: BACI

tion level and also matches export and import reports covering the period 1962-2000[4]. The selection of the BACI was made pursuing the idea that more disaggregated data can feed the MR indicators with more accurate information: when evaluating product sophistication in terms of the amount of capabilities required to produce one good, it is more suitable to use the most disaggregated data available since this allows a sharper distinction between products and thus a better specification of the capabilities required for each one. For example, to have six-digit data allows to differentiate between product 847010 which is the code for electronic calculators and product 847050 which denotes cash registers, or between product 901710, drafting tables and product 901730, micrometers, callipers and gauges. As will be clear in the next section there is valuable information in the fact that some country is for example exporting both products in one of these pairs but some other only exports one of them, and this is exactly the type of information MR indicators nourish from.

Notice the time span allowed by the use of the Feenstra et al. (2005) dataset is much longer than the one in the BACI (although only data starting from 1985 is used by Hidalgo and Hausmann (2009) when testing the three properties this work focuses on). This constitutes an important shortcoming in the use of the later. In particular this work is not going to be able to test the performance of MR indicators as predictors of future growth in a 20-year period as done in Hidalgo and Hausmann (2009). However this should not prevent this work to find that MR indicators significantly predict future growth given that MR indicators are

[4]The authors explain they have checked the validity of their results with different databases. In particular they used UNCOMTRADE HS data at four-digit level (covering 1241 products and 103 countries) and North American Industry Classification System (NAICS) with data at six-digit aggregation level (318 products, 150 countries). Unfortunately results stemming from the use of these datasets are not presented. Although the use of the NAICS has the same aggregation level than the BACI the quantity of products contained in that dataset is much lower.

supposed to perform well as predictors of future growth in the short term as well (Hidalgo and Hausmann (2009) find significant results for MR complexity indicators in growth regressions using only five-years periods). The use of a shorter time period has the benefit of being able to work with a larger quantity of countries: while this work uses trade and income information for 177 countries for the whole period, the same can only be said for 95 countries in the period analysed in Hidalgo and Hausmann (2009).

The use of the HS classification instead of the SITC classification does not imply an important change, results are not expected to differ due to this.

Other auxiliary data comes from the World Development Indicators (WDI) as reported by the World Bank[5], except data on population and per capita GDP at PPP for which the work uses data from the Penn World Tables 7.0 (PWT) as reported by Heston et al. (2011). This is because PWT provides information for a greater number of countries in each year of the time span used here. In fact the only cases of missing values in per capita income and population belong to Timor-Leste in the period 1995-1999.

5 The method of reflections

This section explains how MR indicators are constructed. Every step specified in this section follows the proposals made by Hidalgo and Hausmann (2009) and Hidalgo (2010) unless indicated otherwise.

The first step is to consider as exported by a country only those products for which the country has revealed comparative advantages. By doing this MR indicators will consider only those products for which the country has proven to be competitive in world markets. The authors propose to use Balassa's revealed comparative advantage index (Balassa, 1986), $RCA_{c,p}$, which is computed as follows:

$$RCA_{c,p} = \frac{\frac{x_{c,p}}{\sum\limits_{p} x_{c,p}}}{\frac{\sum\limits_{c} x_{c,p}}{\sum\limits_{c,p} x_{c,p}}} \tag{1}$$

where $x_{c,p}$ is the export value of product p by country c. The $RCA_{c,p}$ gives the importance of a product p in country c's export basket relative to the importance that the same product has in worldwide trade. The importance a product has for a country could be measured differently, for example an indicator where products are weighted by their sophistication could

[5]Available at http://data.worldbank.org/data-catalog/world-development-indicators.

have been used. This work follows strictly MR author's proposal in order to keep results comparable.

A threshold that separates those products that are exported with comparative advantages by a country from those which are not must be established. Then it is possible to build a matrix of countries and products in which every component follows the next rule:

$$M_{c,p} = \begin{cases} 1 \quad if \quad RCA_{c,p} \geq R^* \\ 0 \qquad\qquad otherwise \end{cases} \tag{2}$$

Authors propose R^*=1 as threshold which means the MR indicators will consider as exported by a country only those products that have a higher or equal weight in the country's export basket than in global trade. The R^* threshold will be subject to changes in this work when robustness checks are required.

Using the $M_{c,p}$ matrix, it is possible to build the MR's simpler indicators following:

$$k_{p,0} = \sum_{c=1}^{N_c} M_{c,p} \tag{3}$$

$$k_{c,0} = \sum_{p=1}^{N_p} M_{c,p} \tag{4}$$

being N_p the total number of products considered (here $N_p = 4948$) and N_c the total number of countries used in the dataset ($N_c = 178$). Equation (3) establishes that $k_{p,0}$ measures the number of countries exporting product p, so it is a measure of that product's ubiquity. Indicator $k_{p,0}$ can also be seen as a simple measure of product p's sophistication: if a product is exported by few countries it might indicate that technological capabilities required to do so are rare. Similarly, equation (4) shows how $k_{c,0}$ gives a measure of the number of products exported by country c, and so it measures country's diversification. This indicator can also be seen as a very simple index of country c's complexity, since a diversified economy must have acquired many technological capabilities to be successful in many productive processes.

But these are only rough approximations to the concepts of product sophistication and economic complexity. Suppose we have two different countries both with similar diversification levels, but one is small and has achieved its diversification level by acquiring different capabilities and the other one is large and the only reason it has a diversified export basket is because of its size. It would be desirable for an indicator of economic complexity to discriminate between these two very different countries. The same thing can happen when evaluating product sophistication. It could be possible to find two products with very low ubiquity levels for very different reasons: one could be a very rare extraction product (exported by few countries only because the basic natural resource is not commonly available but not requiring any other valuable asset that could also be used in the production of another sophisticated product), while the other product could be rarely exported because the process to produce it is so complicated and requires so many different capabilities that only few countries manage to do it efficiently. Again, it would be desirable that an indicator of product sophistication is able to discriminate both cases appropriately. This is exactly the purpose of what follows.

The MR proposes to complement the initial information about diversification and ubiquity by exploiting to the fullest the information contained in trade data to better establish each country complexity and each product sophistication. This is done by following the iterative proccess described in the following equations:

$$k_{p,n} = \frac{1}{k_{p,0}} \sum_{c=1}^{N_c} M_{c,p}.k_{c,n-1} \tag{5}$$

$$k_{c,n} = \frac{1}{k_{c,0}} \sum_{p=1}^{N_p} M_{c,p}.k_{p,n-1} \tag{6}$$

where n is the number of iterations used to define indicators $k_{p,n}$ and $k_{c,n}$. The result of these iterations yields two vectors of indicators: on the one hand vector $k_p = \{k_{p,0}, k_{p,1}, ..., k_{p,n}\}$ defined for each product p, and on the other vector $k_c = \{k_{c,0}, k_{c,1}, ..., k_{c,n}\}$ defined for every country c.

5.1 Interpretation of the indicators

This section will provide interpretations for the MR indicators, which will help to understand why the iterative process makes them gain useful information. Focus will be given to k_c components since the final aim of this work is to test whether these indicators are related to income and can predict future growth. To facilitate interpretation let's consider the simplest cases. Equation (4) shows that $k_{c,0}$ is only counting the number of products exported by country c, and by equation (3), $k_{p,0}$ is the counting of countries exporting product p. Following equation (6), it is possible to see that $k_{c,1}$ is the average ubiquity of products exported by country c, while equation (5) shows that $k_{p,1}$ is the average diversification of countries exporting product p. Moving to the second iteration stage, $k_{c,2}$ is the average diversification of countries exporting products that country c exports as well. Similarly, $k_{p,2}$ is the average ubiquity of products exported by countries also exporting product p.

By comparing $k_{c,i}$ results for very different countries it is possible to get a better idea of how the MR uses trade data to get rid of distortionary effects and reach an evaluation of economic complexity. Let's take a look for example at the different trajectories that India and Japan follow as i grows for $k_{c,i}$, using data for the last year in the sample (2007). Results show that $k_{India,0} = 1693$ which ranks India in the 7^{th} place of the ranking of 178 countries, above Japan that has a $k_{Japan,0} = 1259$ and its in the 17^{th} place. This could be considered as a first rough approximation to economic complexity, but of course the level of $k_{c,0}$ only indicates the quantity of products country c is exporting with $RCA \geq 1$, so it is probably very much influenced by country size. To really evaluate economic complexity more information is required.

With $i = 1$ results are $k_{India,1} = 13.85782$ and $k_{Japan,1} = 11.37679$. This is the result of weighting each exported product by the number of countries exporting that product, which gives an idea of how difficult it is to do what the country under evaluation is doing. Notice that even though India exports more products, the average number of countries exporting what Japan is exporting is lower which could imply that Japan is actually a more complex economy. This result is less related to country size but on the other hand it does not say much about the quantity of products being exported by each country. It could be the case that Japan's exports are rare mainly because it is a country that has a very rare natural resource and it concentrates its exports among low sophisticated derivatives of that resource. This situation would not be close to the concept of economic complexity defined by the literature. So again, at this level of iterations the information extracted from trade data is not providing something that could be considered close enough to the idea of complexity.

Now, when $i = 2$ results are $k_{India,2} = 1011.534$ and $k_{Japan,2} = 1126.783$ ranking India in the 22^{th} place while Japan reaches the 2^{nd} position. According to the interpretation given to the indicators, the average diversification of countries exporting what Japan exports is greater than the same figure for India. This gives the idea that the Japanese economy can be considered more complex than the Indian economy. The $k_{c,2}$ is clearly less correlated with distortionary features like country size or specialization in extraction-type products than the less iterated components of the k_c vector. This example has shown that an indicator with $i = 2$ is closer to the idea of economic complexity than other indicators where $i < 2$. Notice that the same could be done for products.

The interpretation of the MR indicators gets harder as the number of iterations is increased, since every vector component gathers information from the preceding components. But this also means that elements coming from higher iterations will have more information and their correlation with economic complexity or product sophistication will be stronger. Therefore, every component of vector k_c can be considered as a measure of an economy's complexity and the higher the iteration the more information it has. On the other hand, components of vector k_p can be considered as measures of product sophistication since they collect information about product's ubiquity and with successive iterations they manage to include information about the complexity of the exporters of those products as well.

If highly iterated k_c indicators approach economic complexity one could expect these indicators to be explained by different kinds of capabilities. Table 2 shows results of pooled OLS estimations with even k_c indicators as dependent variables, and different indexes representing different kinds of capabilities as explanatory variables. Each indicator from the k_c vector is standardized in order to make coefficients comparable with each other. White's estimator is used to obtain robust standard errors.

Table 2: Pooled OLS estimations of different variables explaining k_c even indicators

	1	2	3	4	5	6	7	8	9	10
	skc0	skc2	skc4	skc6	skc8	skc10	skc12	skc14	skc16	skc18
lpop	0.35971***	0.19847***	0.14802***	0.09579***	0.05259**	0.03853*	0.03471*	0.03369	0.03341	0.03333
	(26.39)	(19.22)	(11.75)	(5.16)	(2.54)	(1.84)	(1.65)	(1.60)	(1.59)	(1.59)
openk	0.00310***	0.00179***	0.00173***	0.00271***	0.00318***	0.00331***	0.00335***	0.00336***	0.00337***	0.00337***
	(5.62)	(3.97)	(3.40)	(3.65)	(3.71)	(3.77)	(3.80)	(3.81)	(3.81)	(3.81)
inflation	-0.00158*	-0.00124**	-0.00138***	-0.00155***	-0.00139***	-0.00131***	-0.00128***	-0.00127***	-0.00127***	-0.00127***
	(1.66)	(2.36)	(3.21)	(4.25)	(4.25)	(4.09)	(4.03)	(4.01)	(4.01)	(4.01)
real_int	-0.00996***	-0.00762***	-0.00918***	-0.01168***	-0.01131***	-0.01090***	-0.01077***	-0.01074***	-0.01073***	-0.01072***
	(4.38)	(4.61)	(4.79)	(4.67)	(4.34)	(4.21)	(4.18)	(4.17)	(4.17)	(4.16)
gov_C	0.04821***	0.03614***	0.03124***	0.00911	-0.00951	-0.01572**	-0.01753***	-0.01806***	-0.01821***	-0.01825***
	(12.89)	(10.05)	(7.26)	(1.55)	(1.49)	(2.46)	(2.74)	(2.82)	(2.85)	(2.85)
ltertiary	0.25886***	0.36990***	0.38505***	0.26767***	0.13292***	0.08531***	0.07171**	0.06790**	0.06684**	0.06654**
	(15.21)	(22.56)	(18.92)	(9.64)	(4.45)	(2.85)	(2.40)	(2.27)	(2.24)	(2.23)
indvalue_p	0.00291	0.00812***	0.00354	-0.00887**	-0.01517***	-0.01662***	-0.01696***	-0.01705***	-0.01707***	-0.01708***
	(1.01)	(3.87)	(1.35)	(2.29)	(3.55)	(3.86)	(3.93)	(3.95)	(3.96)	(3.96)
natural_res	-0.02989***	-0.03101***	-0.02018***	0.00125	0.01338***	0.01644***	0.01717***	0.01735***	0.01740***	0.01741***
	(11.10)	(13.62)	(7.54)	(0.37)	(3.74)	(4.59)	(4.79)	(4.84)	(4.86)	(4.86)
Constant	-4.50704***	-3.22838***	-2.69661***	-1.49306***	-0.45887*	-0.12072	-0.02676	-0.00079	0.00643	0.00844
	(27.14)	(22.38)	(15.29)	(5.98)	(1.68)	(0.44)	(0.10)	(0.00)	(0.02)	(0.03)
Observations	1052	1052	1052	1052	1052	1052	1052	1052	1052	1052
Adjusted R-squared	0.66	0.69	0.55	0.18	0.06	0.05	0.05	0.05	0.05	0.05
F-test	218.17	241.84	139.25	29.23	9.51	8.96	9.22	9.33	9.36	9.37
Prob>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Robust t statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

All explanatory variables were taken from the WDI. The logarithm of the gross rate of enrolment in tertiary education ($ltertiary$) is used to approximate human capital, the inflation rate ($inflation$) is used to approximate macroeconomic stability and the real interest rate is incorporated as a measure of the financial cost of engaging a productive project ($realint$). Other variables were included like a measure of economic openness ($openk$), the share of GDP destined to government consumption ($govC$) which measures the importance of the public sector in the economy, the share of GDP coming from industry ($indvaluep$) and total natural resources rents as a percentage of GDP ($naturalres$). Finally a control for the size of the economy was included which is measured by the logarithm of the economy's population ($lpop$).

It is remarkable how, although all regressions are significant as a whole at 1%, the percentage of the k_c indicators explained by these variables is high for low iterated indicators, and low for high iterated indicators. Since every specification uses the same number of regressors and observations, comparisons using adjusted-R^2 are straightforward. In particular, the adjusted-R^2 in specification 1 rises up to 0.66 which implies that explanatory variables account for a large part of the variation of the standardised $k_{c,0}$ (being $lpop$ responsible for the largest share). Specification 10 reports a very little adjusted-R^2 (0.05) implying that the same explanatory variables only explain a small fraction of the standardised $k_{c,18}$ despite being all of them significant (except for $lpop$). These results present evidence supporting the affirmation that highly iterated indicators are much more complex and capture many more dimensions of economic complexity than less iterated indicators, since the greatest part of their variation is explained by unobservables.

Table 2 also shows that, as expected, population looses significance as i increases. Moreover, the worse the macro-environment (the higher the inflation rate or the real interest rate) the lower all k_c indicators will be. Finally, human capital and openness are both always positive and significant at 1% for any iteration level.

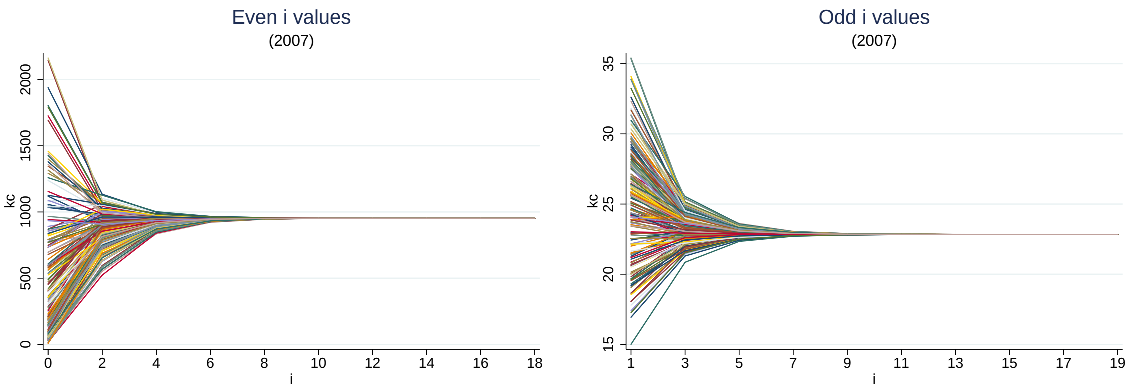
The iterative process in the MR could go on forever, but as will be shown below there exists a threshold after which the marginal information stemming from an extra iteration is not significant in terms of the changes it makes of countries' or products' sorting. As will be shown in the following section there is a limit to the information that can be extracted form trade data and the indicators reach that limit asymptotically as $i \to \infty$.

5.2 Main features of the indicators

Figure 1 shows the value for each country in every $k_{c,i}$ indicator as i grows (for even and odd indicators). Only data from 2007 has been used to simplify the exposition but the same picture emerges every year. As shown in both panels, when i grows the MR indicators converge to their mean, which is not surprising given that they are built as averages of other averages. The figure also shows that odd components inside a vector will converge to a certain mean while even components tend to another (this is shown for $k_{c,i}$ but it also holds for $k_{p,i}$). This too is as expected given the way indicators are constructed: in building $k_{c,i}$ information from $k_{p,i-1}$ is used but information from $k_{c,i-1}$ is not and the same happens in the construction of $k_{p,i}$. Thus, odd components do not contribute with any information in the construction of even components within the same vector, and vice versa.

This convergence-to-the-mean effect implies that highly iterated indicators have a very narrow range (the greatest standard deviation among all years for $k_{c,18}$ is of 0.007 in 1995 where the minimum value is 930.98 and the maximum is 931.02). Despite this, the small differ-

Figure 1: $k_{c,i}$ results for all countries as i grows. Even and odd i (2007)



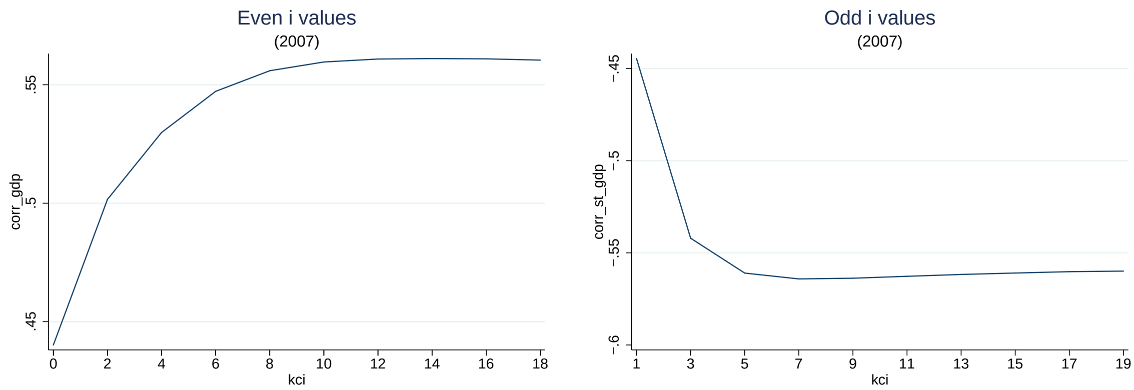
ences between countries that exist in these indicators yield a more stable ranking of countries than those stemming from less iterated indicators. Figure A.1 shows the ranking of the 178 countries for every even i. Colors are assigned according to each country's positioning in the last iteration ($i = 18$). This figure also uses only data for 2007 but the same conclusion arises for every year. Figure A.1 shows how the sorting tends to stabilize as i increases. This fact implies that when i is low, information extracted from trade data has an important marginal contribution, while when i is high the marginal informational contribution of an extra iteration is very low.

As explained in Hidalgo and Hausmann (2009) and was already discussed here, highly-iterated indicators sort countries in a more stable way because they gather more information from trade data and therefore they eliminate important distortionary effects, one of them being country size. Figure A.1 shows how big countries like China or India are ranked highly according to $k_{c,0}$ (which only considers the diversity of exports), not so high according to $k_{c,2}$ (when the index considers which countries are also exporting the same products) and they reach a lower definitive index level at $k_{c,18}$.

Figure 1 also shows that the final mean for even components (i.e. that of $k_{c,18}$) is 953.63 while that for odd components (corresponding to $k_{c,19}$) is 22.84. This shows an evident difference in the units of measure of each of these families, given by the fact that even components are making an average of products while odd components average countries (remember the interpretation done for equation (6) at different i levels). This implies that even indicators are positively correlated with per capita income (the more products being exported the higher economic complexity should be), odd indicators are negatively correlated with per capita income (more countries exporting what country c exports means that capabilities required to do so are not rare and therefore the lower country c's complexity). Obviously, this also means that the two families of indicators are negatively related to each other.

Figure 2 shows the correlations of indicators from each family with per capita income. The figure also shows that the correlation with country's per capita GDP is much higher for higher iterated indicators implying that the sorting stemming from higher iterations could be considered as the one that better reflects countries' complexity.

Figure 2: Correlation between $k_{c,i}$ indicators and per capita GDP as i increases (2007)



Even though even and odd indicators nourish from different sources of information highly iterated indicators from both families yield very similar rankings for countries and products. Figure 3 compares the sorting of countries stemming from $k_{c,17}$ and $k_{c,18}$ (again, the figure is made only with data from the year 2007 to simplify exposition). The second panel adds a reference point by showing the comparison between two indicator from the same family but with very different iteration levels like $k_{c,18}$ and $k_{c,2}$. It can be seen that correlations are important and they are very strong between high iterated indicators. In fact correlations between $k_{c,18}$ and either $k_{c,17}$ or $k_{c,19}$ is lower than -0.995 for every year in the sample used. Strong correlations can also be found between lower iterated indicators, e.g. the correlation between $k_{c,4}$ and $k_{c,5}$ is lower than -0.91 for every year.

When looking at the ranking of countries according to their $k_{c,18}$ sorting, it can be seen that there are some clear evolutions that go along intuition. Figure A.2 presents the evolution of the $k_{c,18}$ ranking over the period 1995-2007 where such evolutions can be found. In this figure colors are assigned according to each country positioning in the last year (2007). There, Malaysia, Thailand and Viet Nam, which are well known cases of increasingly complex economies, exhibit a markedly upward trend in their ranking positioning over the years. Most countries however do not present such a clear trend, which is why most countries end within the same neighbourhood they started in (it is possible to see tranches of colors more or less defined in the figure).

Figure 3: Ranking comparison $k_{c,18}$ vs. $k_{c,2}$ and $k_{c,18}$ vs. $k_{c,17}$ (2007)

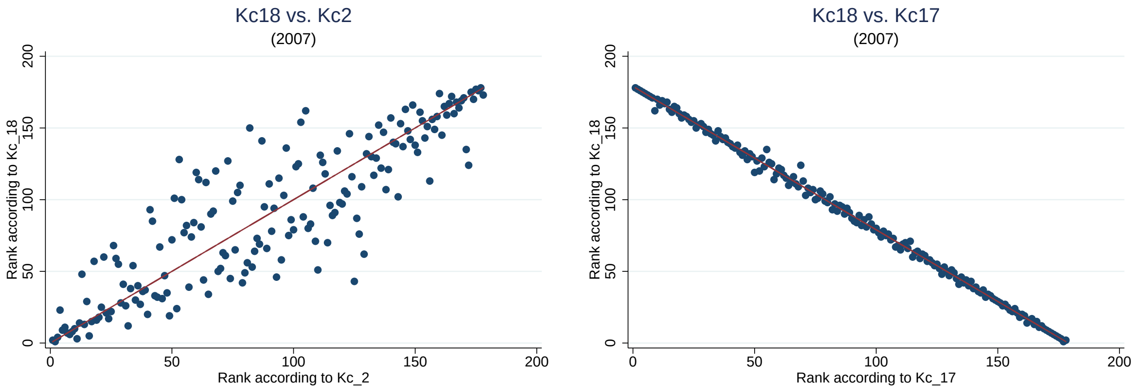
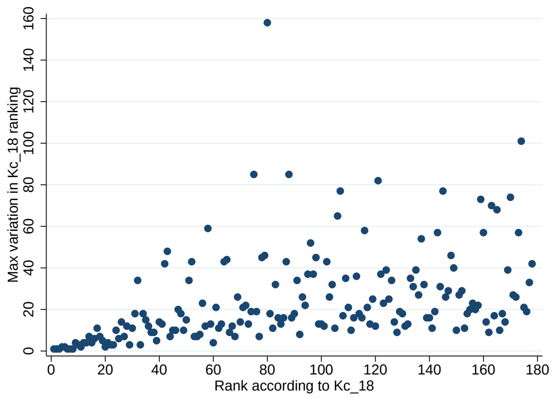


Figure A.2 also shows the variability of the $k_{c,18}$ ranking. Many countries experience large changes from one year to the next. Keep in mind that economic complexity is, according to the literature, a long term phenomenon: countries build their economic complexity through a long and costly process of acquiring (and destroying) capabilities. This implies that strong and sudden changes should not be usual in an indicator that approximates economic complexity.

Figure 4 plots the maximum variation in terms of the $k_{c,18}$ ranking from one year to the next (called f) for each country against its $k_{c,18}$ level in 2007. The figure shows how variation is increasing from the first positions until the 80^{th} place and remains stable after that. This means that more complex countries (i.e. those occupying the higher places in the $k_{c,18}$ ranking) present a more stable position. Given that the dataset used here considers matched values from exporters and importers to reach the final value of a given purchase, it is hard to disregard the observed volatility in the lower positions of the $k_{c,18}$ ranking on the basis of lack of trust in these countries' reports. Rather it should be pointed out that relying solely on export data, MR indicators are vulnerable to sudden changes in export figures (which can happen in contexts of important changes in trade or industrial policies, political environment, etc.). This prevents the achievement of an accurate measure of economic complexity for countries where these kind of changes occur. Explaining the situation in each of these volatile countries escapes the aim of this work, but it will be important to have in mind that there is an important source of noise here that should be addressed.

Figure 4 also shows that it is not usual to see changes in more than 40 positions and most countries never face a change of 20 positions. Table A.1 shows the list of all 178 countries sorted by f. The table also includes population (in thousands), per capita GDP at PPP ($rgdpl$) and the Hirschmann-Herfindahl index of export diversification (HH). This later index will be properly defined in equation (7) of section 7 but it should be pointed that it ranges

Figure 4: Maximum changes in $k_{c,18}$ ranking for each country (sorted by its 2007 level)



between 0 and 1 and that a value close to 1 indicates a very concentrated export basket. The table allows to conclude that those countries having very large changes (say $f > 40$) are either very small, very concentrated or have a well known record of economic instability during the period considered here.

Summing up, indicators that come from higher iterations levels achieve to sort countries in a more stable way and their correlation with per capita GDP is greater than that of less iterated indicators, despite their small variability. This would be indicating that they manage to measure economic complexity more accurately. Although even and odd indicators nourish from different sources of information the outcome they give is practically the same. The correlation between highly iterated indicators of economic complexity is almost 1. Highly iterated indicators exhibit nonetheless strong volatility in their country sorting over the years, which seems to be something to address. Following Hidalgo and Hausmann (2009) and Hidalgo (2009) this work will focus mainly on even indicators although some results will be presented for odd indicators as well. Even indicators, being positively correlated with income yield results that can be read more intuitively. Also following those authors this work will take $k_{c,18}$ as the highest iterated indicator of economic complexity.

5.3 Limitations of the MR

MR indicators have some important limitations that should be kept in mind. First, to measure economic complexity by looking at what a country is exporting implies assuming that every country exports with revealed comparative advantages all products for which it has the required capabilities. But of course this might not be the case. In a context of uncertainty about the results of a given enterprise, as described in Hausmann and Rodrik (2003), some productions might have not being discovered yet, although required capabilities are available in the economy. In such cases MR indicators will be undervaluing countries' complexity. It could be argued that this problem will be strongly affecting those countries that have accumulated a great number of capabilities more recently, since these economies probably had less time to learn what they can do with their capabilities.

The fact that indicators are considering as exported by a country only those products with high $RCA_{c,p}$ is another limitation since it implies that they are also ignoring many processes that might be adding complexity to the country's economy although their RCA level is not that large.

Related to this, an arbitrary decision is taken when choosing a specific R^* threshold. The definition of the $RCA_{c,p}$ index given in (1) expresses that country c has greater revealed comparative advantage in product p whenever the share that product has in the country's export basket increases with respect to its share in global trade. It is only natural, and it is also a widespread convention, to say that product p has RCA in country c whenever $RCA_{c,p} > 1$ which imposes that the numerator in 1 is greater than the denominator. However, as explained, in the construction of MR indicators only products with $RCA_{c,p} > R^*$ are being considered and the rest are overlooked. It seems that the threshold $R^* = 1$ is somewhat arbitrary since there is no good reason to ignore a product that has an RCA just below the threshold.

It should also be noticed that the original proposal for the construction of MR indicators, which uses only product exports, is completely ignoring production of goods for the domestic market and services. This is a strong impediment when trying to get closer to an economy's technological capabilities, since both kinds of production are able to add technological learning into the productive structure of a country. It is not easy to replace the database used since records on domestic market production and services are not available with the same level of comparability and with the same periodicity as product exports are. Still, Hausmann and Hidalgo (2011) addressed this issue. They constructed the MR indicators upon a database of total production from Chile and concluded that results obtained from the MR indicators are not strongly influenced by the fact that it uses only product export data.

None of the limitations stated above imply that MR indicators are useless. Rather they are pointing out that information being considered might not be complete. The fact that MR indicators might be underestimating economic complexity does not prevent the indicators to increase the available knowledge regarding countries' complexity, which can be a very useful thing.

6 The filter used

Economic complexity is typically a long term phenomenon: countries acquire and loose capabilities over time but the global complexity of an economy should not depend strongly on short term issues. However, as previously shown, strong volatility in the $k_{c,18}$ country ranking is not infrequent, especially among less complex economies. This volatility is explained by the fact that MR indicators take information form export data only and can be the result of many diverse factors (sudden changes in trade or industrial policies, political environment, etc.) the study of which exceeds the aim of this work. Still, the resulting volatility does cast doubts about the true complexity of those economies and constitutes an important source of noise for regression analysis.

To clean for these sources of noise a filter will be used here, based on the maximum $k_{c,18}$ ranking change from one year to the next (previously denoted f). That is, countries that have a ranking change between any two years greater than a certain number are being dropped from the analysis. This choice for the filter provides this work with a flexible criterion in which the filter threshold can be changed and it is possible to analyse the impact this has on the results[6].

As the limit imposed to f is decreased, increasingly significant results are expected since this implies getting rid of the noise brought by excess variability in the complexity indicator. Of course if the limit is too low then too many observations will be dropped and the relationship will not appear to be so clear. There is therefore a trade-off to consider here.

Note that Table A.1 shows the list of 178 countries considered in this analysis, sorted according to the f level stemming out from the benchmark scenario used here (R^*=1). The reader can use that table to check which countries are being included in the set of observations of every regression performed here under the benchmark case. As mentioned in Section 5.2 the large majority of countries remain when the limit f is set at 40. The filters actually used in most cases are, as will be shown, less restrictive than that.

7 Main control variables

The only two control variables used in regressions performed by Hidalgo and Hausmann (2009) to show the main three properties that are going to be tested here are the Hirschmann-

[6]There are many ways to perform the same task. A different alternative could have been to base the criterion upon the quantity of times a country changes from one quantile of the $k_{c,18}$ distribution to another, but that would imply a greater probability of deletion of countries close to the quantile limit. The filtering choice made here avoids the latter problem and allows flexibility, without loosing simplicity and transparency.

Herfindahl (HH_c) concentration index and Theil's Entropy index (E_c) of diversification (Theil, 1972). It is not surprising that the authors are not using more control variables in their regressions since, as explained, MR complexity indicators are supposed to be measuring capabilities in a broad sense. The inclusion of most control variables usually included in growth regressions to capture different kinds of capabilities (different resources abundance, geography, institutional quality, etc.) can therefore be redundant.

The main purpose of introducing export diversification (or concentration) controls in income and growth regressions is to show that MR complexity indicators are able to explain a larger percentage of the dependent variable's variability compared to what diversification indicators can explain, which would mean that MR indicators are richer.

The HH_c index is a standard measure of market concentration but can be applied to a country's export basket to evaluate its concentration level, as is done here. The index is defined as follows:

$$HH_c = \sum_{p=1}^{N_p} \left(\frac{x_{c,p}}{\sum_{p=1}^{N_p} x_{c,p}} \right)^2 \tag{7}$$

HH_c ranges between 0 and 1. As can be seen, the term in brackets is the share of product p in country's c export basket, so the higher the index the more concentrated the exports of country c are in fewer products.

The E_c index is a widely used measure of inequality and can be applied to measure the diversification of a country export basket if defined as follows:

$$E_c = -\sum_{p=1}^{N_p} \left(\frac{x_{c,p}}{\sum_{p=1}^{N_p} x_{c,p}} \right) .log \left(\frac{x_{c,p}}{\sum_{p=1}^{N_p} x_{c,p}} \right) \tag{8}$$

E_c is always positive and high values of the index implies that country c has a highly diversified export basket.

8 Results

This section will submit to different robustness checks three of the main properties of the MR complexity indicators: 1) that they are related with countries' current income levels, 2) that they predict future long term growth, and 3) that they predict future short term growth. These properties are originally tested in Tables S6-S10 of the Appendix in Hidalgo and Hausmann (2009). Following the authors focus will be given to even and highly iterated indicators from the k_c vector. As explained in section 5.2 highly iterated indicators present a stronger correlation with per capita income than less iterated indicators. Also, as i grows correlation between even and odd indicator goes to 1, which makes the exposition of odd indicators redundant. Special focus will be given to $k_{c,18}$ which is the highest iterated even indicator computed by the authors and constitutes the main reference used by them when economic complexity needs to be evaluated (see for example Hidalgo (2009)).

For each of the properties the procedure will be as follows. First, results obtained following the same methodological steps as in Hidalgo and Hausmann (2009) will be presented. The only methodological departure in this first step is the use of the more disaggregated six-digit database. If no significant results are found, the next step is to explore conditions under which significant results could be found. This is done by filtering for countries that present too much volatility according to the $k_{c,18}$ indicator, by including more control variables in the regressions and by dropping outliers in countries' income distribution. When significant results appear the procedure will be to test how much results depend on what is considered here to be the most important methodological decision made in the construction of MR indicators, i.e. the choice of the R^* parameter.

At the end of this section an additional part is included in which another important methodological decision in the construction of MR indicators is modified, i.e. the inclusion of intermediate products, with the purpose of analysing how the indicators perform under this new setting.

8.1 Influence of MR indicators on income

This section analyses the relationship between the level of per capita income and different measures of complexity. The first exercise to do, is follow Hidalgo and Hausmann (2009) by computing simple cross-section OLS regressions for a single year where the log per capita income at purchasing parity power is the dependent variable and a measure of complexity is the main regressor. Different components of vector k_c are used as measures of complexity and their performance as explanatory variables are compared against the two diversification indexes presented. Table 3 shows the results for the same specifications presented in Table S6 in the Appendix of Hidalgo and Hausmann (2009) using data of the same year (2000).

All coefficient signs are as expected. The even components of the k_c vector have positive effects on income which is as expected since they measure economic complexity. Additionally, E_c has a positive sign which is as expected too since, according to the literature, diversification is positively related to countries' income levels. The only odd indicator included in Table 3, $k_{c,1}$, presents a negative coefficient which is in line with intuition since this indicator measure the average ubiquity of products exported by each country. Furthermore, HH_c has a negative coefficient which is not surprising either since it is a measure of export concentration and this is, according to the literature, negatively related to income. It can also be seen that, among even components of the k_c vector, higher iteration levels yield greater coefficients. This is due to the fact that, as shown in Figure 1, the variability of the indicator decreases with its iteration level.

Every component of the k_c vector is significant at 1% in each regression. Moreover columns 3-8 show how regressions using k_c indicators have greater adjusted-R^2 than regressions using only HH_c or E_c (columns 1 and 2). Given that the number of regressors and observations are the same in every of these specifications this means that the percentage of income explained by MR indicators is greater than that explained by diversification indicators. Notice also that the adjusted-R^2 grows when the specification uses a higher iterated k_c components as regressor, reaching a level of 0.36 for $k_{c,18}$ in column 8. This is lower that what Hidalgo and Hausmann (2009) find for the same year using a less aggregated dataset.

Finally, columns 9-11 show how little HH_c and E_c add to the explanation of per capita income above what already is explained by $k_{c,18}$. The adjusted-R^2 remains almost unchanged when including both diversification indicators and their coefficient are not significant.

All these conclusions are similar to those extracted by Hidalgo and Hausmann (2009) and arise when performing this exercise for every year of the sample. Table A.2 shows results for a pooled estimation of observations from every year in the period 1995-2007 and including year dummies (not shown in the table to facilitate exposition)[7]. The table depicts the same picture, the only difference being that $k_{c,8}$ and $k_{c,12}$ present adjusted-R^2 that are a little larger than that of $k_{c,18}$ (see columns 6-8 of Table A.2). This is why Table A.2 includes columns 12 and 13 which show results using $k_{c,8}$ and $k_{c,12}$ in specifications that include the controls added in column 11. It can be seen that these less iterated indicators perform as good as $k_{c,18}$. Notice that all these results were obtained without the need of filtering the database to clean for extremely variable countries in terms of $k_{c,18}$.

[7]The reason why the number of observations is 2,309 instead of (178*13=) 2,314 is that, as already explained, Timor-Leste has missing values in their GDP reports for the period 1995-1999.

Table 3: Income regressions. Cross-section for 2000

	1	2	3	4	5	6	7	8	9	10	11
	Dependant variable: log per capita GDP										
entropy	0.332***								0.062		0.346***
	(6.01)								(1.00)		(3.30)
HH		-1.315***								0.483	2.542***
		(2.87)								(1.18)	(3.44)
kc0			0.001***								
			(7.73)								
kc1				-0.138***							
				(6.14)							
kc4					0.022***						
					(9.04)						
kc8						0.322***					
						(10.14)					
kc12							4.254***				
							(10.65)				
kc18								192.714***	177.166***	202.715***	159.224***
								(10.75)	(7.76)	(10.86)	(6.72)
Constant	7.224***	8.679***	7.797***	12.048***	-12.322***	-298.065***	-4,044.926***	-183,659.174***	-168,841.126***	-193,190.523***	-151,742.436***
	(28.25)	(73.28)	(54.59)	(21.38)	(5.29)	(9.85)	(10.62)	(10.75)	(7.76)	(10.86)	(6.72)
Observations	178	178	178	178	178	178	178	178	178	178	178
Adjusted R-squared	0.16	0.03	0.21	0.21	0.33	0.35	0.35	0.36	0.36	0.36	0.37
F-test	36.12	8.22	59.72	37.67	81.74	102.83	113.34	115.55	57.23	62.06	47.19
Prob>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Robust t statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

8.1.1 Changing the R^* threshold in income regressions

This section checks how sensitive the former results are to changes in the R^* threshold. Increasing R^* would mean to be more restrictive regarding what the matrix $M_{c,p}$ assigns a 1 to. This would imply a smaller number of highly competitive exports to be considered in each country and the rest would be ignored. Setting a smaller value for R^* implies the opposite.

Table 4: Income regressions. Pooled OLS estimations for all years with different R^* threshold levels

	1	2	3	4	5	6
	Dependant variable: log per capita GDP					
R* threshold	0.8			0.9		
entropy	0.326***	0.245***	0.280***	0.323***	0.243***	0.279***
	(10.280)	(7.156)	(8.595)	(10.312)	(7.150)	(8.654)
HH	2.274***	2.264***	2.230***	2.256***	2.282***	2.232***
	(10.043)	(9.871)	(9.859)	(10.036)	(10.005)	(9.934)
kc8		0.335***			0.320***	
		(21.092)			(21.624)	
kc12			4.769***			4.182***
			(21.076)			(21.852)
kc18	245.054***			189.695***		
	(19.401)			(20.424)		
Constant	-269,506.227***	-360.276***	-5,237.512***	-191,689.972***	-315.170***	-4,218.471***
	(19.400)	(20.813)	(21.056)	(20.423)	(21.301)	(21.827)
Observations	2,309	2,309	2,309	2,309	2,309	2,309
Adjusted R-squared	0.368	0.391	0.384	0.374	0.393	0.388
F-test	320.3	130.7	123.3	243.7	136.6	130.1
Prob>F	0.000	0.000	0.000	0.000	0.000	0.000

	7	8	9	10	11	12
	Dependant variable: log per capita GDP					
R* threshold	1.1			1.2		
entropy	0.327***	0.238***	0.279***	0.330***	0.238***	0.280***
	(10.651)	(7.019)	(8.757)	(10.741)	(6.904)	(8.718)
HH	2.224***	2.282***	2.210***	2.217***	2.295***	2.210***
	(9.982)	(10.087)	(9.930)	(9.891)	(10.035)	(9.848)
kc8		0.305***			0.303***	
		(21.852)			(21.397)	
kc12			3.451***			3.248***
			(22.439)			(22.268)
kc18	124.430***			106.764***		
	(21.210)			(21.250)		
Constant	-107,468.572***	-255.738***	-2,973.043***	-85,766.464***	-235.897***	-2,601.716***
	(21.209)	(21.454)	(22.403)	(21.249)	(20.977)	(22.227)
Observations	2,309	2,309	2,309	2,309	2,309	2,309
Adjusted R-squared	0.375	0.393	0.389	0.374	0.390	0.387
F-test	255.8	141.1	135.9	227.4	140.2	136.7
Prob>F	0.000	0.000	0.000	0.000	0.000	0.000

Robust t statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4 show results for the same specifications included in columns 11-13 of Table A.2, using MR indicators constructed with alternative values of the R^* threshold, namely 0.8, 0.9, 1.1 and 1.2. Results show how MR complexity indicators still present highly significant coefficients in every case and the percentage explained in each specification is very similar between cases. It is also remarkable how the magnitude of the coefficients of the different MR indicators grow as lower R^* thresholds are imposed. This could be interpreted as resulting from the inclusion of more products into the analysis which could be enriching the indicators with more information. This interesting fact could be subject of further research.

When performing the same cross-section analysis as done in Table 3 for each year and each R^* threshold, the same conclusions always arise. Due to space constraints these results are omitted here. Results indicate that MR complexity indicators, and especially those stemming from a medium-to-large number of iterations, explain countries' per capita income quite robustly. This conclusion holds even using a more disaggregated database (that contains more disaggregated product and also more countries), without the need of filtering the country sample and even when the R^* parameter is modified.

8.2 Potentiality of MR indicators to predict long-term growth

In order to test the performance of the MR indicators as predictors of future growth the first step is to perform a similar analysis as done in Tables S7 and S8 in the Appendix of Hidalgo and Hausmann (2009). In both tables the authors present OLS regressions to explain the average growth rate of long time periods (20-years in Table S7 and 10-years in Table S8). Each specification uses as main regressors a different pair of even and odd k_c indicators. Although the magnitude of the coefficients reported for 20-year periods are greater than those for 10-year periods, the authors conclude that MR indicators significantly predict future growth in both time spans. Therefore, even though the longest time span this work can cover is 13 years, it should still be possible to find significant results.

When computing the same regressions upon the database used here results do not support the conclusion that any of the k_c indicators can be used as predictors of future growth. It should be noticed that original specifications include even and odd indicators which are highly correlated specially when the number of iterations is high. Table A.3 shows results for specifications that do not include odd indicators in order to better capture the effect that a given indicator has on growth, avoiding multicollinearity.

In Sections 8.2.1 8.2.2 and 8.2.3, conditions under which it is possible to find significant results will be explored.

Table 5: Growth regressions (13-year average growth rate as dependent variable). Filter used $f < 55$

	1	2	3	4	5	6	7	8	9	10
	Dependant variable: average growth rate of per capita GDP (1995-2007)									
rgdpl	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.71)	(0.45)	(0.54)	(1.28)	(1.37)	(1.34)	(1.31)	(1.32)	(1.37)	(1.39)
entropy	0.001							-0.000		0.000
	(1.21)							(0.14)		(0.10)
HH		-0.008							0.003	0.004
		(0.80)							(0.27)	(0.23)
kc0			0.000							
			(0.59)							
kc4				0.000**						
				(2.05)						
kc8					0.002**					
					(2.17)					
kc12						0.021**				
						(2.10)				
kc18							0.800**	0.831*	0.835**	0.818*
							(2.04)	(1.91)	(2.14)	(1.80)
Constant	0.023***	0.029***	0.027***	-0.094	-1.697**	-19.807**	-745.033**	-773.819*	-777.507**	-761.659*
	(5.21)	(8.95)	(9.66)	(1.59)	(2.14)	(2.10)	(2.04)	(1.91)	(2.14)	(1.80)
Observations	161	161	161	161	161	161	161	161	161	161
Adjusted R-squared	-0.00	-0.01	-0.01	0.03	0.03	0.03	0.03	0.02	0.02	0.02
F-test	0.73	0.32	0.19	2.25	2.62	2.48	2.34	1.57	1.66	1.27
Prob>F	0.48	0.72	0.82	0.11	0.08	0.09	0.09	0.20	0.18	0.28

Robust t statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

8.2.1 Using the country filter

Significant results are found when filtering for observations with $f < 55$, that is, dropping from the analysis countries for which the maximum variation between any two years is greater than 55 ranking positions. The reader can check in Table A.1 which are the countries being left aside, which in this case rise up to 17. Table 5 shows results, when this filter is applied, for the same OLS regressions specified in Table A.3 (also with robust standard errors). Except for $k_{c,0}$, all other k_c indicators help predict future growth with a confidence level of 5%. It should be noticed that the inclusion of the diversification indexes together with $k_{c,18}$ turns the regressions non significant (see the p-value of the F statistic of the test of joint significance for columns 8-10). Judging by these results, and taking into account the magnitude of the coefficients, the best specification to predict future growth would be one including only $k_{c,18}$ (column 7).

These results are greatly sensible to the filter applied. Table A.4 report results for estimations using $k_{c,18}$ as main regressor, both with and without diversification controls, for different limit values imposed to f. Both the significance and magnitude of the effect the indicator has on growth increases as the variability allowed to each country (f) is reduced. This is also the case for the Adjusted-R^2 and the significance of the regression as a whole, and these conclusions hold whether diversification controls are included (columns 1-3) variables or not (columns 4-6).

Presented evidence seems to be suggesting that $k_{c,18}$ can function as predictor of future growth when the country filter is selective enough.

8.2.2 Including more control variables

Although Hidalgo and Hausmann (2009) do not include any control variables other than diversification indexes in their income and growth regressions, variables accounting for human capital are included in Table 8 of Hausmann et al.(2007) when testing the predictive power of $k_{c,18}$ predecessor, $EXPY$. Table 6 present results using two different measures of human capital: $ltertiary$ (already defined) and $leducexp$ which is the log of the percentage of GNI devoted to education. Dummy variables to signal low and middle income countries were also included to better capture the effect income can have in growth regressions. To construct these dummy variables the World Bank Classification of countries[8] is used. Results are reported for three different country filter levels: $f < 45$, 70 and 95.

[8] Available at http://data.worldbank.org/about/country-classifications/country-and-lending-groups.

Table 6: Including controls in long term growth regressions. Different filters used

	1	2	3	4	5	6	7	8	9	10	11	12
	Dependant variable: average growth rate of per capita GDP (1995-2007)											
Filter used: f<	45				70				95			
rgdpl	-0.000***	-0.000***	-0.000***	-0.000***	-0.000	-0.000***	-0.000***	-0.000***	-0.000	-0.000***	-0.000***	-0.000***
	(4.070)	(3.688)	(3.990)	(4.657)	(1.597)	(3.346)	(4.047)	(4.727)	(1.622)	(3.332)	(3.856)	(4.693)
entropy	-0.000	0.000	0.000	-0.002	0.000	0.001	-0.000	-0.001	0.002	0.002	0.001	-0.001
	(0.099)	(0.089)	(0.052)	(0.671)	(0.148)	(0.266)	(0.043)	(0.525)	(0.476)	(0.546)	(0.435)	(0.326)
HH	-0.005	0.008	0.005	0.001	0.013	0.004	0.002	0.004	0.023	0.010	0.017	0.007
	(0.172)	(0.356)	(0.177)	(0.059)	(0.475)	(0.213)	(0.093)	(0.211)	(0.868)	(0.463)	(0.674)	(0.421)
ltertiary	0.003		0.004		0.004		0.004		0.006*		0.006*	
	(1.072)		(1.207)		(1.382)		(1.202)		(1.924)		(1.718)	
leducexp		-0.002	0.004	-0.005		0.000	0.004	-0.004		0.002	0.006	-0.003
		(0.316)	(0.457)	(0.924)		(0.009)	(0.432)	(0.755)		(0.335)	(0.773)	(0.546)
poor				-0.034***				-0.037***				-0.037***
				(3.528)				(3.991)				(3.948)
middle				-0.013*				-0.013**				-0.012*
				(1.950)				(2.054)				(1.873)
kc18	1.221**	1.517***	1.232*	1.568***	0.473	1.257**	1.251*	1.401***	0.121	0.944*	0.656	1.121**
	(2.027)	(2.851)	(1.870)	(3.190)	(0.612)	(2.359)	(1.923)	(2.936)	(0.172)	(1.731)	(0.951)	(2.351)
Constant	-1,136.496**	-1,412.720***	-1,146.546*	-1,459.725***	-440.424	-1,170.477**	-1,164.723*	-1,304.300***	-112.980	-878.765*	-611.135	-1,043.261**
	(2.027)	(2.851)	(1.870)	(3.190)	(0.612)	(2.359)	(1.923)	(2.936)	(0.172)	(1.731)	(0.951)	(2.351)
Observations	96	139	92	139	99	148	94	148	100	150	95	150
Adjusted R-squared	0.124	0.076	0.133	0.182	0.030	0.059	0.133	0.198	0.042	0.052	0.131	0.198
F-test	3.820	3.649	3.065	4.789	0.987	3.081	3.224	5.297	1.259	3.266	3.262	5.737
Prob>F	0.003	0.004	0.009	0.000	0.430	0.011	0.007	0.000	0.288	0.008	0.006	0.000

Robust t statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6 shows again how magnitude and significance of $k_{c,18}$ coefficients grow in almost every specification as the limit for f is decreased. Columns 1-3 show that, when the filter is set at $f < 45$, $k_{c,18}$ significantly predicts future growth even when both human capital controls are included. It is also possible to find significant values for larger country samples (i.e. for less restrictive f levels) if *leducexp* is included[9].

Columns 4, 8 and 12 include the *poor* and *middle* dummy variables to the specification presenting higher and more significant coefficients for $k_{c,18}$ (i.e. the one including only *leducexp* to approximate human capital). Both dummy variables are jointly significant and present negative signs which implies that richer countries had a greater average growth over this period after controlling for export diversification, complexity and human capital. Most important to the purposes of this work, it can be seen that the inclusion of these controls do not hinder the significance of $k_{c,18}$, but rather they enhance it. This suggests that there is some difference in observations (specifically a negative effect upon growth for poor and middle income countries) that is not captured by $k_{c,18}$ alone, but once this effect is controlled for the predictive power of $k_{c,18}$ increases.

8.2.3 Removing fast growing and decreasing countries

Besides variability in the complexity index, outliers from the growth rate distribution could bring noise to the true relationship between the two variables. As explained in Section 5.3, MR indicators probably underestimate economic complexity in countries that are experiencing rapid structural changes. This justifies the introduction of an alternative filter: one that ignores countries going through extraordinarily rapid processes, in order to avoid this source of noise.

Table A.5 presents results for the same specifications in Table 6 having dropped observations belonging to either the top or bottom 5% of the distribution of the average growth rate (*avggr*). Results show how this modification makes $k_{c,18}$ more significant in some specifications but less significant in others so there is no clear conclusion for the effect that these outliers have on the regressions used here.

[9]Notice that both human capital measures are available for a limited number of countries so less countries are used when these variables are included. This problem is more severe for *ltertiary* than for *leducexp* since the former is reported for a smaller number of countries. Given that most countries with high f are also countries for which human capital variables are not available, the inclusion of these variables makes the filter less effective in removing countries for higher filter levels. This explains why relaxing the filter from $f < 70$ to $f < 95$ only two observation are gained.

8.2.4 Changing the R^* threshold

This section will test the robustness of the former results to changes in the R^* threshold using alternative values R^*=0.8, 0.9, 1.1 and 1.2. Section 8.1.1 showed that by changing the threshold up or down it is possible to find significant results in income regressions as specified by Hidalgo and Hausmann (2009). The link between MR indicators of complexity and income proved to be a fairly robust result. Non significant results arise however when performing the same exercise on growth regressions.

Table A.6 show results for the same specifications computed in columns 7-10 of Table 5 (f <55 is used here too), which follow the specifications used in Hidalgo and Hausmann (2009). Results indicate that, using these specifications, growth regression outcomes are very sensitive to the R^* threshold chosen. Significant coefficients for $k_{c,18}$ are only found in some specifications for R^*=1.1.

It is possible to find a filter level for which significant results are obtained with all alternative R^* values. In Table A.7 results are presented for each of the alternative R^* thresholds, with a country filter set at $f < 30$. That table shows significant results for $k_{c,18}$ as predictor of future growth in every case. Figure A.3 shows the magnitude and confidence interval of the $k_{c,18}$ coefficients in growth regressions using only that complexity indicator (besides GDP level in 1995 and a constant) to predict the 13-year average growth, for every value of country filter, (i.e. for every f allowed). Each panel depicts the picture for each of the four alternative R^* thresholds used here. These figures show how, in order to get significant results, it is necessary to apply a very strong country filter. Some of them also show that when the filter applied is too strong, coefficients go back to non-significant due to the little amount of observations.

Evidence suggests that $k_{c,18}$ is a weak predictor of future growth when applied under specifications used by Hidalgo and Hausmann (2009) since its significance suffers greatly when changing the R^* threshold and depends strongly upon the country sample used. A different situation arises when more control variables are included into specifications. As shown in section 8.2.2 the growth predicting power of $k_{c,18}$ can be greatly enhanced when introducing more controls, especially dummies for poor and middle income countries. Table A.8 shows results of growth regressions including both diversification indexes, $leducexp$ to proxy human capital and both dummies for poor and middle income countries. Variable $ltertiary$ is not included because there are many countries that do not report that information and thus, when the variable is included, filters do not make a difference in the country sample. It is remarkable how the inclusion of these controls makes $k_{c,18}$ highly significant for all the selected R^* thresholds. This implies that R^* is not strongly determining the results when these controls are included. Regarding differences brought about by changing the country filter level the usual conclusion applies: magnitude and significance of the $k_{c,18}$ coefficient increases as the allowed f is reduced.

8.3 Potentiality of MR indicators to predict short-term growth

This section analyses how much MR indicators can contribute to the prediction of short term growth. In Table S9 of Hausmann and Hidalgo (2009), the authors present regressions with MR indicators in one year as explanatory variables and the following 5-year average growth rates as independent variables. They use observations from years 1985, 1990, 1995 and 2000 to do this. Since the total time span in this work is 13-years Table A.9 is constructed using years 1995 and 2000 with the purpose of finding similar results, but of course there are only two observations per country instead of four. Regressions in Table A.9 are also performed with robust standard errors and odd complexity indicators are not included, again, to avoid multicollinearity. Results show how every MR indicator used has a very small and non significant coefficient and no single regression can be considered a good fit.

These results are dependent on which five-year period is considered. It is possible to find significant coefficients for $k_{c,18}$ if different five-year periods are used. This is shown in Table A.10 where results are obtained for the same specifications from Table A.9 but the five-year periods used are those starting in 1998 and 2003. Still, the magnitude of these coefficients is very small. As has been discussed, the variability of $k_{c,18}$ is very small which means that the coefficients in the regressions should be large if the indicator is to have some impact upon the dependent variable[10].

It is possible to get more observations for each country by specifying regressions where the dependent variable is the average growth rate for each of the five-year periods starting in years 1995 to 2003, and explanatory variables take their values from the initial year of each of these five-year periods. This procedure yields nine observations per country. Table A.11 shows results for the same specifications from Tables A.9 and A.10 using these rolling five-year periods. It is noticeable that $k_{c,18}$ has a significant but very small and negative coefficient. The negative sign is at odds with intuition and it is also appearing in Table S9 for the specification including only $k_{c,18}$ and income level as explanatory variables. In order to check whether the sign changes when $k_{c,19}$ is added to the regression, as it is the case in Table S9 of Hidalgo and Hausmann (2009), that indicator is introduced. However signs do not change as shown in columns 11-14 of the table.

[10] A coefficient of 0.0113 for $k_{c,18}$ as shown in Table A.10 implies that an increase of 0.02 in the complexity measure (that would be enough to take a country from the bottom of the indicator distribution and place it at the very top) would imply an increase of 0.0002 in the average growth rate of a country if other controls are held constant. Given that the average five-year growth rate for any five year period is of 0.02168, the enormous increase assumed for $k_{c,18}$ would impact the growth rate of the country only by around 1%.

Another interesting exercise is to perform regressions using the panel structure of the database which allows to incorporate country fixed-effects as done in Table S10 of Hidalgo and Hausmann (2009). Table A.12 report results for the different specifications using a fixed effects estimator. These results show again coefficients for $k_{c,18}$ being negative and very small (columns 7-10), and the same happens for $k_{c,8}$ in column 6.

8.3.1 Exploring for more meaningful results

Results do not change when control variables are added and different country filter levels are used as shown in columns 1-5 of Table A.13. Columns 6-10 compute the same specifications upon a database in which outliers from the growth rate distribution have been removed and, as can be seen, this does not make the coefficient of $k_{c,18}$ greater or positive either.

The fact that coefficient the of $k_{c,18}$ is so small leads to conclude that MR indicators are not contributing much in predicting future growth in the short term. This result does not seem surprising. After all, the literature explains that economic complexity is something that materializes over time and therefore the link between complexity and growth is typically a long term phenomenon.

8.4 Removing intermediate products from the construction of MR indicators

Relying solely on export data as information source the MR indicators are vulnerable to changes in export figures. These changes can be reflecting many different things and some of them could be considered as unrelated to economic complexity. For example, the increasing fragmentation of production across national boundaries due to firms' strategical decisions could be considered as a source of distortion to the ability of MR indicators to capture economic complexity. This section proposes the exercise of constructing the MR indicators upon a database that does not consider intermediate products with the aim of eliminating that source of distortion. Of course, to eliminate intermediate products trade from the analysis can yield a great informational loss. By comparing results stemming under the setting proposed here with those previously obtained it will be possible to evaluate how important is intermediate product trade information to MR indicators.

To filter out intermediate products this work uses the *upstreamness* index presented in Antras et al. (2012) which measures the average distance each product has to the final consumer market. The authors construct such a measure using data from the US Input-Output matrix of the year 2002 and computing the weighted average position of the output of industry i in the value chain following the next formula:

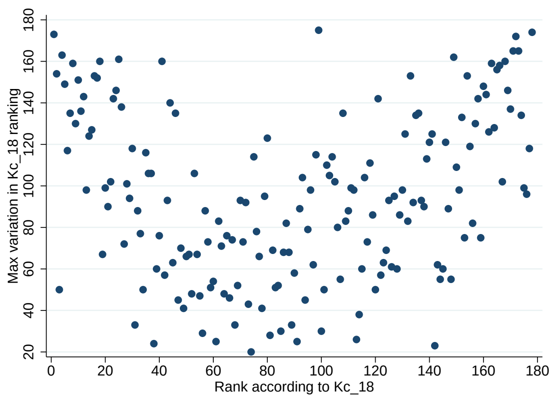
$$u_i = 1.\frac{F_i}{Y_i} + 2.\frac{\sum_{j=1}^{N} d_{ij}F_j}{Y_i} + 3.\frac{\sum_{j=1}^{N}\sum_{k=1}^{N} d_{ik}d_{kj}F_j}{Y_i} + 4.\frac{\sum_{j=1}^{N}\sum_{k=1}^{N}\sum_{l=1}^{N} d_{il}d_{lk}d_{kj}F_j}{Y_i} + \ldots \tag{9}$$

where Y_i is the gross product of industry i, F_i represents the amount of total outcome of product i destined to the final good market, N is the total amount of industries in the economy and $d_{i,j}$ is the value of good i required to produce a unit of good j. The authors themselves provide a database with their u_i for each product in the HS classification at a six-digit aggregation level[11] in which they also include a correction to account for the impact of international trade on the I-O information (see Antras et al. (2012) for details).

Data availability does not allow to build the indicators for the countries in this analysis so the author's dataset is used here as a rough approximation to global upstreamness. Then, MR indicators are constructed upon the BACI keeping only products with $u_i < 1.41$ which is the threshold of the first quartile in the distribution of the index when considering only manufacturing industries, i.e. these are the products that can be considered as closer to final consumption.

The resulting MR indicators have greater variability in terms of $k_{c,18}$ which is not a good sign since this variability was one of the sources of noise that has to be addressed in previous sections in order to get significant results. As shown in Figure 5 (built for year 2007) new volatility is especially high among high $k_{c,18}$ countries.

Figure 5: Maximum changes in $k_{c,18}$ ranking for each country, sorted by its 2007 level



[11] Available at http://www.economics.harvard.edu/faculty/antras/papers_antras.

Table A.14 shows results for cross-section income regressions for three different years (1995, 2000 and 2007) using indicators $k_{c,12}$ and $k_{c,18}$ as main regressors. Section 8.1 showed these indicators are significantly explaining income, but results after filtering for intermediate products are not so clear. It is noticeable how results vary strongly between years: MR indicators have huge, significant and positive coefficients in 1995, they are not significant in 2000 and they become again significant but negative in 2007. There is no reasonable explanation for these strong changes so these results lead to the conclusion that the loss of information brought by the deletion of intermediate product is too strong and MR indicators have lost their explanatory power.

Long and short term growth regressions were also performed to compare results with those from sections 8.2 and 8.3. Long term regressions present no significant results when performed without any kind of country filter. Table A.15 show results following the same specifications used in Table 6. The same filter f levels could not be applied since they imply a huge loss of observations. The country filter used is therefore less demanding. Notice that the allowed volatility is very large (only countries with position changes of more than 125 places from one year to the next in a ranking of 178 countries are being dropped) and still the amount of countries left-out is very important. Results in Table A.15 show that there is no filter level for which MR significantly predict long-term growth. Table A.16 replicate results from short-term growth regressions in Table A.12. Again, no significant results are found.

Results are clearly showing that MR indicators suffer greatly from the informational loss derived from the exclusion of intermediate products in their construction. This is not really surprising since intermediate products exports are actually one of the main sources of information nourishing MR indicators. The main idea behind these indicators is that whenever data shows country A exporting product z and its input y this should be interpreted as evidence of A being a more complex economy than B who only exports product z. Under the broad definition of capabilities that has been adopted here, there is no reason, other than lack of capabilities,, that could explain why B is not exporting y. Wages that have become too high for competitive production, tax incentives in the new host country, and every other component in the large list of reasons that could be behind the decision of a firm in B to shift y's production to another country should be included in the list of capabilities that are required to the production of that good. It can be seen then how intermediate product trade information is of crucial importance in the construction of MR indicators.

9 Conclusions

Many works have discussed the relationship between a country's current production and its long term growth possibilities. Recently, some of them have entered the discussion empirically, in what appeared to be a difficult but potentially very important task. Hidalgo and Hausmann (2009) presented a very strong tool, the Method of Reflections (MR) which yields indicators of both economic complexity and product sophistication. The work finds that indicators of economic complexity significantly explain current per capita GDP and also contribute in the prediction of its growth. Previous works from the same group of researchers suggested measures of distance between current production and potentially produced goods. All these tools combined can provide policy-makers with detailed insights to better design industrial policies that help economies diversify "the right way" and accumulate valuable capabilities, which would enhance their growth prospectives. This potentiality provides enough justification to take a closer look at MR indicators. This work has tested the explanatory and predictive power of MR indicators of economic complexity by comparing results in Hidalgo and Hausmann (2009) with new results obtained under different conditions.

This work first computed MR indicators upon a different dataset (the BACI) which allows a closer approximation to actual products (it reports goods at a six-digit aggregation level instead of the four-digits originally used). This feature makes the database more suitable to extract economic complexity information. The use of the BACI has the shortcoming of reporting data for a shorter time span (1995-2007) than the one used to find MR properties (1962-2000), but it also presents the benefit of including a greater number of countries with enough information for the analysis done here (95 against 178). The main characteristics of MR indicators also arise when computed upon the BACI. MR indicators get more complex as i increases: low iterated indicators are rough approximations to economic complexity and are vulnerable to different distortionary effects, but highly iterated indicators are less dependent on these effects and present a much richer informational basis.

The main properties attributed to MR complexity indicators are tested then, i.e. that they are related with countries' income levels, that they predict future long term growth, and that they also predict growth in the short term. For this task the first step was to compute the same regressions used by Hidalgo and Hausmann (2009) to sustain these conclusions, but using this work's proposed database. When no significant results are found the regression analysis is modified to explore conditions under which significant results could be found. This implies using a country filter to remove countries that present a too large $k_{c,18}$ volatility, including more control variables in the regressions and dropping countries that are outliers in the growth rate distribution. These changes allowed this work to state the circumstances under which significant results can be found. When significant results are found their robustness to alterations in the R^* parameter is tested. This parameter appears to be a reasonable but arbitrary choice in MR indicators construction that allows for modifications.

Results support the conclusion that MR indicators of economic complexity perform well as explanatory variables of a country's current per capita GDP. Every component of the k_c vector tested here has a significant coefficient in cross section regressions performed for every year in the sample, and their signs are as expected. The only important difference found here with respect to results from Hidalgo and Hausmann (2009) is that some indicators with an intermediate iteration level (like $k_{c,8}$ or $k_{c,12}$) are found to explain a higher proportion of income variability than the highest iterated indicator considered $k_{c,18}$. This is also found in pooled OLS regressions using data for the entire period. Results also hold when the R^* threshold is modified around its original value of 1.

Testing whether MR's complexity indicators can function as predictors of future growth in the long-term results show that this depends greatly on the country sample used. Given that economic complexity is built over the long term, indicators measuring that phenomenon should not present large variations from one year to the next. MR indicators of economic complexity, being constructed solely upon export data, show variations that indicate the existence of some noise between their information source and what they are trying to measure. The regression analysis done here shows that the noise can be too much when the country sample is not filtered for too volatile $k_{c,18}$ countries, and this can prevent the indicators to properly predict future growth.

Adding control variables previously used in the literature, like human capital indicators and dummy variables for poor and middle income countries can also increase the significance of $k_{c,18}$ as predictor of future growth in the long term. The inclusion of these variables can also make $k_{c,18}$ overcome the test of moving the R^* threshold: when no control variables are included it is required to strengthen the country filter level too much in order to get significant results for $k_{c,18}$ for alternative values of R^*, while including control variables makes significant coefficients appear even when no country filter is used. Finally removing fast growing or decreasing countries does not seem to have an important effect on the results.

The fact that the time span used here is only 13 years long could partly explain why MR indicators do not appear to be as strong predictors of long term growth as in Hidalgo and Hausmann (2009). That work shows that there are great differences in the effects MR indicators exhibit over the average growth rate when this rate is the average of a 20-year time period in contrast to when it corresponds to a 10-year time span.

Results do not support the conclusion that MR economic complexity indicators are good predictors of growth in the short term. Outcomes differ greatly when changing the initial year of the five-year periods used in estimations. In every regression performed, coefficients for MR indicators are too small and some of them present signs that are at odds with intuition. This is why this work concludes that complexity indicators are not good predictors of short-term growth. This conclusion is supported by the literature reviewed here which states that the relationship between economic complexity and growth materializes over the long term.

Finally this work presented a brief but interesting exercise by comparing previous results with those coming from the use of a set of MR indicators built upon a database that excluded intermediate products. The exclusion would oblige MR indicators to gather information only from final products trade which could be considered helpful to avoid the misinformation intermediate trade data could bring. In contrast, by using only final products this proposal is ignoring one of the sources of information that nourishes the MR indicators the most and helps distinguishing countries capabilities. Results show that the MR indicators lose their power to explain current income and predict future growth when the proposed deviation is applied, which implies that MR indicators are enriched by the information delivered by intermediate products.

This work has also pointed at some interesting possibilities for future research. The finding that the magnitude of the coefficients of MR indicators grow as lower R^* thresholds are imposed is something to be explored. It would also be interesting to look for some other variables that could be included in growth regressions enhancing their predicting possibilities.

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Appendix

Table A.1: All countries sorted by maximum change in $k_{c,18}$ ranking (f)

n	country	f	pop	rgdpl	HH	n	country	f	pop	rgdpl	HH
1	Timor-Leste	158	1086,17	1086,85	0,301565	41	Suriname	35	470,784	10169,3	0,286858
2	Chad	101	9885,66	1216,7	0,893369	42	Afghanistan	34	31889,9	736,48	0,031112
3	Somalia	85	9238	455,29	0,075042	43	Armenia	34	2971,65	5603,83	0,063014
4	Micronesia	85	107,848	3459,25	0,240642	44	St. V.and Gren.	34	105,307	6774,5	0,219774
5	Eritrea	82	5357,68	668,078	0,484823	45	Bermuda	34	66,921	50487,9	0,263617
6	Kiribati	77	107,915	3623,06	0,111618	46	Congo	33	3802,33	1912,89	0,652168
7	Palau	77	20,591	15043	0,413497	47	Belize	32	294,61	9251,59	0,08747
8	Iraq	74	27500	3948,59	0,979519	48	Yemen	32	21591	2421,06	0,555162
9	Marshall Isds	73	61,815	7350,88	0,300723	49	Azerbaijan	32	8120,25	7969,98	0,609793
10	Brunei D.	70	374,577	49063	0,520847	50	Tajikistan	31	7076,6	1764,08	0,429195
11	Guinea-Bissau	68	1472,78	790,91	0,786911	51	Tanzania	31	39384,2	1039,1	0,047559
12	Rwanda	65	10141	924,106	0,12687	52	Turkmenistan	29	4774	6195,14	0,563299
13	Bahamas	59	302	29114,8	0,179394	53	Mongolia	29	2951,79	3040,43	0,201678
14	Ctrl African R.	58	4544	614,929	0,187505	54	Guinea	27	9569,22	834,13	0,236281
15	Djibouti	57	694	2163,58	0,163228	55	Burkina Faso	27	14797,2	904,828	0,504744
16	Liberia	57	3270	403,546	0,27621	56	Côte d'Ivoire	27	19746,9	1299,97	0,088069
17	Eq. Guinea	57	599,763	18065,5	0,746179	57	Dominican Rep.	26	9426	9341,09	0,038829
18	Maldives	54	364,968	4689,11	0,161234	58	Georgia	26	4646	4708,76	0,043104
19	Burundi	52	8783	370,88	0,158174	59	Cameroon	26	18060,4	1826,42	0,274496
20	Qatar	48	814,897	123307	0,272779	60	Togo	26	6042	743,425	0,106294
21	Mali	46	12769	937,231	0,543219	61	Macao SAR	26	525,531	50192,2	0,033739
22	Comoros	46	711,417	927,715	0,125649	62	Fiji	25	852	4470,62	0,044983
23	Cape Verde	45	486	3498,44	0,188435	63	Viet Nam	25	86519	2584,62	0,031208
24	Jamaica	45	2782,22	9232,01	0,256183	64	Gambia	23	1630	1325,67	0,100369
25	Sierra Leone	44	4918	830,022	0,138264	65	Benin	23	8278,16	1254,22	0,132982
26	Saint Lucia	43	158,875	12684	0,116261	66	Grenada	23	106	12910,2	0,113957
27	Seychelles	43	85,702	26659,9	0,24076	67	Lebanon	22	3896	11102,8	0,021924
28	Cuba	43	11160	10955,6	0,202379	68	Kyrgyzstan	22	5284,15	2034,36	0,077921
29	Ant. and Barb.	43	83,425	17449,4	0,276869	69	Nigeria	22	143312	1941,63	0,739259
30	Bhutan	42	673,353	4077,33	0,150523	70	Bahrain	21	1054	24388,7	0,46103
31	Gabon	42	1456,45	10300,2	0,523353	71	Zambia	21	12341	1794,78	0,317118
32	Mozambique	40	20905,6	715,726	0,247699	72	Sudan	21	40526	2065,73	0,787094
33	Solomon Isds	39	566,948	1598,01	0,513748	73	Albania	21	2992	6017,55	0,024363
34	Libya	39	6036,91	19822	0,72609	74	Kuwait	21	2376	51608,9	0,450997
35	Angola	39	12263,6	4353,26	0,907839	75	Bosnia Herz.	20	4552,2	6245,46	0,013148
36	Tonga	37	104	7585,63	0,122921	76	Lao	20	6035	2338,74	0,211075
37	Niger	37	14214,7	532,473	0,191329	77	Ghana	20	22981	1143,45	0,164632
38	Senegal	37	11394	1494,68	0,038779	78	Jordan	19	5997	4412,85	0,014041
39	Algeria	36	33362,7	6062,33	0,331637	79	Uganda	19	30263	1063,86	0,043404
40	Samoa	35	188	7000,89	0,355918	80	Trin. & Tobago	19	1233	26286,3	0,146997

Table A.1(cont.): All countries sorted by maximum change in $k_{c,18}$ ranking (f)

n	country	f	pop	rgdpl	HH	n	country	f	pop	rgdpl	HH
81	Papua New Guin.	19	5806,04	2417,56	0,148204	130	Estonia	11	1315,91	19047,4	0,016827
82	Guyana	19	764	4028,27	0,09473	131	Guatemala	11	12728,1	6043,28	0,020175
83	Madagascar	18	19448,8	776,605	0,033567	132	Bangladesh	10	148894	1290,07	0,048414
84	Sao Tome & P.	18	165	1522,38	0,179595	133	Saudi Arabia	10	24499	20449,2	0,621102
85	UAE	18	4444	53847,8	0,280468	134	Haiti	10	9500	1383,01	0,176634
86	Syria	18	20488	3955,62	0,15499	135	Russia	10	141378	14495,7	0,150595
87	Cyprus	18	1049	19463,2	0,032326	136	Kenya	10	36913,7	1233,46	0,035966
88	Paraguay	18	6113	3785,18	0,130105	137	Iceland	10	301,931	43125,3	0,092013
89	Vanuatu	18	212	6042,99	0,25204	138	Barbados	10	282,359	24556,1	0,045758
90	Macedonia	18	2055,92	7330,34	0,031947	139	Cambodia	9	13719	1800,39	0,055581
91	China	18	1310584	5889,78	0,006719	140	Lithuania	9	3575,44	15648,4	0,022448
92	Mauritania	17	2981,45	1619,2	0,169208	141	Latvia	9	2259,81	15486,3	0,039695
93	Zimbabwe	17	11443,2	158,696	0,065195	142	Pakistan	9	175495	2291,78	0,012672
94	Nepal	16	27827,9	1092,18	0,029289	143	Chile	9	16303,9	12135,4	0,134625
95	Oman	16	2800	20761,8	0,40396	144	El Salvador	8	5982	6501,72	0,017453
96	Bolivia	16	9425,94	3619,5	0,1912	145	Portugal	8	10642,8	20700,2	0,006611
97	Nicaragua	16	5408	2113,12	0,035454	146	Argentina	7	40048,8	11344,8	0,030331
98	Peru	16	28050	6750,19	0,070943	147	Ukraine	7	46300	7123,5	0,009935
99	Iran	16	74093	10059,1	0,647413	148	Hungary	7	9956,11	17486,9	0,017818
100	Moldova	16	4328,82	2376,18	0,017708	149	Bulgaria	7	7322,86	10529,3	0,018364
101	Malta	15	401,88	21891,9	0,095977	150	Turkey	7	74768	10549,5	0,007656
102	Dominica	15	72,377	5585,79	0,07416	151	Rep. of Korea	7	48250,1	25061,7	0,019491
103	Belarus	14	9724,72	11177,4	0,106575	152	Colombia	7	42597	7522,18	0,060776
104	Congo	14	64355	227,135	0,135064	153	Australia	7	20749,6	40290,1	0,033097
105	Malaysia	14	26896	11643,6	0,021171	154	Slovakia	6	5447,5	19495,1	0,02168
106	Kazakhstan	14	15284,9	10845	0,257445	155	Poland	6	38518,2	15249,1	0,004783
107	Mauritius	14	1263,9	9001,03	0,059851	156	Norway	5	4627,93	50959,3	0,169396
108	Malawi	14	14233	581,423	0,17664	157	New Zealand	5	4132,34	28297	0,015447
109	Uzbekistan	13	27079	2081,98	0,083025	158	Slovenia	4	2009	26593,1	0,00884
110	Thailand	13	65110	7752,5	0,011399	159	Ireland	4	4420	39168	0,04142
111	Egypt	13	75677	4684,57	0,053065	160	Czech Rep.	4	10228,7	23518,8	0,005864
112	Costa Rica	13	4331	11215,6	0,069125	161	Denmark	4	5468,12	36335,8	0,008107
113	Panama	13	3258,33	9290,75	0,024457	162	Netherlands	4	16570,6	40691,2	0,011061
114	Ecuador	13	14135	5972,97	0,259532	163	India	4	1124135	2999,89	0,023729
115	Romania	13	22106	9523,52	0,009853	164	Belgium	3	10392,2	35574	0,009099
116	Uruguay	13	3279	9959,75	0,025546	165	Italy	3	59627	30199,6	0,003516
117	Tunisia	13	10213	5938,28	0,02254	166	Spain	3	45212	29133,5	0,008828
118	Indonesia	12	234694	3626,22	0,016828	167	Brazil	3	193919	9040,19	0,013486
119	Croatia	12	4493,31	15620,3	0,015098	168	Israel	3	6990	25473,6	0,062931
120	Honduras	12	7516	3625,6	0,041514	169	Switzerland	2	7555	39912,1	0,019024
121	Morocco	12	30594	3327,02	0,013326	170	France	2	63681,7	32015,4	0,006256
122	Greece	12	10706,3	27963,8	0,020284	171	Canada	2	32936	37703	0,023094
123	Hong Kong SAR	12	6980,41	37366,7	0,010937	172	Finland	2	5238,46	34888,8	0,017606
124	Mexico	12	108701	12696,9	0,03316	173	Sweden	1	9031	37358,7	0,007255
125	Ethiopia	11	79935,8	593,063	0,103722	174	Japan	1	127433	34223,8	0,011747
126	Philippines	11	94157,5	2963,96	0,046826	175	Austria	1	8199,78	38232,8	0,003751
127	Sri Lanka	11	20508	3738,78	0,017016	176	United Kingdom	1	61249	35649	0,011113
128	Singapore	11	4553,01	48215,1	0,050863	177	USA	1	301580	43697,5	0,005304
129	Venezuela	11	26415	9545,42	0,46222	178	Germany	1	82237	33638,2	0,005786

Table A.2: Income regressions. Pooled OLS for all years

	1	2	3	4	5	6	7
	Dependant variable: log per capita GDP						
entropy	0.331***						
	(22.091)						
HH		-1.386***					
		(10.403)					
kc0			0.001***				
			(27.633)				
kc1				-0.157***			
				(-25.432)			
kc4					0.023***		
					(34.607)		
kc8						0.336***	
						(38.506)	
kc12							4.356***
							(39.082)
Constant	7.130***	8.587***	7.743***	12.202***	-12.724***	-303.311***	-4,045.845***
	(65.251)	(88.015)	(84.653)	(72.832)	(20.399)	(37.418)	(38.997)
Observations	2,309	2,309	2,309	2,309	2,309	2,309	2,309
Adjusted R-squared	0.169	0.041	0.219	0.245	0.337	0.364	0.361
F-test	38.91	9.139	60.10	50.75	95.75	116.7	119.3
Prob>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000

	8	9	10	11	12	13
	Dependant variable: log per capita GDP					
entropy		0.077***		0.325***	0.240***	0.279***
		(4.352)		(10.456)	(7.030)	(8.676)
HH			0.219*	2.222***	2.258***	2.200***
			(1.742)	(9.877)	(9.873)	(9.778)
kc8					0.310***	
					(21.628)	
kc12						3.750***
						(22.088)
kc18	187.612***	169.117***	191.622***	150.403***		
	(36.296)	(24.884)	(33.951)	(20.804)		
Constant	-174,658.979***	-157,440.671***	-178,392.393***	-140,019.207***	-281.091***	-3,483.417***
	(36.295)	(24.883)	(33.949)	(20.803)	(21.270)	(22.058)
Observations	2,309	2,309	2,309	2,309	2,309	2,309
Adjusted R-squared	0.341	0.346	0.341	0.374	0.393	0.388
F-test	190.3	286.1	219.8	251.6	138.6	133.0
Prob>F	0.000	0.000	0.000	0.000	0.000	0.000

Robust t statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table A.3: Growth regressions (13-year average growth rate as dependent variable). No filter used

	1	2	3	4	5	6	7	8	9	10
	Dependant variable: average growth rate of per capita GDP (1995-2007)									
rgdpl	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(1.17)	(0.96)	(1.13)	(1.14)	(1.18)	(1.20)	(1.22)	(1.21)	(1.25)	(1.35)
entropy	0.001							0.000		0.002
	(0.73)							(0.29)		(0.85)
HH		-0.002							0.003	0.016
		(0.19)							(0.27)	(0.88)
kc0			0.000							
			(0.65)							
kc4				0.000						
				(0.48)						
kc8					0.001					
					(0.56)					
kc12						0.009				
						(0.60)				
kc18							0.338	0.280	0.369	0.202
							(0.64)	(0.47)	(0.66)	(0.34)
Constant	0.026***	0.029***	0.028***	-0.014	-0.622	-7.929	-314.571	-260.363	-343.924	-187.748
	(4.36)	(8.33)	(7.58)	(0.15)	(0.53)	(0.60)	(0.64)	(0.47)	(0.66)	(0.34)
Observations	177	177	177	177	177	177	177	177	177	177
Adjusted R-squared	-0.00	-0.01	-0.01	-0.00	-0.00	-0.00	-0.00	-0.01	-0.01	-0.01
F-test	0.76	0.46	0.65	0.71	0.75	0.77	0.78	0.53	0.61	0.80
Prob>F	0.47	0.63	0.52	0.49	0.47	0.47	0.46	0.66	0.61	0.53

Robust t statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table A.4: Growth regressions (13-year average growth rate as dependent variable). Sensitivity to different filter levels

	1	2	3	4	5	6
	Dependant variable: average growth rate of per capita GDP (1995-2007)					
Filter used: f<	45	55	65	45	55	65
rgdpl	-0.000***	-0.000	-0.000	-0.000***	-0.000	-0.000
	(3.28)	(1.39)	(0.90)	(3.23)	(1.31)	(0.83)
entropy	0.000	0.000	0.001			
	(0.12)	(0.10)	(0.23)			
HH	0.004	0.004	0.008			
	(0.21)	(0.23)	(0.42)			
kc18	1.128***	0.818*	0.225	1.122***	0.800**	0.210
	(2.63)	(1.80)	(0.33)	(3.35)	(2.04)	(0.34)
Constant	-1,050.076***	-761.659*	-209.545	-1,044.665***	-745.033**	-195.749
	(2.63)	(1.80)	(0.33)	(3.35)	(2.04)	(0.34)
Observations	154	161	166	154	161	166
Adjusted R-squared	0.06	0.02	-0.02	0.07	0.03	-0.01
F-test	3.23	1.27	0.36	6.10	2.34	0.44
Prob>F	0.01	0.28	0.84	0.00	0.10	0.64

Robust t statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table A.5: Growth regressions (13-year average growth rate as dependent variable). Cleaning for outliers in the *avggr* distribution

	1	2	3	4	5	6	7	8	9	10	11	12
	Dependant variable: average growth rate of per capita GDP (1995-2007)											
Filter used: f<	45				55				65			
rgdpl	-0.000***	-0.000***	-0.000***	-0.000**	-0.000	-0.000***	-0.000***	-0.000**	-0.000	-0.000***	-0.000***	-0.000***
	(4.408)	(3.350)	(4.275)	(2.145)	(1.120)	(3.202)	(4.365)	(2.227)	(1.120)	(4.043)	(4.365)	(2.838)
entropy	-0.002	0.001	-0.001	0.001	-0.001	0.001	-0.002	0.001	-0.001	0.001	-0.002	0.001
	(0.868)	(0.585)	(0.584)	(0.599)	(0.444)	(0.563)	(0.726)	(0.514)	(0.444)	(0.547)	(0.726)	(0.509)
HH	-0.023	0.014	-0.014	0.014	-0.004	0.009	-0.016	0.009	-0.004	0.009	-0.016	0.009
	(1.087)	(0.742)	(0.658)	(0.747)	(0.180)	(0.504)	(0.822)	(0.511)	(0.180)	(0.494)	(0.822)	(0.505)
ltertiary	0.000		0.001		0.002		0.001		0.002		0.001	
	(0.171)		(0.420)		(0.659)		(0.410)		(0.659)		(0.410)	
leducexp		0.002	0.005	0.002		0.003	0.005	0.003		0.003	0.005	0.003
		(0.411)	(1.140)	(0.426)		(0.848)	(1.113)	(0.793)		(0.843)	(1.113)	(0.792)
poor				0.002				-0.000				0.000
				(0.283)				(0.012)				(0.043)
middle				0.002				0.001				0.001
				(0.314)				(0.176)				(0.249)
kc18	1.256***	0.790*	1.138**	0.784*	0.490	0.656	1.149**	0.664	0.490	0.637	1.149**	0.648
	(2.735)	(1.728)	(2.218)	(1.688)	(0.687)	(1.440)	(2.258)	(1.426)	(0.687)	(1.481)	(2.258)	(1.479)
Constant	-1,169.432***	-735.461*	-1,059.099**	-729.636*	-455.884	-610.433	-1,070.036**	-618.242	-455.884	-593.472	-1,070.036	-603.335
	(2.735)	(1.728)	(2.218)	(1.688)	(0.687)	(1.440)	(2.258)	(1.426)	(0.687)	(1.481)	(2.258)	(1.479)
Observations	89	128	85	128	92	136	87	136	92	137	87	137
Adjusted R-squared	0.153	0.051	0.164	0.035	-0.003	0.044	0.166	0.029	-0.003	0.062	0.166	0.048
F-test	4.961	2.498	3.641	1.787	0.389	2.380	3.784	1.751	0.389	3.978	3.784	3.178
Prob>F	0.001	0.034	0.003	0.096	0.855	0.042	0.002	0.103	0.855	0.002	0.002	0.004

Robust t statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table A.6: Growth regressions (13-year average growth rate as dependent variable). Different R^* thresholds ($f < 55$)

	1	2	3	4	5	6	7	8
	Dependant variable: log per capita GDP							
R* threshold	0.8				0.9			
rgdpl	-0.000**	-0.000**	-0.000**	-0.000**	-0.000	-0.000	-0.000	-0.000
	(2.21)	(2.19)	(2.09)	(2.07)	(1.06)	(1.07)	(1.08)	(1.06)
entropy		0.001		-0.001		-0.000		-0.000
		(0.41)		(0.37)		(0.24)		(0.16)
HH			-0.008	-0.014			0.002	-0.001
			(0.93)	(0.81)			(0.18)	(0.04)
kc18	1.001	0.870	0.837	0.946	0.446	0.511	0.477	0.515
	(1.02)	(0.80)	(0.80)	(0.88)	(0.57)	(0.60)	(0.58)	(0.61)
Constant	-1,100.568	-956.336	-921.005	-1,040.338	-451.059	-516.686	-482.286	-520.082
	(1.02)	(0.80)	(0.80)	(0.88)	(0.57)	(0.60)	(0.58)	(0.61)
Observations	162	162	162	162	162	162	162	162
Adjusted R-squared	0.01	0.01	0.01	0.00	-0.00	-0.01	-0.01	-0.02
F-test	3.23	2.47	2.65	1.98	0.61	0.44	0.45	0.34
Prob>F	0.04	0.06	0.05	0.10	0.54	0.73	0.71	0.85

	9	10	11	12	13	14	15	16
	Dependant variable: log per capita GDP							
R* threshold	1.1				1.2			
rgdpl	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(1.26)	(1.27)	(1.31)	(1.34)	(0.85)	(0.84)	(0.83)	(0.83)
entropy		-0.000		0.000		0.000		0.000
		(0.04)		(0.17)		(0.10)		(0.00)
HH			0.002	0.005			-0.001	-0.001
			(0.19)	(0.26)			(0.13)	(0.07)
kc18	0.632*	0.639*	0.652**	0.627	0.150	0.134	0.137	0.137
	(1.93)	(1.75)	(2.01)	(1.64)	(0.33)	(0.27)	(0.29)	(0.28)
Constant	-545.469*	-551.695*	-563.504**	-541.426	-120.606	-107.833	-110.372	-110.289
	(1.93)	(1.75)	(2.01)	(1.64)	(0.33)	(0.27)	(0.29)	(0.28)
Observations	162	162	162	162	161	161	161	161
Adjusted R-squared	0.02	0.02	0.02	0.01	-0.01	-0.01	-0.01	-0.02
F-test	2.08	1.38	1.46	1.15	0.47	0.31	0.31	0.24
Prob>F	0.13	0.25	0.23	0.34	0.62	0.82	0.82	0.91

Robust t statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table A.7: Growth regressions. Results for different R^* values ($f < 30$)

	1	2	3	4	5
	Dependant variable: average growth rate of per capita GDP (1995-2007)				
R* threshold	0.8	0.9	1.0	1.1	1.2
rgdpl	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(2.89)	(2.87)	(2.65)	(2.97)	(3.01)
kc18	1.538***	1.352***	0.933***	0.780***	0.664***
	(2.73)	(2.99)	(2.64)	(2.63)	(2.63)
Constant	-1,691.485***	-1,366.492***	-868.478***	-673.522***	-533.383***
	(2.73)	(2.99)	(2.64)	(2.63)	(2.63)
Observations	127	129	127	130	132
Adjusted R-squared	0.06	0.06	0.05	0.06	0.05
F-test	4.51	4.85	3.96	4.53	4.65
Prob>F	0.01	0.01	0.02	0.01	0.01

Robust t statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table A.8: Growth regressions with controls. Sensitivity to R^* and f

	1	2	3	4	5	6	7	8
	Dependant variable: log per capita GDP							
R* threshold	0.8				0.9			
Filter used: f<	35	55	75	no filter	35	55	75	no filter
rgdpl	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(4.721)	(4.812)	(4.860)	(4.810)	(4.783)	(4.803)	(4.800)	(4.760)
entropy	-0.002	-0.002	-0.002	-0.001	-0.002	-0.003	-0.002	-0.001
	(0.715)	(1.010)	(0.695)	(0.450)	(0.754)	(1.034)	(0.599)	(0.356)
HH	-0.002	-0.008	0.004	0.010	-0.002	-0.009	0.004	0.010
	(0.082)	(0.454)	(0.219)	(0.553)	(0.108)	(0.502)	(0.221)	(0.556)
leducexp	-0.007	-0.005	-0.004	-0.003	-0.007	-0.007	-0.004	-0.003
	(1.143)	(0.895)	(0.772)	(0.635)	(1.247)	(1.219)	(0.766)	(0.627)
poor	-0.038***	-0.037***	-0.036***	-0.037***	-0.037***	-0.035***	-0.036***	-0.037***
	(3.964)	(3.959)	(3.874)	(3.956)	(3.809)	(3.792)	(3.836)	(3.921)
middle	-0.015**	-0.014**	-0.012*	-0.013*	-0.015**	-0.014**	-0.012*	-0.012*
	(2.180)	(2.118)	(1.887)	(1.899)	(2.116)	(2.059)	(1.854)	(1.871)
kc18	2.493***	2.427***	2.174***	1.953**	2.005***	2.057***	1.624***	1.449**
	(2.936)	(3.213)	(2.898)	(2.564)	(3.173)	(3.601)	(2.807)	(2.474)
Constant	-2,741.376***	-2,669.424***	-2,390.454***	-2,147.602**	-2,025.755***	-2,078.694***	-1,641.321**	-1,464.290**
	(2.936)	(3.213)	(2.898)	(2.564)	(3.172)	(3.601)	(2.807)	(2.474)
Observations	127	146	149	151	127	144	149	151
Adjusted R-squared	0.214	0.208	0.207	0.202	0.205	0.210	0.202	0.198
F-test	5.354	5.514	5.704	5.742	5.367	5.633	5.672	5.728
Prob>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

	9	10	11	12	13	14	15	16
	Dependant variable: log per capita GDP							
R* threshold	1.1				1.2			
Filter used: f<	35	55	75	no filter	35	55	75	no filter
rgdpl	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(4.796)	(4.638)	(4.618)	(4.712)	(4.867)	(4.586)	(4.566)	(4.670)
entropy	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.000
	(0.321)	(0.561)	(0.427)	(0.227)	(0.448)	(0.487)	(0.367)	(0.169)
HH	0.017	0.001	0.005	0.010	0.010	0.001	0.004	0.010
	(0.845)	(0.080)	(0.250)	(0.560)	(0.471)	(0.080)	(0.248)	(0.559)
leducexp	-0.004	-0.004	-0.004	-0.003	-0.004	-0.004	-0.003	-0.003
	(0.741)	(0.799)	(0.677)	(0.565)	(0.695)	(0.753)	(0.629)	(0.518)
poor	-0.038***	-0.037***	-0.037***	-0.036***	-0.039***	-0.037***	-0.037***	-0.037***
	(3.956)	(3.953)	(3.988)	(3.936)	(4.095)	(3.965)	(3.993)	(3.941)
middle	-0.014*	-0.014**	-0.013**	-0.012*	-0.015**	-0.014**	-0.013**	-0.013*
	(1.965)	(2.090)	(2.048)	(1.898)	(2.157)	(2.100)	(2.055)	(1.907)
kc18	1.126***	1.137***	1.104***	0.905**	1.009***	0.941***	0.915***	0.742**
	(2.621)	(2.790)	(2.751)	(2.277)	(2.713)	(2.654)	(2.629)	(2.164)
Constant	-972.346***	-982.051***	-953.483***	-781.345**	-810.247***	-755.657***	-735.426***	-596.409**
	(2.621)	(2.790)	(2.751)	(2.277)	(2.712)	(2.654)	(2.629)	(2.164)
Observations	125	146	148	151	128	145	148	151
Adjusted R-squared	0.213	0.187	0.191	0.191	0.210	0.182	0.187	0.187
F-test	5.598	5.049	5.137	5.724	5.489	4.998	5.091	5.692
Prob>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Robust t statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table A.9: Short-term growth regressions (5-year average growth rate for periods starting in 1995 and 2000 as dependant variable)

	1	2	3	4	5	6	7	8	9	10
	Dependant variable: average growth rate of per capita GDP (five year periods starting in 1995 and 2000)									
rgdpl	-0.0000	-0.0000	-0.0000*	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000*
	(1.475)	(1.134)	(1.743)	(1.473)	(1.432)	(1.289)	(1.114)	(1.522)	(1.181)	(1.783)
entropy	0.0011		0.0032					0.0012		0.0033
	(0.853)		(1.310)					(0.855)		(1.307)
HH		-0.0024	0.0206						-0.0024	0.0207
		(0.186)	(0.858)						(0.187)	(0.855)
kc0				0.0000						
				(1.002)						
kc4					0.0001					
					(0.598)					
kc8						0.0001				
						(0.625)				
kc18							0.0001	0.0001	0.0001	0.0001
							(0.515)	(0.522)	(0.515)	(0.527)
Constant	0.0170***	0.0212***	0.0064	0.0196***	-0.0339	-0.0963	-0.0672	-0.0723	-0.0669	-0.0841
	(2.606)	(6.842)	(0.488)	(5.218)	(0.364)	(0.510)	(0.391)	(0.416)	(0.389)	(0.475)
Observations	355	355	355	355	355	355	355	355	355	355
Adjusted R-squared	-0.001	-0.003	-0.001	-0.002	-0.000	-0.002	-0.003	-0.003	-0.005	-0.003
F-test	1.298	0.665	1.334	1.297	1.127	1.093	0.899	0.975	0.653	1.021
Prob>F	0.274	0.515	0.263	0.275	0.325	0.336	0.408	0.404	0.581	0.396

Robust t statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table A.10: Short-term growth regressions (5-year average growth rate for periods starting in 1998 and 2003 as dependant variable)

	1	2	3	4	5	6	7	8	9	10
	Dependant variable: average growth rate of per capita GDP (five year periods starting in 1998 and 2003)									
rgdpl	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000*	-0.0000	-0.0000	-0.0000	-0.0000
	(0.358)	(0.142)	(0.799)	(0.567)	(0.725)	(1.800)	(0.565)	(0.745)	(0.491)	(1.156)
entropy	0.0005		0.0045**					0.0008		0.0046**
	(0.407)		(2.146)					(0.707)		(2.390)
HH		0.0074	0.0395*						0.0045	0.0371**
		(0.615)	(1.904)						(0.409)	(1.989)
kc0				0.0000						
				(1.030)						
kc4					0.0001					
					(0.905)					
kc8						0.0033***				
						(2.829)				
kc18							0.0113***	0.0113***	0.0112***	0.0112***
							(7.242)	(7.261)	(7.198)	(7.255)
Constant	0.0244***	0.0248***	0.0038	0.0247***	-0.0499	-2.9739***	-10.2619***	-10.3120***	-10.2282***	-10.2643***
	(4.549)	(8.668)	(0.374)	(8.299)	(0.591)	(2.804)	(7.224)	(7.243)	(7.180)	(7.250)
Observations	355	355	355	355	355	355	355	355	355	355
Adjusted R-squared	-0.005	-0.004	0.007	-0.003	-0.000	0.044	0.124	0.123	0.122	0.134
F-test	0.103	0.218	1.647	0.531	0.413	4.054	26.71	17.92	17.80	14.43
Prob>F	0.903	0.805	0.178	0.589	0.662	0.0182	0.000	0.000	0.000	0.000

Robust t statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table A.11: Short-term growth regressions (moving averages growth rates for all 5-year periods starting between 1995 and 2003 as dependant variable)

	1	2	3	4	5	6	7
	Dep. variable: 5-yr. periods moving avg. growth rate of per capita GDP (between 1995 and 2003)						
rgdpl	-0.0000	-0.0000	-0.0000**	-0.0000*	-0.0000	-0.0000	-0.0000
	(1.456)	(0.704)	(2.119)	(1.695)	(1.500)	(0.368)	(0.624)
entropy	0.0014**		0.0038***				
	(2.270)		(3.440)				
HH		-0.0031	0.0238**				
		(0.542)	(2.245)				
kc0				0.0000***			
				(2.888)			
kc4					0.0001		
					(1.433)		
kc8						-0.0001**	
						(1.984)	
kc18							-0.0002***
							(2.700)
Constant	0.0175***	0.0226***	0.0052	0.0204***	-0.0317	0.1463**	0.1936***
	(6.293)	(16.484)	(0.915)	(12.960)	(0.834)	(2.334)	(3.051)
Observations	1,597	1,597	1,597	1,597	1,597	1,597	1,597
Adjusted R-squared	0.003	-0.001	0.007	0.003	0.002	0.001	0.003
F-test	2.958	0.371	4.668	4.327	1.313	2.214	4.012
Prob>F	0.052	0.690	0.003	0.013	0.269	0.110	0.018

	8	9	10	11	12	13	14
	Dep. variable: 5-yr. periods moving avg. growth rate of per capita GDP (between 1995 and 2003)						
rgdpl	-0.0000	-0.0000	-0.0000**	-0.0000	-0.0000	-0.0000	-0.0000**
	(1.475)	(0.727)	(2.146)	(0.786)	(1.641)	(0.885)	(2.331)
entropy	0.0013**		0.0038***		0.0013**		0.0038***
	(2.251)		(3.448)		(2.258)		(3.489)
HH		-0.0030	0.0239**			-0.0028	0.0245**
		(0.520)	(2.264)			(0.491)	(2.304)
kc18	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	(2.674)	(2.692)	(2.692)	(3.334)	(3.311)	(3.326)	(3.340)
kc19				0.0063***	0.0063***	0.0062***	0.0063***
				(3.188)	(3.189)	(3.184)	(3.225)
Constant	0.1872***	0.1936***	0.1756***	0.1023	0.0960	0.1024	0.0830
	(2.953)	(3.050)	(2.770)	(1.523)	(1.426)	(1.525)	(1.223)
Observations	1,597	1,597	1,597	1,597	1,597	1,597	1,597
Adjusted R-squared	0.006	0.002	0.010	0.011	0.014	0.010	0.018
F-test	4.416	2.782	5.313	6.037	5.289	4.563	5.288
Prob>F	0.004	0.040	0.000	0.000	0.000	0.001	0.000

Robust t statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table A.12: Short-term growth regressions with country fixed effects. Moving averages

	1	2	3	4	5	6	7	8	9	10
	Dep. variable: 5-yr. periods moving avg. growth rate of per capita GDP (between 1995 and 2003)									
rgdpl	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(2.910)	(2.958)	(2.833)	(2.864)	(2.878)	(2.953)	(2.964)	(2.987)	(3.031)	(2.930)
entropy	0.0006		-0.0016					0.0000		-0.0028
	(0.139)		(0.224)					(0.005)		(0.386)
HH		-0.0062	-0.0127						-0.0048	-0.0160
		(0.217)	(0.256)						(0.168)	(0.323)
kc0				0.0000						
				(1.136)						
kc4					0.0000					
					(0.166)					
kc8						-0.0002***				
						(6.404)				
kc18							-0.0002***	-0.0002***	-0.0002***	-0.0002***
							(6.883)	(6.191)	(6.426)	(6.553)
Constant	0.0549***	0.0582***	0.0657	0.0484***	0.0467	0.2402***	0.2556***	0.2555***	0.2553***	0.2715***
	(2.733)	(4.149)	(1.533)	(3.215)	(0.712)	(7.586)	(8.211)	(5.781)	(8.172)	(4.980)
Observations	1,597	1,597	1,597	1,597	1,597	1,597	1,597	1,597	1,597	1,597
Number of countries	178	178	178	178	178	178	178	178	178	178
Adjusted R-squared	0.030	0.030	0.030	0.031	0.030	0.038	0.039	0.039	0.039	0.039
F-test	4.235	4.618	3.526	5.084	4.203	23.83	28.23	19.35	19.21	14.72
Prob>F	0.016	0.011	0.016	0.007	0.016	0.000	0.000	0.000	0.000	0.000

Robust t statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table A.13: Short-term growth regressions with country fixed effects and some control variables. Moving averages

	1	2	3	4	5	6	7	8	9	10
	Dependant variable: average growth rate of per capita GDP (five year periods starting in every year of between 1995 and 2003)									
Filter used: f<	35	45	55	65	no filter	35	45	55	65	no filter
rgdpl	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(4.160)	(4.161)	(4.292)	(4.292)	(4.578)	(5.808)	(5.812)	(5.866)	(5.866)	(6.257)
entropy	-0.0022	-0.0005	-0.0028	-0.0028	-0.0023	0.0010	0.0010	0.0012	0.0012	-0.0003
	(0.320)	(0.079)	(0.477)	(0.476)	(0.372)	(0.167)	(0.190)	(0.245)	(0.245)	(0.057)
HH	0.0605	0.0653	0.0353	0.0354	0.0406	0.0173	0.0138	0.0094	0.0094	-0.0039
	(1.065)	(1.273)	(0.998)	(1.000)	(1.070)	(0.450)	(0.401)	(0.416)	(0.416)	(0.165)
ltertiary	0.0245***	0.0252***	0.0235***	0.0235***	0.0247***	0.0238***	0.0225***	0.0212***	0.0212***	0.0214***
	(4.453)	(4.775)	(4.658)	(4.660)	(4.889)	(4.630)	(4.726)	(4.918)	(4.918)	(5.048)
leducexp	0.0028	0.0012	0.0013	0.0013	0.0017	-0.0041	-0.0048	-0.0050	-0.0050	-0.0023
	(0.330)	(0.146)	(0.163)	(0.164)	(0.189)	(0.513)	(0.637)	(0.673)	(0.673)	(0.316)
poor	-0.0111	-0.0099	-0.0068	-0.0068	-0.0028	-0.0003	-0.0001	0.0023	0.0023	0.0031
	(0.942)	(0.915)	(0.653)	(0.653)	(0.265)	(0.041)	(0.015)	(0.326)	(0.326)	(0.462)
middle	-0.0092**	-0.0085**	-0.0094**	-0.0094**	-0.0091**	-0.0086**	-0.0086**	-0.0090***	-0.0090***	-0.0090***
	(2.127)	(2.040)	(2.202)	(2.202)	(2.119)	(2.443)	(2.596)	(2.712)	(2.712)	(2.713)
kc18	-0.0002***	-0.0002***	-0.0001***	-0.0001***	-0.0001**	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	(3.683)	(3.527)	(3.251)	(3.247)	(2.592)	(5.347)	(5.178)	(4.708)	(4.708)	(4.815)
Constant	0.1625**	0.1430**	0.1432**	0.1426**	0.1176*	0.1642***	0.1596***	0.1457***	0.1457***	0.1521***
	(2.319)	(2.106)	(2.206)	(2.203)	(1.772)	(3.045)	(3.113)	(3.037)	(3.038)	(3.186)
Observations	800	845	874	878	908	751	794	823	824	845
Number of countries	121	133	139	142	148	120	132	138	139	145
Adjusted R-squared	0.154	0.162	0.150	0.150	0.138	0.192	0.183	0.176	0.176	0.182
F-test	6.832	7.362	7.035	7.033	6.830	10.18	10.21	9.908	9.909	10.82
Prob>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Robust t statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table A.14: Cross section income regressions filtered for intermediate products (years 1995, 2000 and 2007)

	1	2	3	4	5	6	7	8	9
	Dependant variable: log per capita GDP								
year	1995			2000			2007		
entropy			0.436***			0.683***			0.620***
			(4.933)			(7.412)			(6.529)
HH			1.997**			3.341***			2.750***
			(2.283)			(3.914)			(2.855)
kc12	113.001***			10.594			-7.573*		
	(7.562)			(1.398)			(1.937)		
kc18		16,287.398***	10,936.956***		-288.476	-364.361		-363.410***	-410.045***
		(7.188)	(5.080)		(1.064)	(1.443)		(3.531)	(3.923)
Constant	-27,230.722***	-3926159.833***	-2636407.828***	-2,612.471	71,376.549	90,147.111	1,872.040*	89,425.322***	100,897.025***
	(7.560)	(7.190)	(5.064)	(1.394)	(1.064)	(1.443)	(1.946)	(3.532)	(3.923)
Observations	177	177	177	177	177	177	175	175	175
Adjusted R-squared	0.229	0.242	0.340	0.004	0.001	0.241	0.015	0.055	0.267
F-test	57.18	51.67	43.87	1.955	1.132	22.54	3.752	12.47	34.63
Prob>F	0.000	0.000	0.000	0.164	0.289	0.000	0.054	0.001	0.000

Robust t statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table A.15: Long Term growth estimations filtered for intermediate products (f=45, 55, 65)

	1	2	3	4	5	6	7	8	9	10	11	12
	Dependant variable: average growth rate of per capita GDP (1995-2007)											
Filter used: f<	65				95				125			
rgdpl	-0.000**	-0.000*	-0.000**	-0.000*	-0.000***	-0.000**	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(2.544)	(1.923)	(2.422)	(2.169)	(2.835)	(2.513)	(2.951)	(3.915)	(3.712)	(3.056)	(3.719)	(4.449)
entropy	0.006	0.005	0.006	-0.021	0.003	0.003	0.003	0.001	0.003	0.005*	0.003	0.002
	(0.968)	(0.859)	(0.944)	(0.909)	(0.655)	(0.808)	(0.637)	(0.177)	(0.975)	(1.857)	(0.977)	(0.699)
HH	0.084	0.003	0.050	-0.399	0.035	0.011	0.038	0.023	0.036	0.037*	0.039	0.031
	(1.513)	(0.068)	(0.880)	(0.848)	(1.017)	(0.365)	(1.097)	(0.790)	(1.338)	(1.760)	(1.435)	(1.647)
ltertiary	0.013*		0.015**		0.008*		0.007		0.008**		0.008**	
	(1.753)		(2.157)		(1.729)		(1.474)		(2.349)		(2.053)	
leducexp		-0.018	-0.034	-0.080		0.005	0.008	0.003		0.005	0.007	0.001
		(1.362)	(1.557)	(1.826)		(0.663)	(0.771)	(0.432)		(0.811)	(0.829)	(0.134)
poor				-0.106*				-0.046***				-0.041***
				(2.158)				(3.313)				(3.638)
middle				-0.081**				-0.014				-0.015*
				(2.411)				(1.542)				(1.946)
kc18	-9.050	83.344	-33.877	1,245.251*	101.445	97.388	92.009	45.519	106.615	96.204	98.392	104.187
	(0.064)	(0.523)	(0.222)	(2.324)	(0.707)	(0.713)	(0.710)	(0.433)	(1.201)	(1.178)	(1.108)	(1.457)
Constant	2,181.621	-20,090.506	8,166.212	-300,174.396*	-24,453.887	-23,475.802	-22,179.172	-10,972.474	-25,700.019	-23,190.423	-23,717.940	-25,114.888
	(0.063)	(0.518)	(0.220)	(2.136)	(0.710)	(0.710)	(0.712)	(0.432)	(1.192)	(1.174)	(1.116)	(1.462)
Observations	32	44	32	15	58	82	56	82	76	115	74	115
Adjusted R-squared	0.075	0.004	0.179	0.138	0.094	0.023	0.091	0.215	0.153	0.041	0.151	0.204
F-test	1.837	4.884	2.858	2.804	2.837	2.375	2.306	5.173	3.509	2.669	2.794	5.364
Prob>F	0.141	0.002	0.029	0.099	0.024	0.047	0.049	0.000	0.007	0.026	0.017	0.000

Robust t statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table A.16: Short Term growth estimations filtered for intermediate products (f=45, 55, 65)

	1	2	3	4	5	6	7	8	9	10
	Dependant variable: average growth rate of per capita GDP (five year periods starting in every year of between 1995 and 2003)									
rgdpl	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(3.513)	(3.450)	(3.236)	(3.462)	(3.583)	(3.568)	(3.568)	(3.529)	(3.462)	(3.250)
entropy	-0.0007		0.0044					-0.0007		0.0045
	(0.169)		(0.845)					(0.160)		(0.862)
HH		0.0113	0.0292						0.0113	0.0299
		(0.468)	(0.836)						(0.469)	(0.851)
kc0				0.0001						
				(1.274)						
kc4					0.0001					
					(0.545)					
kc8						0.0001				
						(0.623)				
kc18							0.0001	0.0001	0.0001	0.0001
							(0.686)	(0.657)	(0.684)	(0.746)
Constant	0.0492***	0.0445***	0.0239	0.0377***	0.0175	0.0203	0.0174	0.0207	0.0155	-0.0096
	(2.655)	(5.396)	(0.900)	(3.569)	(0.325)	(0.478)	(0.407)	(0.399)	(0.365)	(0.163)
Observations	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577
Number of countries	178	178	178	178	178	178	178	178	178	178
Adjusted R-squared	0.015	0.016	0.016	0.017	0.015	0.015	0.015	0.015	0.016	0.016
F-test	6.234	6.078	4.319	8.135	6.645	6.523	6.532	4.312	4.212	3.291
Prob>F	0.002	0.003	0.006	0.000	0.002	0.002	0.002	0.006	0.007	0.013

Robust t statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Figure A.1: $k_{c,i}$ results as i grows (even i, 2007)

Figure A.2: $k_{c,18}$ ranking over the period 1995-2007

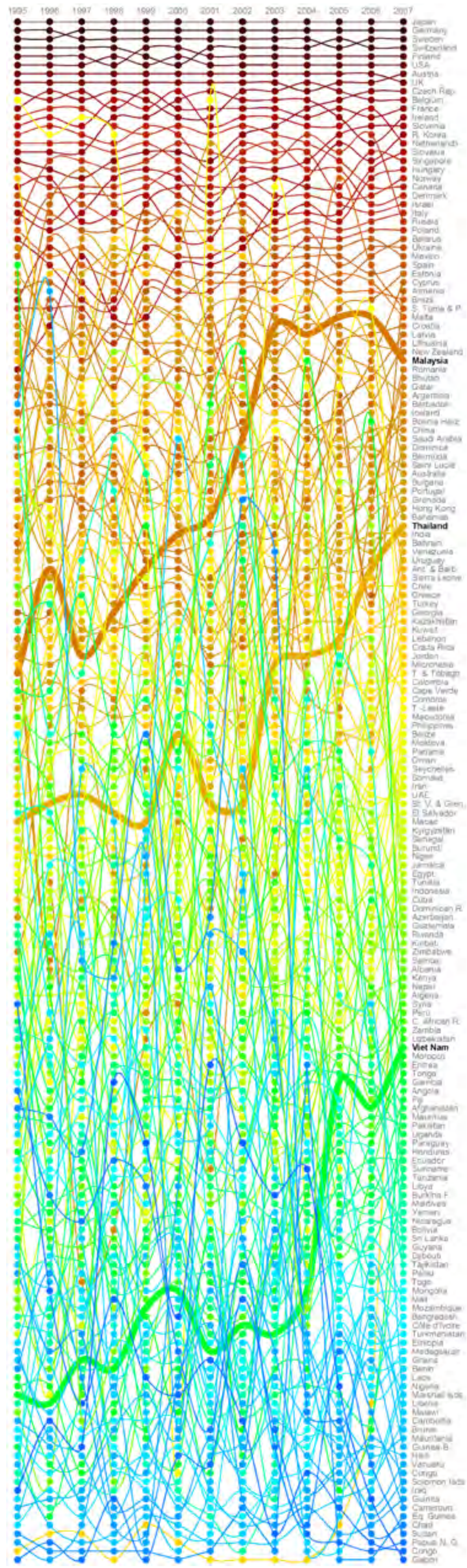

Figure A.3: Influence of 1995 $k_{c,18}$ as predictor of next 13-year average growth as f varies and for different R^* thresholds