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Economic complexity, export diversification and sustainable growth in oil-rich countries: the case of Saudi Arabia

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Abstract

This research has a two-fold objective. First, it aims to study the economic complexity of the Saudi economy through the measurement of the diversity and ubiquity of its exportations. We assess our analysis on the concept of the "Economic Complexity Index" developed by Haussmann and Hidalgo (2009) in order to rank Saudi Arabia among developed and oil-rich countries. We also use the concept of "product space" to visualize the path Saudi Arabia can borrow to diversify its export products and identify the know-how required to produce them. Second, we study the effect of economic complexity on development and sustainable Saudi economic growth. In this regard, many empirical works have confirmed a positive link between economic complexity of a country and its rate of economic growth. Moreover, such works showed that countries with more sophisticated products and highly diversified production grow faster and are usually more advanced. Our empirical results show that there exists a causal relationship between the economic complexity index and economic growth in Saudi Arabia during the period 1980-2019. Moreover, the interaction between economic complexity and human development indicator has a positive impact on economic growth. We believe that the empirical findings of this study can offer several conspicuous implications and operational recommendations for policymakers and regulators in Saudi Arabia, especially when elaborating development plans and industrial strategies.

Keywords: *Complexity, sophistication, diversity, ubiquity, growth, Saudi Arabia.*

JEL Classifications: *C32, F1, F14, F43, O10, O11, O14, O33*

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Introduction

The production and spread of knowledge is cucial for a countries' comprehensive and sustainable development. Hidalgo and Hausmann (2009) introduced the Economic Complexity Index (ECI) to measure the complexity of a country's economy. This index is based on the effective role of knowledge. It allows to explain the differences in the level of per capita income and the rate of economic growth and development of countries.

Literature on economic development was initiated beginning in the second half of the previous century by Lewis (1955), Rostow (1959), Kuznets (1966), and Chenery and Taylor (1968), among others. These authors view development and growth as a process of structural transformation of the productive structure. They argue that in order to develop, societies should transfer resources from activities of lower productivity into activities of higher productivity. This theory has been revised recently by Hidalgo et al. (2007), Hidalgo and Haussmann (2009), and Felipe et al. (2012), among others. According to this new strand of literature, the development and economic growth of countries are mainly explained by the complexity of their productive structure and by-product diversity. They argue that the capacity of a country to accumulate capabilities[1] in order to produce more sophisticated goods explains its performance. Moreover, they document that knowledge-based societies, where investment in science and research-development is a priority, are susceptible to be more innovative and create sophisticated products, a source of competitive advantages. In this regard, empirical works show that countries with more sophisticated products and more diversified production grow faster, experience sustainable development, and are usually more economically advanced. Consequently, raw materials based countries experience low level of their exports and are at risk of being trapped in a Dutch disease condition.

As an oil-rich country, during the past decades, Saudi Arabia has assessed its economic growth process on mineral-product exportation. While the country has a promising pattern of export growth through diversification, the structural transformation (reallocation of economic activity from low to high productivity sectors) has started but very slowly.

[1] According to Haussmann and Hidalgo (2009) the frontiers of what a country can produce is conditioned by the combinaition of productive capabilities which are all inputs, technologies, and ideas.

Recently, and since 2003, Saudi Arabia has introduced only 17 new products, and these products contributed to $143 in income per capita in 2018, but this diversification and complexity remain too small to contribute to economic growth (Atlas Economic Complexity 2019).

This paper aims to study the economic complexity of the Saudi economy and its product space in order to identify what products could increase the complexity of Saudi's economy and which strategy should Saudi Arabia adopt in the future. We also study the interactions and causality feedbacks between economic complexity, human capital and economic growth during the period 1980-2019. The remaining of this paper will be organized as follows: section two reviews the concept of economic complexity and its measurement as it has been proposed by Hidalgo and Haussmann (2009, 2014) with an illustrative example of the method of reflections. Section three uses calculations elaborated by the Atlas Economic Complexity Center and Economic Complexity Observatory to analyze Saudi economic complexity and its product space. Section four explores interactions and causality feedbacks between economic complexity, human capital development, and economic growth using ARDL methodology. Section five proposes some policy recommendations and concludes.

2- Methodology

2-1- Economic Complexity: Concept and Measurement

Following a series of recent contributions (see among others, Hidalgo et al. (2007, 2014), Hidalgo and Haussmann (2009, 2010, 2011, 2014)), the last decade has seen the development and refinement of theoretical and empirical methods to apprehend and quantify economic complexity. According to Hidalgo et al. (2014), economic complexity can be defined as a measure of the amount of knowledge that society can mobilize. This definition implies that economic complexity measures two fundamental phenomena for development and competitiveness. The first concerns the existence of diversified accumulated knowledge, know-how, or the tacit ability to produce products. Know-how refers to productive knowledge that allows societies to grow faster by creating a wider variety of products and increasing their complexity. In a given society, know-how and capabilities are distributed in tiny parts among individuals (each individual can have particular skills: scientific, technological, design, finance, marketing …). This quantity of knowledge does not increase by the multiplication of the same knowledge among individuals, but by their diversification and specialization. In fact, the more sophisticated the product, the greater number of individual knowledge and capacities are required to produce it. The second phenomenon concerns the capacity of society to mobilize this knowledge and capacities. For a country, the amount of knowledge effectively mobilized depends on the quality of institutions, whether they are organizations or markets.

In practice, it is very difficult (even impossible) to determine exhaustively the productive capacities of a country and the degree of interactions between them. To overcome this difficulty, Haussmann and Hidalgo (2009) propose an indirect measure based on neuronal techniques. They propose the concept of the "Economic Complexity Index" (ECI) based on the idea that productive capacities and knowledge endowments of a country can be revealed by exported products. The calculus of ECI takes into account the diversity (the number of products that a country can produce and export competitively) and ubiquity (the number of countries exporting the same product). The main idea behind ECI is that sophisticated and diversified economies export products that, on average, have low ubiquity, because only a few countries have the capabilities and know-how to produce and export such products. To measure these two dimensions (diversity and ubiquity), Haussmann and Hidalgo (2009, 2014) propose the method of reflection allowing to avoid the limit of each dimension and corrects the information contained in each one. In practice, from one side, diversity suffers from the fact that two countries having different levels of development can export the same number of products, but of very different levels of sophistication. On another side, ubiquity suffers from the existence of certain products that few countries export, but their low ubiquity is not explained by particular knowledge, but by chance of geology or climate, which is the case of mineral-rich countries like Saudi Arabia.

The method of reflections consists, for a country, to calculate iteratively the average ubiquity of the products it exports and the average diversity of the countries that export the same products. Symmetrically, the measure of the complexity of a given product involves the calculation of the average diversity of the countries that export that product and the average ubiquity of the other products that these countries export. Practically, in order to identify those products, the method of Haussmann and Hidalgo (2009, 2014) consists in the construction of a bipartite network of countries and products they produce and, for a number of iterations, $N \geq 1$, iteratively calculates measures of diversification and ubiquity that are generalized as follows:

$$k_{c,N} = \frac{1}{k_{c,0}} \sum_{p} M_{cp} k_{p,N-1}$$

$$k_{p,N} = \frac{1}{k_{p,0}} \sum_{c} M_{cp} k_{c,N-1}$$

where M_{cp} is the adjacency matrix summarizing the connections between countries and the products they export. When $M_{cp} = 1$ this means that country c is a significant exporter of product p and 0 otherwise. For a country c, if the Revealed Comparative Advantage (RCA)[2] (the share of product p in the export basket of country c to the share of product p in world trade) is greater than some threshold value, which usually taken as 1, it is said to be a significant exporter of the product p.

The number of links of countries and products defines initial conditions as follows:

$$k_{c,0} = \sum\nolimits_{p} M_{cp} \qquad \text{diversity}$$

$$k_{p,0} = \sum\nolimits_{c} M_{cp} \qquad \text{ubiquity}$$

For a country c, $k_{c,0}$ and $k_{p,0}$ are, respectively, the observed levels of diversification and the ubiquity of a product p . Hence, each country is characterized through the vector $K_c = (k_{c,0}, k_{c,1}, k_{c,2} ... k_{c,N})$ and each product is characterized by the vector $K_p = (k_{p,0}, k_{p,1}, k_{p,2} ... k_{p,N})$. For products, odd variables are related to the diversification of countries exporting those products, whereas even variables are related to their ubiquity and the

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[2] Balassa (1964) states that a country *c* has a comparative advantage in product *p* if RCA is larger than 1, where RCA stands for the Revealed Comparative Advantage defined as follows:

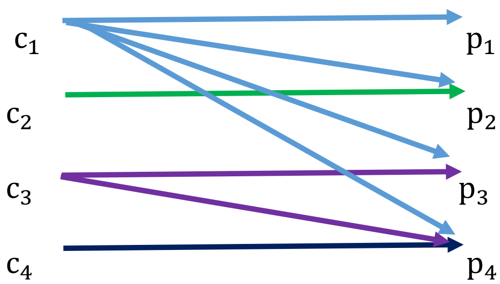
$$RCA_{cp} = \frac{X_{cp} / \sum_p X_{cp}}{\sum_c X_{cp} / \sum_c \sum_p X_{cp}}$$

where X_{cp} is the total export of country c in product p.

ubiquity of other related products. For countries, odd variables ($k_{c,1}$, $k_{c,3}$, $k_{c,5}$ ….) are generalized measures of the ubiquity of their exports, whereas even variables ($k_{c,0}$, $k_{c,2}$, $k_{c,4}$ ….) are generalized measures of diversification.

To capture the method of reflection and understand how the diversity should be corrected to ubiquity to reflect a country's capabilities, consider the following simple example. Suppose we have 4 countries (c_j , $j = 1,2,3,4$) and 4 products (p_i, $i = 1,2,3,4$) and the following scheme of exportation (figure 1): country 1 exports the 4 products, country 2 only exports, p_2, country 3 exports, p_3 and, p_4 and country 4 only exports, p_4.

Figure 1: Method of reflections (4 countries, 4 products)



Then we can write the diversity of countries and ubiquity of products for iterations 0, 1, and 2 as follows:

Iteration 0

Diversity	Ubiquity
$k_{C_1,0} = 4$	$k_{P_1,0} = 1$
$k_{C_2,0} = 1$	$k_{P_2,0} = 2$
$k_{C_3,0} = 2$	$k_{P_3,0} = 2$
$k_{C_4,0} = 1$	$k_{P_4,0} = 3$

Iteration 1

Diversity	Ubiquity
$k_{C1,1} = (\frac{1}{4})(1 + 2 + 2 + 3) = 2$	$k_{P1,1} = \left(\frac{1}{1}\right) 4 = 4$

$k_{C2,1} = \left(\frac{1}{1}\right) 2 = 2$

$k_{C3,1} = \left(\frac{1}{2}\right)(2 + 3) = 2.5$

$k_{C4,1} = \left(\frac{1}{1}\right) 3 = 3$

$k_{P2,1} = \left(\frac{1}{2}\right)(4 + 1) = 2.5$

$k_{P3,1} = \left(\frac{1}{2}\right)(4 + 2) = 3$

$k_{P4,1} = \left(\frac{1}{3}\right)(4 + 2 + 1) = 2.333$

Iteration 2

Diversity

$k_{C1,2} = (\frac{1}{4})(4 + 2.5 + 3 + 2.333) = 2.9583$

$k_{C2,2} = \left(\frac{1}{1}\right) 2.5 = 2.5$

$k_{C3,2} = \left(\frac{1}{2}\right)(3 + 2.333) = 2.666$

$k_{C4,2} = \left(\frac{1}{1}\right) 2.333 = 2.333$

Ubiquity

$k_{P1,2} = \left(\frac{1}{1}\right) 2 = 2$

$k_{P2,2} = \left(\frac{1}{2}\right)(2 + 2) = 2$

$k_{P3,2} = \left(\frac{1}{2}\right)(2 + 2.5) = 2.25$

$k_{P4,2} = \left(\frac{1}{3}\right)(2 + 2.5 + 3) = 2.5$

We observe that after two iterations, country c_1 is ranked first, followed by country c_3, c_2, and c_4. While c_2 and c_4 export each only one product, the process ranks c_2 before c_4. The reason is that c_2 exports a more non-ubiquitous product, namely, p_2, which is exported only by c_2 and c_1 , while c_4 exports p_4 which is also exported by c_1 and c_3.

It is clear that at each step, diversity is corrected by ubiquity and vice versa. New information about the countries and products of each iteration is taken into account in the following iteration. Iterations will stop when the process converges and this represents the Economic Complexity Index (ECI) of each country. Haussmann et al. (2011) show that the process converges at the 18th iteration.

3- Measuring Economic Complexity in Saudi Arabia

Nowadays, the world economy is changing rapidly and each country looks to diversify its production in order to make a place in the global chessboard. Countries are continually creating competitive advantages to cope with competitive pressures exerted by competitors. Recent literature retains three main sources of export performance:

- Export diversification, based on county's characteristics such as income level and revealed comparative advantage.
- Product-space that illustrates the relatedness of a country's exports and paths to diversify its economy based on the connectedness of its know-how.

- Economic complexity, a measure of the amount of knowledge that society can mobilize.

Consequently, production and export patterns reflect, for each country, historical circumstances and geographical position. Saudi Arabia is endowed with considerable mineral resources and a strategic position. Consequently, it has the potential to become a more complex and diversified economy.

In this section, we look to determine Saudis' economic complexity and position in the product space. This analysis will allow assessing the current extend of productive knowledge in Saudi Arabia and identify the exported products with the corresponding RCA greater than the unity. It also allows pointing several emergent sectors for which Saudi Arabia may be able to leverage for future diversification. It is then worthy to have an outlook of the main products Saudi Arabia exports for which the country has an RCA>1.

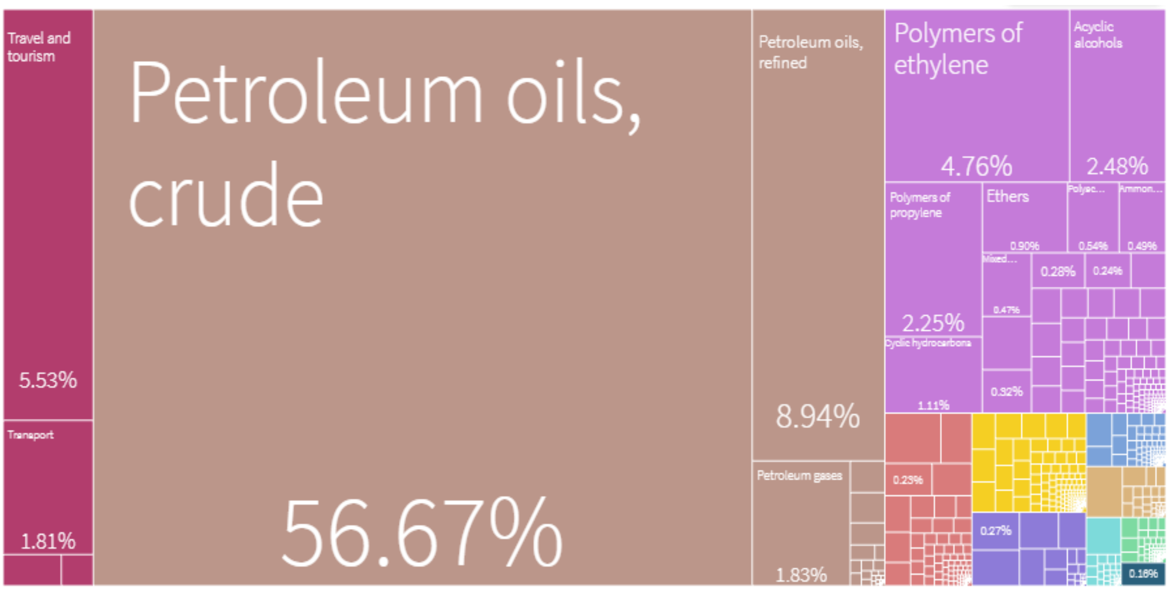
3-1 Exports structure and revealed comparative advantage

Saudi Arabia's economy has been largely dependent on oil and related derivatives, which account, in 2019, for about 80% of its export earnings, 70% of government revenues, and more than 40% of GDP. Figure 2 shows that during the last two decades, Saudi exports were highly dominated by mineral products with a diminishing share in world exportations as they represent 13% in 1998 and only 6% in 2018, followed by chemical products which have never surpassed 2%. The top five exports of Saudi Arabia are crude petroleum, refined petroleum, ethylene polymers of ethylene, acyclic alcohols, and polymers of propylene (see figure 3 and table 0). These five products participate approximately to 75% of total exportations with a dominant share of about 57% for crude oil.

In the objective to reduce the country's dependency on oil and diversify its economic resources, Saudi authorities launched in 2016 Saudi Vision 2030. The reform program is wide-ranging, but the main element is large-scale privatization. Its first step was the sale of less than 5 percent of the shares of Aramco, the most valuable oil-producing company in the world. In addition, the program aims to monetize the country's geographical position by the construction of a logistic transport highway from Egypt to Saudi Arabia. Moreover, the plan aims to increase the share of small businesses' economic contribution to attain 35% of GDP in 2030. Reforms also concern the development of the non-oil sector of raw materials and renewable energy. Moreover, the reform program includes strategies to develop tourism by creating coastal resorts on the Red Sea and investing in science and education.

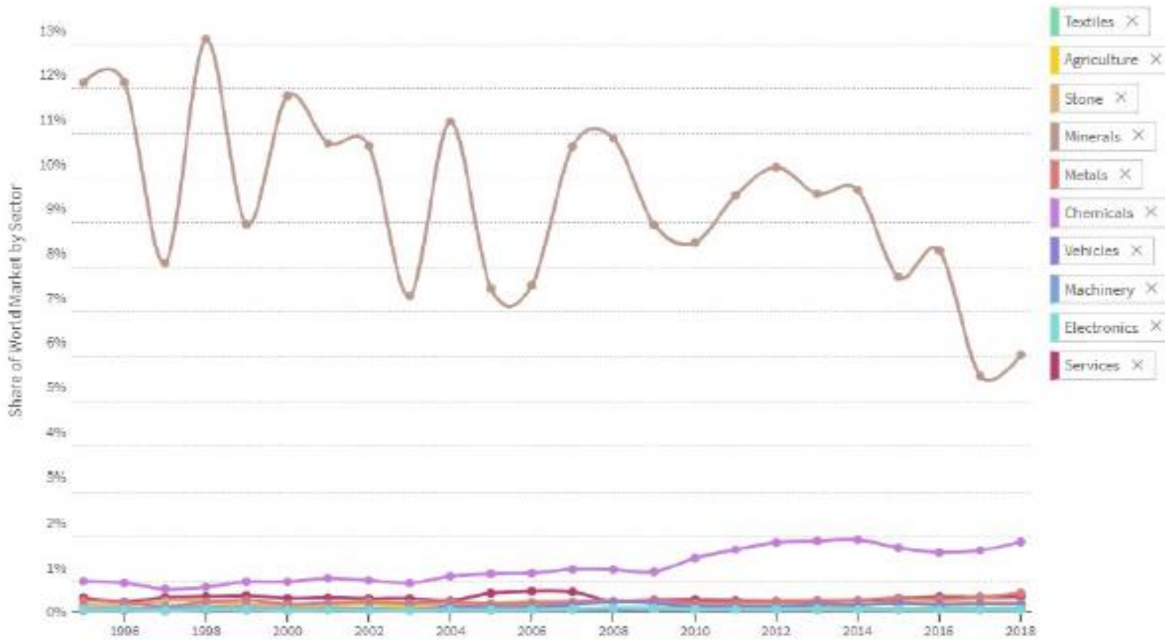
In five years' experience, this strategy has led to an increase in the share of the non-oil industrial sector and to more diversification. The number of exported products for which Saudi Arabia has an RCA bigger than one has increased from 25 in 2014 to 57 in 2018 (see table 1). The calculation of RCA and color group will help to visualize products in the product space.

Figure 2: Export structure of Saudi Arabia 2018



Source: Atlas economic complexity

Figure 3: Main Product-Exportation share 1995-2018



Source: Observatory of economic complexity

Table 1: Revealed Comparative advantage for Saudi Arabia 1995-2018

1995		2000		2006		2010		2014		2018	
Product	RCA	Product	RCA	Product	RCA	Product	RCA	Product	RCA	Product	RCA
Agriculture	1.91	Agriculture	2.07	Agriculture	1.58	Agriculture	2.55	Agriculture	1.51	Agriculture	1.2
Agriculture	1.17	Agriculture	2.67	Agriculture	1.15	Agriculture	1.43	Minerals	3.58	Agriculture	1.12
Agriculture	3.33	Agriculture	3.63	Minerals	6.46	Agriculture	1.17	Minerals	1.59	Agriculture	3.46
Agriculture	1.28	Minerals	4.8	Minerals	1.46	Minerals	5.68	Minerals	9.01	Agriculture	1.04
Agriculture	4.06	Minerals	1.49	Minerals	1.05	Minerals	1.63	Minerals	1.23	Agriculture	1.39
Minerals	6.58	Minerals	1.75	Minerals	1.82	Minerals	9.16	Minerals	4.33	Minerals	7.2
Minerals	3.33	Minerals	12.6	Minerals	9.29	Minerals	1.29	Chemicals	4.74	Minerals	1.76
Minerals	17.6	Minerals	2.46	Minerals	1.96	Minerals	1.1	Chemicals	1.54	Minerals	9.98
Minerals	5.85	Minerals	2.74	Minerals	1.86	Minerals	3.7	Chemicals	1.32	Minerals	2.15
Minerals	4.78	Minerals	1.22	Minerals	3.87	Chemicals	2.19	Chemicals	1.75	Minerals	1.06
Minerals	1.22	Minerals	2.6	Minerals	3.18	Chemicals	1.89	Chemicals	7.39	Minerals	1.37
Chemicals	4.89	Chemicals	1.29	Chemicals	1.7	Chemicals	1.8	Chemicals	2.3	Chemicals	13.6
Chemicals	2.08	Chemicals	2.41	Chemicals	3.15	Chemicals	2.39	Chemicals	11.5	Chemicals	1.53
Chemicals	1.4	Chemicals	2.93	Chemicals	1.83	Chemicals	8.87	Chemicals	2.28	Chemicals	2.22
Chemicals	1.27	Chemicals	1.49	Chemicals	2.04	Chemicals	7.06	Chemicals	1.72	Chemicals	4.03
Chemicals	7.42	Chemicals	1.99	Chemicals	9.92	Chemicals	5.36	Chemicals	1.38	Chemicals	13.3
Chemicals	11.8	Chemicals	1.18	Chemicals	9.51	Chemicals	2.45	Chemicals	1.51	Chemicals	4.87
Chemicals	3.95	Chemicals	8.55	Chemicals	8.05	Chemicals	1.27	Chemicals	3.97	Chemicals	2.16
Chemicals	1.28	Chemicals	3.55	Chemicals	3.82	Chemicals	1.18	Chemicals	5.43	Chemicals	11.6
Chemicals	1.35	Chemicals	9.12	Chemicals	3.01	Chemicals	2.6	Chemicals	5.52	Chemicals	5.67
Chemicals	1.71	Chemicals	2.55	Chemicals	7.57	Chemicals	1.19	Agriculture	1.44	Chemicals	1.09
Chemicals	4.39	Chemicals	2.26	Chemicals	4.78	Chemicals	2.21	Stone	1.43	Chemicals	2.27
Chemicals	1.17	Chemicals	2.72	Chemicals	2.63	Chemicals	5.43	Metals	1.24	Chemicals	4.23
Chemicals	2.4	Agriculture	1.5	Agriculture	2.44	Chemicals	5.15	Vehicles	5.96	Chemicals	1.32
Agriculture	2.87	Agriculture	1.31	Agriculture	1.34	Agriculture	1.62	Vehicles	8.48	Chemicals	1.11
Agriculture	1.52	Textiles	1.23	Textiles	1.96	Agriculture	1.07			Chemicals	2.99
Agriculture	1.08	Stone	1.12	Stone	13.8	Textiles	1.78			Chemicals	3.46
Textiles	1.85	Metals	1.52	Stone	1.29	Textiles	1.21			Chemicals	3.78
Stone	1.31	Metals	1.2	Metals	1.1	Stone	2.02			Chemicals	1.11
Metals	1.77	Metals	2.1	Metals	1.01	Stone	1.73			Chemicals	1.1
Metals	1.05	Metals	1.69	Metals	1.04	Metals	1.72			Chemicals	7.36
Metals	1.94	Vehicles	2.46	Vehicles	5.16	Metals	1.44			Chemicals	11.1
Metals	1.21	Machinery	1.27	Vehicles	1.26	Vehicles	2.97			Chemicals	9.53
Metals	2.82					Vehicles	2.24			Chemicals	1.13
Metals	1.38									Chemicals	1.78
Metals	2.91									Chemicals	2.88
Metals	1.95									Agriculture	2.51
Machinery	1.12									Agriculture	1.39
										Agriculture	3.02
										Textiles	1.07
										Stone	1.5
										Stone	2.38
										Stone	1.42
										Stone	3.19
										Metals	1.04
										Metals	2.09
										Metals	1.59
										Metals	2.08
										Metals	1.46
										Metals	1.63
										Metals	1.23
										Metals	1.83
										Metals	1.46
										Vehicles	2.44
										Vehicles	6.93
										Vehicles	10.1
										Vehicles	6.06

Source: Observatory of Economic Complexity

For a country, a value of RCA equal to 3, for example, means that per capita exports of the product in question are three times the world's exports per capita. From table 1 we can observe that the number of products with RCA>1 has been multiplied by more than two between 2014 and 2018. In addition, a study by Chemingui and Park (2019) shows that Saudi Arabia has reduced the proportion of products of level 9 in the scale of sophistication from about 90% in 2006 to about 64% in 2016 (see figure 4). This ascertainment proves that Saudi Arabia has begun its structural transformation and improved its production sophistication. Its product space is denser and contains more sophisticated products with high RCA.

Figure 4: Comparative changes in the structure of exports by sophistication level (in %) in 2006 and 2016: Saudi Arabia versus the OECD countries.

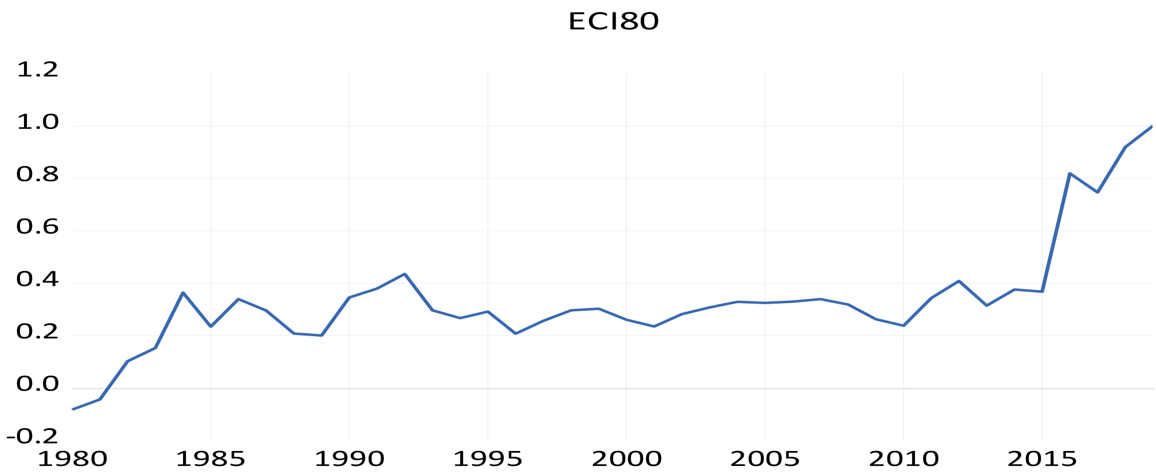
Source: Chemingui and Park (2019).

3.2 Saudi Arabia economic complexity ranking

Based on the methodology developed in section 2, Hidalgo and Haussmann (2009, 2010, 2011) have elaborated the Economic Complexity Index (ECI) to rank countries according to the complexity of their exports. The ECI takes into account the two dimensions of diversity and ubiquity. The index of economic complexity reveals the accumulation of productive knowledge and capabilities by a country and their use to produce more complex products. A high ECI indicates that the country has specialized and sophisticated capabilities and has, therefore, potentialities to produce a highly diversified set of complex products. The calculated index takes values between -2.5 for less complex countries and 2.5 for the more complex ones. From 2000 till 2019 the ranking of Saudi Arabia and its

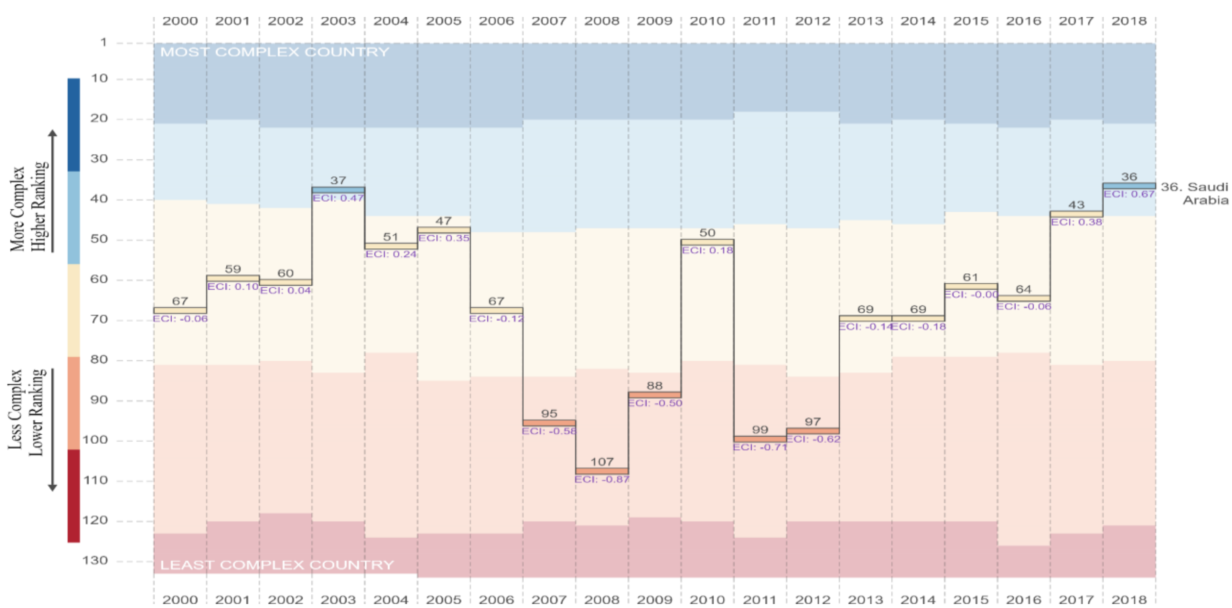
ECI have a saw-tooth trend with a net progression during the last five years in concordance with the implemented reforms. In 2019, Saudi Arabia had an ECI of 1.002 making it the 29th most complex economy in the World.

Figure 5: Economic Complexity Index for Saudi Arabia 1980-2019



Source: Authors' and OEC**.**

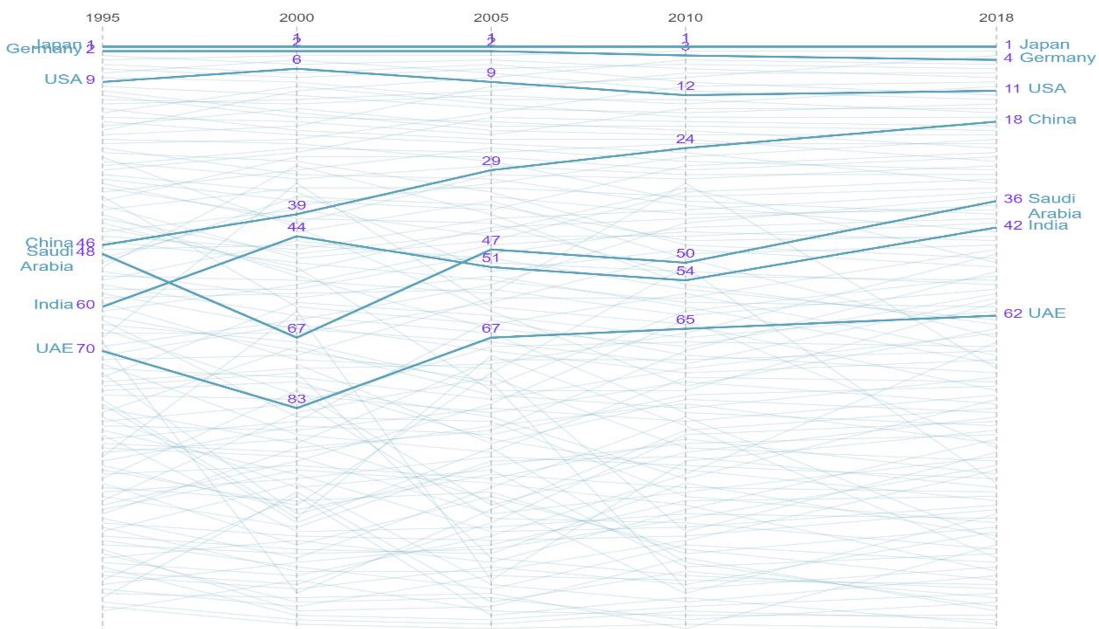
Figure 6: Economic complexity index and ranking evolution of Saudi Arabia



Source: Atlas of economic complexity

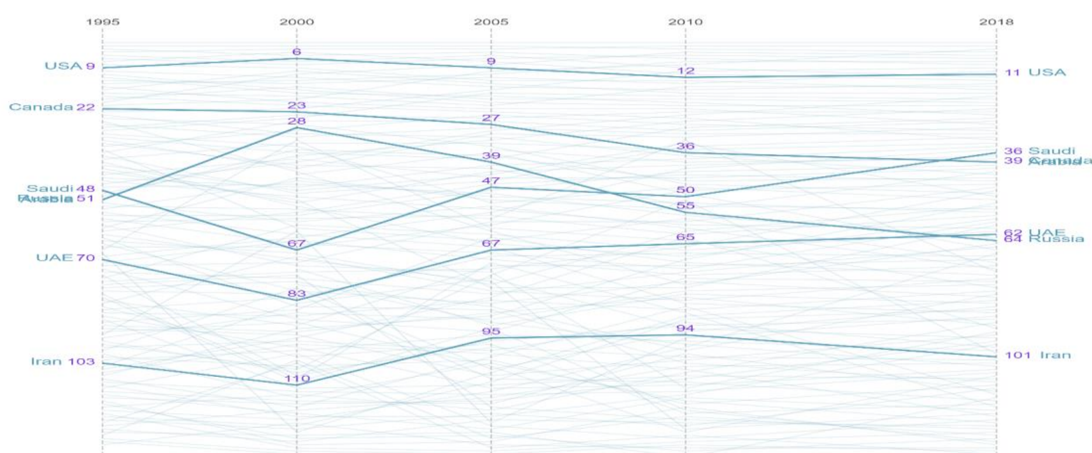
Compared to its main trade partners Saudi Arabia is behind developed countries but is better classified than India and UAE. When compared to oil-rich countries, Saudi Arabia surpasses all its rivals and is only surpassed by the USA. Compared to MENA countries, Saudi Arabia is classified first since 2012 till nowadays surpassing Jordan and Tunisia that were leaders till 2012.

Figure 7: Economic complexity ranking of Saudi Arabia and its main trade partners



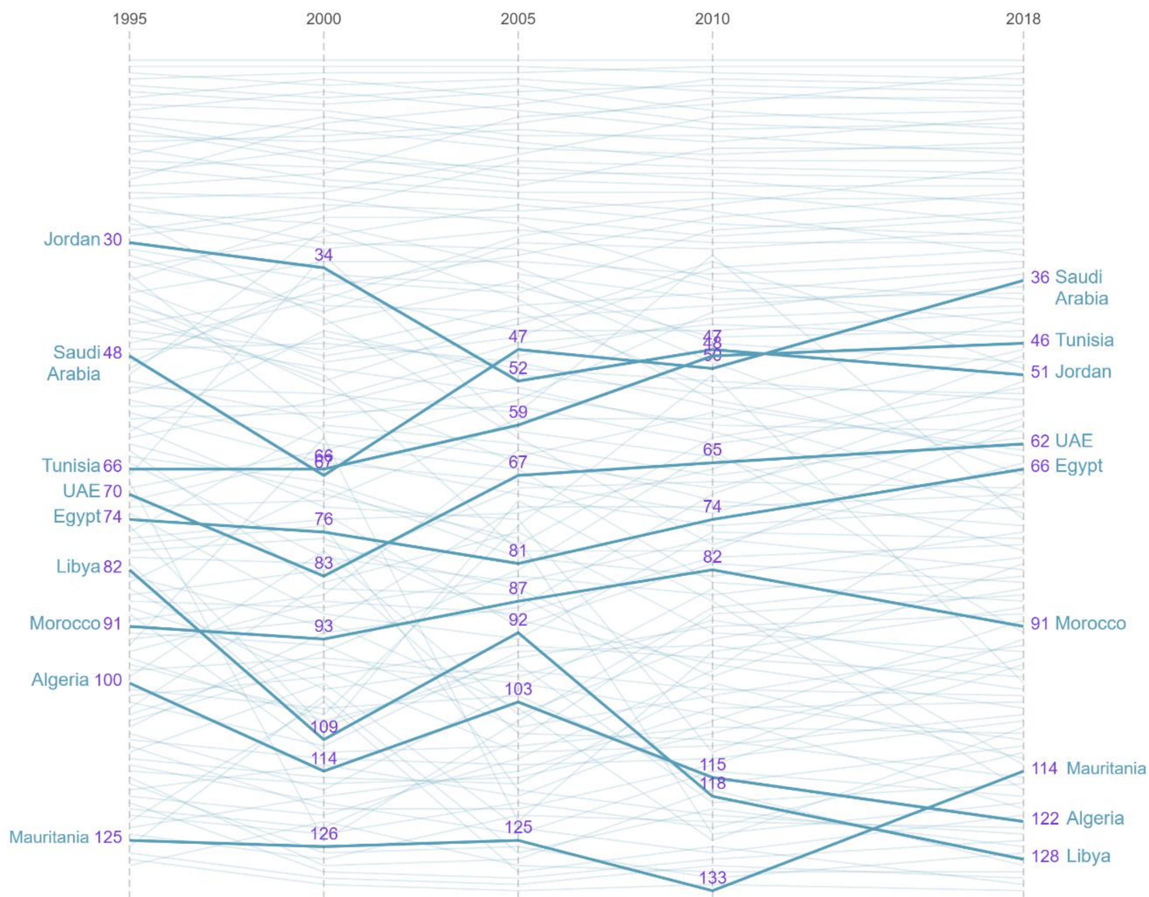
Source: Atlas of economic complexity.

Figure 8: Economic complexity ranking of Saudi Arabia and oil-rich countries



Source: Atlas of economic complexity.

Figure 9: Economic complexity ranking of Saudi Arabia and MENA countries



Source: Atlas of economic complexity.

The different graphics comparing Saudi Arabia's complexity ranking to developed countries, oil-rich countries, and developing countries indicate an improvement in the level of economic complexity relative to its pairs. In this sense, Saudi Arabia progressed between 2000 and 2018, from 66th rank to 36th out of 125 countries. These positive changes in the classification by level of economic complexity imply that the productive structure of the country has evolved. According to Hidalgo et al. (2007), the acquisition of a new product position does not happen randomly but is based on the existence of already productive knowledge.

3-3 Discovering new products at Saudi's knowledge frontier

We try to identify which products could increase the complexity of Saudi's economy, resulting in a more diverse and attractive product mix, but lie nearby Saudi's current capabilities so as to be feasible. These "Frontier Products" should satisfy many criteria: (i) they are more complex than Saudi already exports, (ii) they are feasible given Saudi's productive knowledge, and (iii) they open up paths for future diversification.

To do so, we follow Haussmann and Hidalgo (2011) and use measures of product complexity (PCI), Proximity (Distance between products), and opportunity gain.

To be optimal, a country should diversify by creating new products that have the highest PCI, shortest distance, and highest opportunity gain. However, it is usually difficult to attain simultaneously the three properties and the country should make a trade-off.

For most countries, we usually observe that the products that have the highest PCI and the highest opportunity gain are farthest away in terms of Distance.

Product Complexity Index (PCI): this index captures the amount and sophistication of know-how (capabilities) required to produce a product. It allows ranking the diversity and sophistication of the productive know-how required to produce a product. Using definitions of diversity and ubiquity presented below, for a country c and products p_1 and p_2 we can set PCI as follows:

$$\mathrm{PCI}_{p_1,p_2} = \sum_c \frac{M_{cp_1} M_{cp_2}}{k_{c,0} k_{p_1,0}}$$

Proximity: it determines how far or nearby a country is to a new product. It captures the ease of obtaining the know-how needed to move from a product to another product. We use the minimum conditional probability to calculate the proximity between any two products, that is if a country exports one also exports the other[3].

$$\theta_{p_1,p_2} = \min(P(p_1|p_2), P(p_2|p_1))$$

For example, suppose 20 countries export product p_1, 28 export product p_2, and 12 export both, all with RCA>1. The minimum conditional probability is:

[3] Hidalgo and Haussmann suggest taking the minimum probability of product P_1, given product P_2, and vice versa, since conditional probabilities are not symmetric.

$$\theta_{p_1,\,p_2} = \min(\frac{12}{20}, \frac{12}{28})$$

Then, the proximity between product p_1 and product p_2 is equal to 12/28=0.428. This means that a country that exports p_1 has a 42.3% of chance to export p_2.

Formally, for a country c, exporting product p_1 will also export product p_2, the minimum conditional probability is calculated as follows:

$$\theta_{p_1,p_2} = \frac{\sum_c M_{cp_1} M_{cp_2}}{Max(k_{0,p_1}, k_{p_2,,0})}$$

Then, the distance of a product is calculated as the sum of the proximities connecting that product to all the products that the country is not currently exporting. Formally, for a product p_1 and a country c, the distance is:

$$d_{cp_1} = \frac{\sum_p (1-M_{cp})\theta_{p_1,p}}{\sum_p \theta_{p_1,p}}$$

A distance close to 0 means that the country produces and exports most of the products connected to the product p_1 while a distance close to 1 indicates that the country exports a small ratio of products that are close to p_1.

The term $\left(1 - M_{cp}\right)$ counts only the products the country is not currently producing.

Opportunity gain: it allows to measure the improvement of a country's position in the product space by the development of a new product. It reveals the incidence of new products on country's future opportunity for diversification. It accounts for the complexity of the products not being produced in a country and the distance for how close to existing capabilities that new product is. Using opportunity value which summarizes the value of a country's strategic position in the product space, we can calculate opportunity gain as the change in opportunity value from developing RCA in new product.

Formally, for a country c and a product p_1, opportunity gain (OG) is as follows:

$$OG_{cp} = \sum_{p_2} \frac{\theta_{p_1,p_2}}{\sum_{p_3} \theta_{p_3,p_2}} (1 - M_{cp_2}) PCI_{p_2}$$

Where PCI_{p_2} is the product complexity of the product p_2. A higher value of OG indicates that a product is in the proximity of more products and/or products that are more complex.

According to Haussmann et.al (2011), countries with higher complexity have many opportunities and vice versa. Having assessed the different measures to design product space, we try in what follows to look to the case of Saudi Arabia.

3.4 Product space for Saudi Arabia 1995-2018 and scheme of evolution

The concept of product space introduced by Hidalgo et al. (2007) can be defined as the network of relatedness between products and is used to study the evolution of a country's productive structure. Knowing the product space for a country can help to identify which products might be developed based on existing know-how and capabilities. It's easier for a country to develop new products that have near neighbors in the product space and need similar capabilities which are already present in the country. Moreover, if a country has the requisite capabilities and know-how to produce a complex product, it can redeploy them to make another. Consequently, the more the product space is dense the more the country can jump to produce a set of new more sophisticated products. A country can't accumulate know-how in things that it doesn't produce and can't produce things without the requisite know-how. According to Haussmann (2016), this dilemma could be solved when the country diversifies into products requiring already existing know-how.

The intuitive analogy, developed by Haussmann (2016), of monkeys, jumping from a tree to another in a forest and a country improving its economic complexity through product-space is very informative to understand the country's process of development. When the forest (the product space) is dense, monkeys (countries) can progress rapidly and easily. When trees (products) are distant from each other, monkeys (countries) need many additional capabilities, that could not have, to progress.

The concept of product space shows that countries have different opportunities for economic development: countries situated in the dense zone of the product space will have many possibilities of diversification while those in the periphery will face many challenges and are usually "stuck" at a certain level of income.

However, capabilities are not observed but according to Hidalgo and Haussmann (2009), it is possible to weigh them in a country without making any assumption on their nature. To create measures, their methodology incorporates information that combines the diversification of countries and ubiquity of products. They propose to measure complexity and know-how indirectly by using trade data. In this vein, they construct a model in which they combine two matrices, a country-capability matrix C_{ca}, and a product capability matrix P_{pa} to obtain the matrix M_{cp} connecting countries to the products that they make or export. In the matrix C_{ca} each row summarizes the capability endowment of country c, while in the matrix P_{pa} each row summarizes the capability requirements of product p. Then C_{ca}=1 means that country c has capability a and 0 otherwise and P_{pa}=1 if product p requires capability a and 0 otherwise. The system of matrices (C_{ca}, P_{pa}, M_{cp}) is interpreted as a bipartite network connecting countries to the capabilities they have, products to the capabilities they require, and countries to the products they make or export.

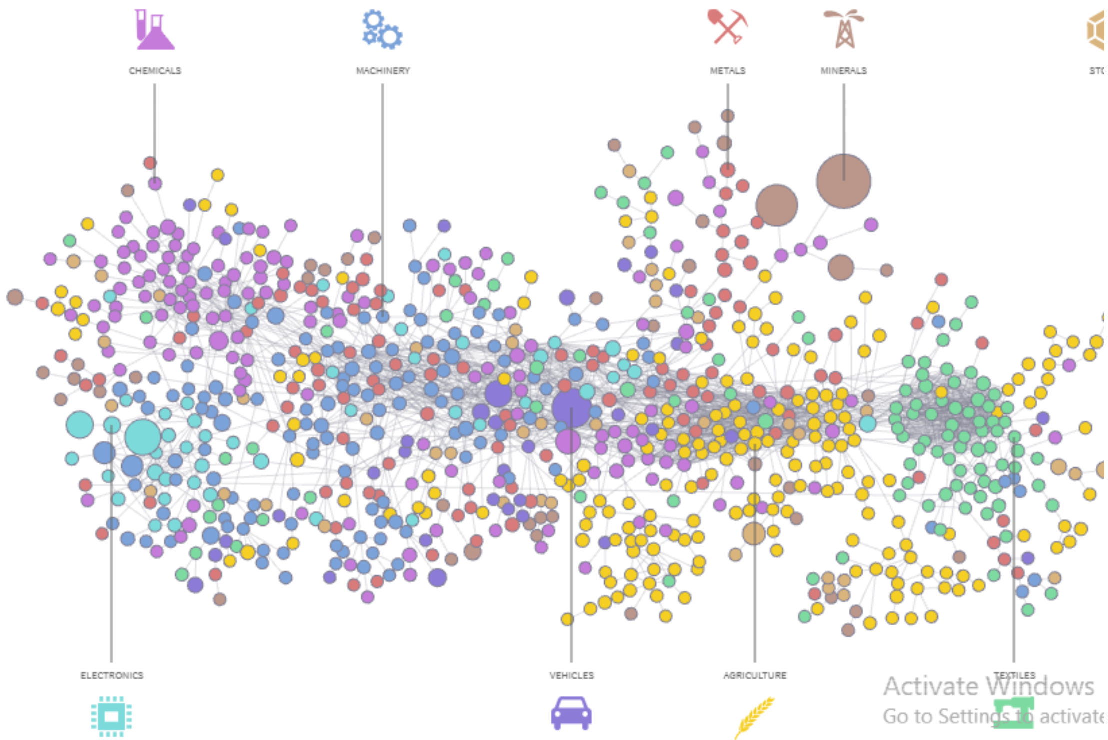
According to this configuration, in a world composed by N_c countries, N_p products, and N_a capabilities, a country can be located in the product space by the knowledge of the products in which it has a comparative advantage. Moreover, by calculating the weighted distance between products in which the country has a comparative advantage and those in the neighborhood, one can calculate the probability that a country will improve its comparative advantage and broaden its productive structure by looking at the possibility of moving into new products.

Briefly, the product space provides a unique path of transformation for each country depending on its capabilities and know-how taking into account proximity and distance measurements.

In order to represent the product space of a country, researchers use nodes and colors. Each node and color represent a product. The size of nodes represents the share of the product in world trade and is proportional, but not linearly, to the complexity of the product. That is, bigger nodes imply a high volume of trade.

In general, the product space demonstrates that products with high complexity have intense connections with other products and are at the core of the product space. These products, such as machinery or chemicals are usually produced by advanced economies. On the other hand, low product complexity has weak connections and appears in the periphery of the product space. These kinds of products, such as agricultural goods or mineral products are usually produced by developing or less developed countries. Product space is then an instructive tool to study the evolution of a country's productive structure. Figure 10 presents a typical product space for a given country and shows the localization of each product or group of products in the product space.

Figure 10: Theoretical product space



Source: Observatory of Economic complexity

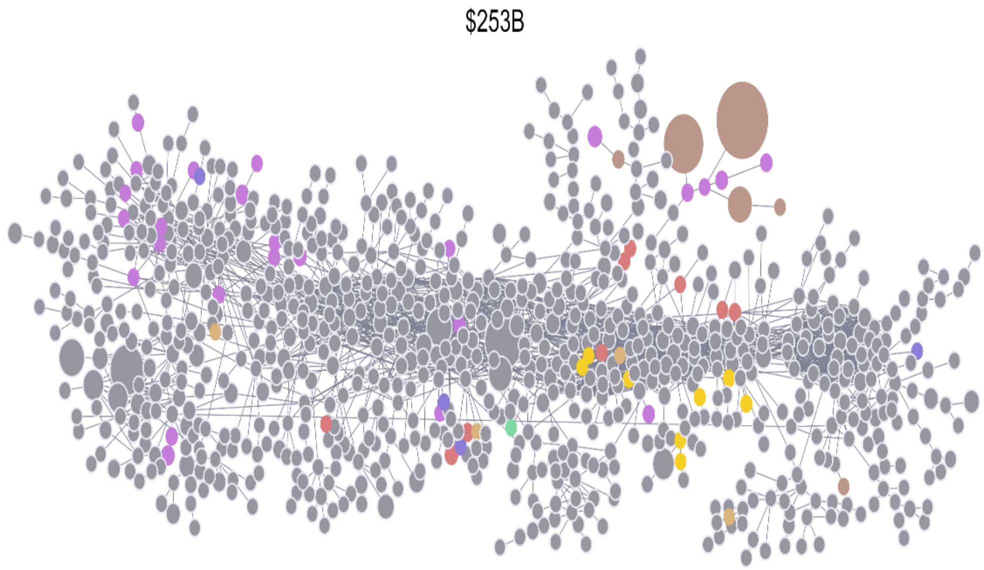
The visualization of the product space for Saudi Arabia for different years (2018, 2014, 2010)[4] is presented in figures 11-12-13. We can depict that these nodes are very distant from each other. Nodes representing minerals are the most important and are localized in the periphery of the product space. The product space is dominated by grey nodes which are products not produced by Saudi Arabia. This indicates that Saudi Arabia's existing know-how affords a moderate number of opportunities to diversify into new more complex products. To exploit nearby opportunities for future potential diversification, Saudi Arabia should make long jumps into the product space.

Nevertheless, the product space of 2018 is relatively denser than prior years indicating that the number of exported complex products (products with RCA>1) has substantially

[4] See also for (1995, 2000, 2005) in the appendix.

increased. This performance is essentially observed in the sector of complex chemical products. This dynamic reveals the clear orientation of Saudi Arabia in the sophistication of its economy. These efforts have been confirmed by the complexity outlook index, which ranks, in 2018, Saudi Arabia 80th among 133 countries[5].

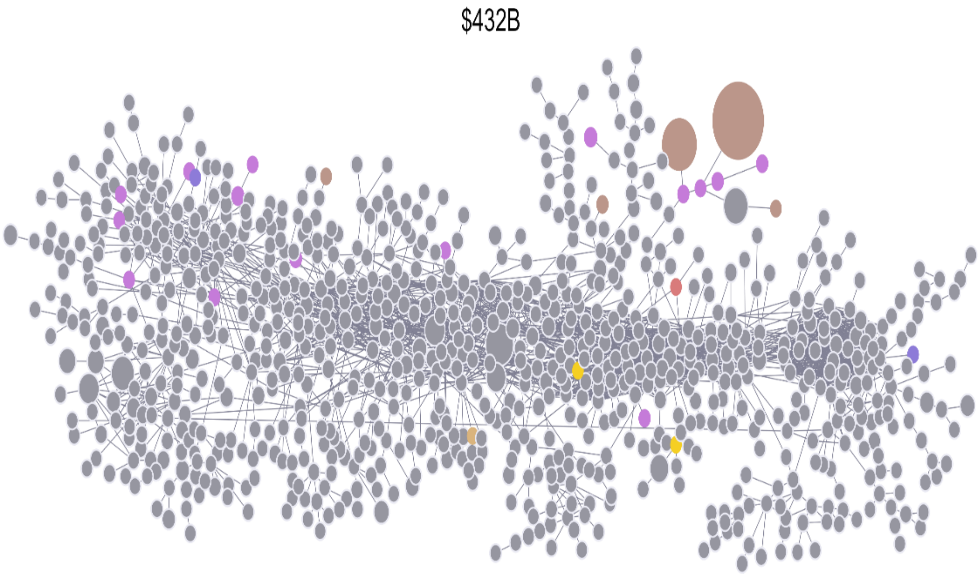
Figure 11: Product space 2018 of Saudi Arabia



Source: Observatory of Economic complexity

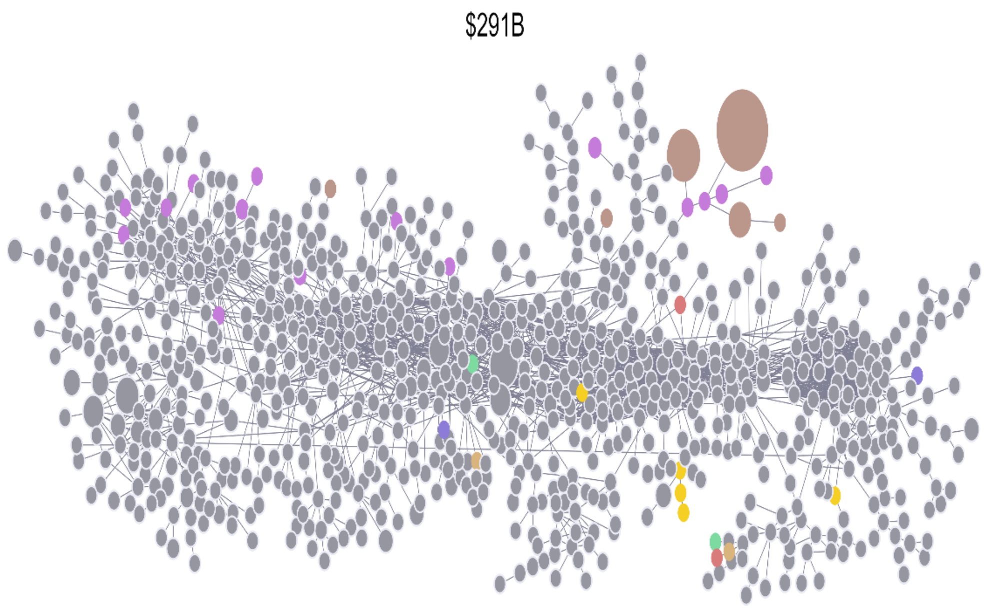
Figure 12: Product space 2014 of Saudi Arabia

[5] The complexity outlook index measures the number of complex products which are near a country's set of productive capabilities.



Source: Observatory of Economic complexity

Figure 13: Product space 2010 of Saudi Arabia



Source: Observatory of Economic complexity

3. Economic complexity and sustainable growth

Recent theoretical and empirical works argue that the modernization of economies is crucially based on the sophistication and complexity of their export products. For an economy, product complexity reveals the amount of knowledge available in the country and is a reflection of national production capabilities (non-tradable inputs). The more a country has greater capabilities, the higher its productivity will be, and thus, the country will grow rapidly and develop faster (Felipe et al. 2012). Rodrik (2014) argues that economic complexity defines a wider term for capabilities and the accumulation of capabilities is necessary for sophisticated production which induces higher economic growth in the long run. According to Yildirim (2014), the process of diversification leads to production sophistication which allows a country to jump to new and more productive activities which is the key driver behind economic growth.

Many empirical works show that there is a positive relationship between diversification and growth and between sophistication and growth. In recent papers, these two proprieties of diversification and sophistication are represented through the new concept of the economic complexity index. As has been assessed in previous sections, for each country, the diversity and sophistication of the productive capabilities embedded in its exports are an expression of its economic complexity. Most of the recent empirical works have confirmed a positive association between the rate of economic growth of a country and its economic complexity.

Furthermore, cross-country studies show that differences in income are mainly due to complexity differences. Among others, Haussmann et al., (2011) find that on average countries whose export baskets are less complex than their income tend to grow slower, and those whose exports are more complex than their income tend to grow faster.

Analyzing the relationship between economic growth and complexity of 128 countries, they find that complexity explains 73% of the variation of income per capita. More deeply, Haussmann et al. (2011) compare the effect of complexity on growth with three other determinants of growth, institutional quality, human capital, and competitiveness, and conclude that the economic complexity index is the best contributor to economic growth. In the same line, using a panel of 103 countries for the period 1970-2010, Bastos and Wang (2015) examined the importance of diversification and complexity. They conclude that complexity and diversification have positive and significant effects on economic growth. By controlling for years of schooling, labor force participation rate, and active population and using the concept of product space density, Ferrari and Scaramozzino (2013) show that countries with denser product space enjoy relatively faster growth. More recently, Camargo and Gala (2017) by comparing the case of Nigeria and Indonesia as oil-rich countries, examine whether Dutch disease can be explained through economic complexity. Their empirical findings show that Dutch disease is identified only for Nigeria which has low economic complexity. Using panel dynamic OLS for long-run effects and system GMM for short-run effects and a panel of southeastern and central European countries, Stojkoski and Kocarev (2017) find a significant and positive long-run relationship between economic complexity and economic growth, but no evidence for a short run.

Literature (see among others Felipe et al. (2010)) shows also that the reason behind the high growth rate of some Asian countries such as Korea, Singapore, and China during the last decade, is due to a successful implementation of structural transformation these countries have undergone.

Table 2 Shows that there is a high correlation between the degree of complexity and the level of wealth of a country. That is, countries with high complexity also have relatively higher GDP per capita and vice versa.

Table 2: Complexity and GDP per capita Rankings for 2018

Rank	Country	ECI	PCGDP $2010
1	Japan	2.43	48766
2	Switzerland	2.17	79235
3	South Korea	2.11	28158
4	Germany	2.09	47314
5	Singapore	1.85	59073
6	Austria	1.81	27596
7	Czechia	1.80	23801
8	Sweden	1.70	57911
9	Hungary	1.66	16793
10	Slovenia	1.62	26760
36	**Saudi Arabia**	**0.67**	**20820**
133	Nigeria	-1.90	2383

Source: Atlas economic complexity and World Bank.

In reality, most of the empirical studies on the relationship between economic complexity and economic growth have been using cross-section or panel data. Works interested in one country case are very scarce because of the lack of data.

One of the main goals of this research is to fill the gap in the literature and study the effect of complexity on economic growth in Saudi Arabia and try to detect the possible interaction effects between complexity and human capital on growth. One possible motivation to detect such a connection is that we believe that there is unexploited productive potential in Saudi Arabia and that the country is below the income expected from its capability endowment and should develop all of the products that are feasible with its existing capabilities.

4- Model specification, data, and econometric methodology

4.1 Model specification

The new theoretical framework developed by Haussmann et al. (2007) and Hidalgo et al. (2007) relating the growth and development of countries to the complexity of products they produce and export, received justified attention among researchers and generated many empirical works. In this section, we aim to contribute to the economic growth-economic complexity nexus by studying the effects of economic complexity and human capital on economic growth in Saudi Arabia. In this context, we estimate the following model:

$$\mathbf{PCGDPG_t = \alpha + \beta_1 HDI_t + \beta_2 ECI_t + \beta_3 (HDI_t \times ECI_t) + \sum \gamma_j x_{t,j} + \varepsilon_t}$$

where $\mathrm{PCGDPG_t}$ represents real per capita GDP growth as a measure of economic growth, $\mathrm{HDI_t}$ is human development index, $\mathrm{ECI_t}$ is economic complexity index, and $\mathrm{x_{t,j}}$ are control variables. In this model economic growth is mainly explained by the economic complexity index (ECI) for all the considerations developed above, and by human capital and the interactions between them. Accordingly, in endogenous growth theory, the main driver of economic growth is human capital and its cooperation with physical capital. Investment in education, which is the main component of human capital, not only increases the productivity of the worker but increases the social rate of return. In addition, more education helps to accumulate more capabilities which are a source of economic growth (see, for example, Pelinescu (2015)).

In the literature, many other determinants of growth have been suggested and can be divided into two main groups. The first group concerns macroeconomic variables such as investment or gross capital formation to GDP ratio, inflation rate, school enrollment, foreign direct investment, competitiveness, research and development investment, and labor force participation rate. The second group is related to institutional variables that measure the quality of the institution and good governance. In this paper, we consider four control variables, trade openness, quality of institutions, foreign direct investment, and gross capital formation ratio. The choice of control variables is assessed on theoretical considerations. In both classical and Keynesian theory, investment is recognized as the most important factor of growth. Increasing capital stock through investment will help to increase aggregate demand generating short-run economic growth. Moreover, investing in new capital goods could improve the productive capacity of a country and increase the productivity of labor yielding long-run growth.

The second control variable is trade openness (TO), measured by the weight of exports and imports on GDP. New international trade theory developed by Krugman and Obstfeld (2006) and Grossman and Helpmann (1991) recognizes that international trade helps economic growth through innovation and knowledge diffusion. Moreover, as developed previously there exist a link between export sophistication and the level of per capita GDP. The third control variable is the foreign direct investment (FDI). The idea that inward FDI helps recipient countries to accumulate capabilities and recombine them has been introduced by Romer (1993) when developing endogenous growth models. The main idea behind these models is that foreign investments is one of the most important channels for the introduction of new ideas, and new products, into less developed economies that lack the know-how to produce them. FDI can improve the average economic complexity of a country, directly by producing technology and knowledge-intensive goods and indirectly through the knowledge spillover that can occur between foreign multinational enterprises and local firms. Then countries can increase product diversity and exclusivity and raise their average complexity through their degree of attraction for FDI. The FDI-growth nexus can then be interpreted through economic complexity By attracting more FDI, countries. In this vein, Antonietti and Franco (2021), using a sample of 117 countries over 22 years, show that increasing the amount of inward FDI per capita Granger causes improvement in the country's economic complexity.

The last control variable we introduce in our empirical model is institutional variable. Many contributions argue that institutions' quality is one of the main drivers of long-run economic performance. Works by North (1990), Acemoglu et al. (2005) emphasized the importance of institutions as "the rule of the game in a society" and argued that the main factor behind economic growth is institutions' quality. Moreover, the quality of institutions institutional enhances motivations to invest in human and physical capital and innovative activities leading to more sophisticated products and a more complex economy. Hence, countries can improve their human capital and enhance economic complexity through good institutions and this could explain wealth differences across countries.

4.2 Data sources and statistical proprieties of variables

4.2.1 Data sources

Our data are gathered from different sources. Two fundamental sources calculate the economic complexity index, the Atlas of Economic complexity[6] developed by Haussmann et al. (2011) and the Observatory of Economic complexity[7] by Simoes and Hidalgo (2011). In this work, we use the ECI calculated by Simoes and Hidalgo because it covers a long period going back to 1961 and uses both Standardized International Trade Classification (SITC) and Harmonized System (HS).

Macroeconomic variables such as per capita GDP, Exports, imports, and foreign direct investment, and gross capital formation are from the World Development Indicators (WDI)[8] database of the World Bank. The human development index is from the Human Development Report of the United Nations Development Programme (UNDP)[9].

World Bank's Worldwide Governance Indicators database (WGI) reports the rule of law, government efficiency, and other indices of institutional quality. Nevertheless, data exist only for the years 1996, 1998, and 2000–2014. Lucking many observations for the period 1980-2019, we have introduced such an index in our empirical model by estimating a separate equation with the rest of the control variables.

In what follows we study the statistical proprieties of the series and run unit root tests to determine the degree of integration of the series and assess the econometric methodology.

4.2.2 Statistical proprieties of the variables

Table 3 presents statistical indicators of the variables and table 4 concerns pairwise correlation matrix. We can observe that there exists a positive correlation between economic growth and economic complexity and between economic growth and human

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[6] https://atlas.cid.harvard.edu.

[7] https://oec.world.

[8] http://wdi.worldbank.org.

[9] http://hdr.undp.org.

development index, and between economic growth and their combined effect. Economic complexity is positively correlated to human development and gross capital formation but negatively influenced by trade openness and by foreign direct investment. The latter result appears strange but could be explained in the case of oil-rich countries in general and in the particular case of Saudi Arabia. In fact, exports of Saudi Arabia are dominated by mineral products which present a low degree of sophistication and low level of complexity. In addition, till recent years and before Saudi Arabia has assessed its new investment policy and economic reform program in concordance with Vision 2030 which aims at improving the investment environment in the country and promoting economic diversity, more than 66% of FDI were oriented to sectors producing low complex products such as, coal, oil and natural gas, metals, and real estate. These intuitive results will be consolidated or mitigated by econometric and causality tests.

Table 3: Descriptive statistics

	PCGDPG	ECI80	HDI	ECI80HDI	FDIP	TOP	GCFP
Mean	-0.020864	0.334612	0.732283	0.256520	0.016355	0.741644	0.238336
Median	-0.004842	0.305181	0.73990	0.219134	0.010437	0.714141	0.225623
Maximum	0.113127	1.002000	0.859000	0.855708	0.084964	0.961026	0.343505
Minimum	-0.382104	-0.081941	0.583000	-0.047772	-0.019401	0.560884	0.156841
Std.Dev.	0.096355	0.210647	0.087074	0.184936	0.025947	0.111202	0.049674
Skewness	-1.722659	1.466224	-0.084906	1.780878	1.069807	0.396269	0.592151
Kurtosis	7.035454	6.091250	1.754669	6.388837	3.337992	1.968621	2.249349
Jarque-Bera	46.92517	30.25846	2.632810	40.28387	7.820311	2.819766	3.276746
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	-0.834570	13.38449	29.29130	10.26078	0.654195	29.66575	9.533423
Sum Sq. Dev	0.362090	1.730513	0.295639	1.333848	0.026257	0.482266	0.096232
Observations	40	40	40	40	40	40	40

Table 4: Correlation matrix

	PCGDPG	ECI80	HDI	ECI80HDI	FDIP	TOP	GCFP
PCGDPG	1.000000	0.357493	0.438624	0.319846	-0.057171	-0.259440	-0.229582
ECI80		1.000000	0.642433	0.990467	-0.112940	-0.365974	0.283037
HDI			1.000000	0.702400	0.112356	-0.040609	0.397616
ECI80HDI				1.000000	-0.092722	-0.313630	0.327024
FDIP					1.000000	0.643962	0.507259
TOP						1.000000	0.352771
GCFP							1.000000

4.2.3 Unit Roots Tests

Unit root tests are usually performed to avoid spurious regression. In the literature, many tests are proposed according to the nature of the non-stationarity. In this work, we use the NP test of Ng-Perron (2001) and the DF-GLS test of Elliot-Rothenberg-Stock (1996) unit root tests because ADF tests are known to suffer potentially severe finite samples power and size problem. When the results of the two tests above are inconclusive, we perform the Phillips-Perron test (PP) which estimates the non-augmented Dickey-Fuller equation and allows controlling for serial correlation.

Results of table 5 show that the series under study have a mixed level of stationarity. This result induces that, traditional econometric techniques are not suitable and we have to perform the ARDL model to take into account series specificities. ARDL model allows also to look for cointegration relationships and test for short and long-run causality.

Table 5. Unit Root Tests on levels and Differences

	Ng-Perron test statistics*				DF-GLS test**	PP***	Result
Variables	MZα	MZt	MSB	MPT			
ECI	-2.56	-0.85	0.33	8.36	-1.20		
ΔECI	-44.18	-4.69	0.10	0.55	-6.93	-7.74	I(1)
PCGDPG	-17.99	-2.99	0.16	1.36	-4.63	-4.65	I(0)
GCF	-8.45	-1.99	0.23	3.12	-2.25		
	-18.58	-2.97	0.16	1.59	-5.21	-8.28	I(1)
HDI	-12.05	-2.30	0.19	2.28	-1.43		
ΔHDI	0.35	0.26	0.74	36.47	-1.04	-3.98	I(1)
TO	-3.07	-1.09	0.35	7.72	-1.28		
	-17.1	-2.91	0.17	1.48	-4.39	-4.40	I(1)
FDI	--7.52	-1.93	0.25	3.25	-2.23		
ΔFDI	-11.7	-2.39	0.20	2.19	-3.16	-6.64	I(1)
IQ[a]	-1.567	-0.622	0.397	11.12	-0.68		
Δ IQ	-9.30	-2.15	0.231	2.64	-6.91	-6.81	I(1)
Asymptotic critical values 1%	-13.8	-2.58	0.174	1.78	-2.63	-3.61	
5%	-8.1	-1.98	0.233	3.17	-1.95	-2.94	
10%	-5.7	-1.62	0.275	4.45	-1.61	-2.60	

Note: * Perron (2001). ** Elliot et al. (1996). *** Phillips Perron (1988) and are calculated only for differences. a: the series has 25 observations.

4.3 ARDL model, implementation, and estimation

ARDL models are a combination of AR (Autoregressive models) and DL (Distributed Lag models). Consequently, they can accommodate a variety of lag structures and include well-known models such as static regressions. ARDL are dynamic models taking into account temporal dynamics (adjustments, expectations) to explain a variable (time series) improving its prevision and policy efficiency.

The general form of the ARDL(p,q) model can be written as follows:

$$y_t = \mu + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{j=0}^{q} \beta_j x_{t-j} + \varepsilon_t \qquad (4)$$

Where y_t is the dependent variable and x_t is a vector of explanatory variables, and $\varepsilon_t \sim iid(0, \sigma)$ is the error term. The lag orders are usually chosen according to an information criterion. The optimal model is the one with the smallest value of the AIC or

BIC[10]. In this model, the short-term effect of the variable x on y is revealed by β_0 while the long-run effect is obtained through $\gamma = \frac{\sum \beta_j}{1-\sum \alpha_i}$.

In order to investigate the existence of cointegration relationships among ARDL variables, Pesaran et al. (1995, 2001) developed the ARDL-Bounds test. This methodology has many advantages. First, unlike the multivariate procedure of Johansen and Juselius (1990) which is eager in data, the bounds test procedure is suitable for a small sample size. Second, unlike conventional cointegration procedures, the ARDL model can circumvent the problem of the order of integration of the series. Third, the ARDL model can provide unbiased estimates in the long run even when some variables are endogenous. Moreover, ARDL models are useful to disentangle long-run relationships from short-run dynamics which is interesting propriety when studying economic problems.

To test the existence of cointegration relationships between variables in the ARDL model we first estimate the following specification using OLS.

$$\Delta y_t = \mu + \varphi_1 y_{t-1} + \varphi_2 x_{t-1} + \sum_{i=1}^{p-1} \alpha_i \Delta y_{t-i} + \sum_{j=0}^{q-1} \beta_j \Delta x_{t-j} + \varepsilon_t \qquad (5)$$

Second, the existence of a long-run relationship among the variables is conducted using an F-test for the joint significance of the coefficients of the lagged levels of the variables that are:

$$H_0: \varphi_1 = \varphi_2 = 0 \quad \text{against} \quad H_1: \varphi_1 \neq \varphi_2 \neq 0$$

The procedure of the test consists of comparing the calculated F to the critical bounds (lower, upper) value developed by Pesaran et al. (2001)[11]. If the calculated F-statistic is above the upper critical value, the null hypothesis of no long-run relationship can be rejected irrespective of the orders of integration for the variables. Conversely, if the calculated F-statistic falls below the lower critical value, the null hypothesis cannot be rejected. Finally, if the F-statistic falls between the lower and upper critical values, the result is inconclusive.

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[10] The information criteria are only comparable when the sample is held constant.

[11] Recently, Kripfganz and Schneider (2018) obtain asymptotic critical values for the lower and upper bound of all independent variables being purely $I(0)$ or purely $I(1)$ and not mutually cointegrated.

Once the cointegration relationship is established, the ARDL long-run model can be estimated as it is in equation (4). The final step is to disentangle short-run and long-run dynamics by estimating an ARDL-EC model.

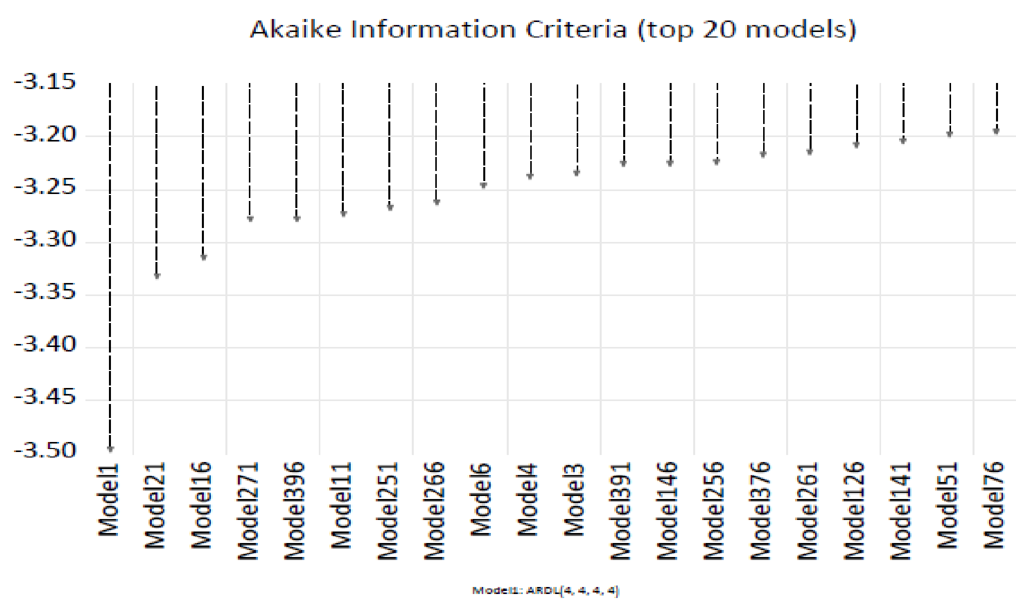
$$\Delta y_t = \mu + \sum_{i=1}^{p-1} \alpha_i \Delta y_{t-i} + \sum_{j=0}^{q-1} \beta_j \Delta x_{t-j} + \theta(ECM)_{t-1} + \varepsilon_t \qquad (6)$$

Here α and β are the short-run dynamic coefficients, $(ECM)_{t-1} = (y_{t-1} - \gamma x_{t-1})$ is the error correction term and θ is the speed of adjustment.

4-4 Empirical results

Unit root tests ensure that all variables are I(0) or I(1) and no variable is I(2). We can so perform ARDL-OLS regressions to depict cointegration relationships between the growth rate of real per capita GDP, economic complexity index, and human development index. We first estimate the lag structure of the ARDL using Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) and correct for heteroskedasticity using the Newey-West matrix. Results of graphic 14 show that among 20 estimated ARDL, the minimum value of AIC corresponds to the optimal ARDL(4,4,4,4)[12].

Graphic 14: ARDL lag structure



[12] The same result is given by SIC.

Table 6: Optimal ARDL(4,4,4,4) estimation

Variable	Coefficient	Std.Error	t-Statistic	Prob
PCGDPG(-1)	-0.456152	0.129379	-3.525690	0.0037
PCGDPG(-2)	-0.097279	0.226711	-0.429089	0.6749
PCGDPG(-3)	0.049239	0.133317	0.369339	0.7178
PCGDPG(-4)	-0.425364	0.080283	-3.056225	0.0092
ECI80	3.161428	1.012006	3.123921	0.0081
ECI80(-1)	-1.649110	1.371237	-1.202644	0.2506
ECI80(-2)	-0.657826	1.399597	-0.470011	0.6461
ECI80(-3)	-1.139424	2.296142	-0.496234	0.6280
ECI80(-4)	4.684926	1.410885	3.320583	0.0055
HDI	0.610417	4.821043	0.126615	0.9012
HDI(-1)	6.172638	3.280094	1.881848	0.0824
HDI(-2)	-6.783963	7.310956	-0.927917	0.3704
HDI(-3)	-11.36663	7.342963	-1.547962	0.1456
HDI(-4)	13.02643	5.131079	2.538731	0.0247
HDI*ECI80	-3.677180	1.383917	-2.657081	0.0197
HDI(-1)*ECI80(-1)	2.290002	1.764341	1.297936	0.2169
HDI(-2)*ECI80(-2)	0.912429	1.948211	0.468342	0.6473
HDI(-3)*ECI80(-3)	1.246872	3.651768	0.341443	0.7382
HDI(-4)*ECI80(-4)	-6.636480	2.138656	-3.103107	0.0084
C	-1.191842	1.106012	-1.077604	0.3008
R-squared	0.785726		**Mean dependent var**	0.005035
Adjusted R squared	0.472556		**S.D. dependent var**	0.058619
S.E. of regression	0.042572		**Akaike info criterion**	-3.194662
Sum squared resid	0.023561		**Schwarz criterion**	-2.287687
Log likelihood	72.71192		**Hannan –Quinn**	-2.889492
F-statistic	2.508943		**Durbin-Watson**	1.403421
Prob(F-statistic)	0.047298			

Results of table 6 show that economic growth in Saudi Arabia is highly correlated to economic complexity and human development and their combined effect with a backward effect going to 4 years. Table 7 reports the calculated F-statistic for bounds test when each variable is considered as dependent.

Table 7: ARDL Bounds test

Dependent variable	**F-statistic**		**Lags**	**Results**
PCGDPGR	**7.70**		**3**	**Cointegration**
ECI	**3.70**		**3**	**Inconclusive**
HDI	**2.23**		**3**	**No-cointegration**
ECIxHDI			**3**	**Cointegration**
Bounds test critical values	**Lower**	**Upper**		
10%	**2.618**	**3.532**		
5%	**3.164**	**4.194**		
1%	**4.428**	**5.816**		

Source: Authors' calculation

Table 8: ARDL long run form and bounds test (4,4,4,4)

condition error correction regression

Variable	Coefficient	Std.Error	t-Statistic	Prob
C	-1.3400	1.0698	-1.2525	0.2389
PCGDPG(-1)	-1.9161	0.3822	-5.0133	0.0005
ECI80(-1)	4.6297	3.7348	1.2236	0.2491
HDI(-1)	1.6715	1.4425	1.1573	0.2740
ECI80(-1)*HDI(-1)	-6.656	5.4496	-1.2213	0.2500
D(PCGDPG(-1))	0.2863	0.2892	0.9898	0.3456
D(PCGDPG(-2))	0.1859	0.1716	1.0829	0.3043
D(PCGDPG(-3))	0.2469	0.1201	2.0453	0.0680
D(ECI80)	3.46100	1.6457	2.1029	0.0618
D(ECI80(-1))	-3.8864	3.64612	-1.0659	0.3115
D(ECI80(-2))	-4.7079	3.00093	-1.5644	0.1488
D(ECI80(-3))	-5.3357	2.3429	-2.2773	0.0460
D(HDI)	-1.5676	3.4060	-0.4902	0.662
D(HDI(-1))	3.2196	4.1614	0.7736	0.4570
D(HDI(-2))	-1.676	5.73911	-0.2920	0.7762
D(HDI(-3))	-17.46388	9.1470	-1.9094	0.0853
D(ECI80*HDI))	-4.1016	2.2804	-1.7985	0.1023
D(ECI80(-1)*HDI(-1))	6.1762	5.50700	1.1215	0.2858
D(ECI80(-2)*HDI(-2))	7.1780	4.5638	1.572	0.1468
D(ECI80(-3)*HDI(-3))	7.6795	3.5560	2.1595	0.0562
FDP	-1.2179	0.76733	-1.58728	0.10435
TOP	0.2558	0.11385	2.2468	0.0484
GCFP	0.58744	0.5708	1.02914	0.3277
Variable	Coefficient	Std.Error	t-Statistic	Prob
ECI80	2.416186	1.2564	1.9228	0.0834
HDI	0.87233	0.55222	1.57966	0.1453
HDI’ECI80	-3.473499	1.932223	-1.79766	0.1024
C	-0.69934	0.36176	-1.93313	0.0820
EC = PCGDPG – (2.4162*ECI80 + 0.8723*HDI-3.4735*HDI*ECI80-0.6993)				
Test statistic	Value	Signif.	I(0)	I(1)
F-statistic	7.705195	10%	2.37	3.2
K	3	5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66
Actual sample size	33	Final Sample: n=35		
		10%	2.618	3.532
		5%	3.164	4.194
		1%	4.428	5.816
		Final sample: n =30		
		10%	2.676	3.586
		5%	3.272	4.306
		1%	4.614	5.966

Table 9: ARDL long run form and bounds test (4,0,4,2)

condition error correction regression				
Variable	Coefficient	Std.Error	t-Statistic	Prob
C	0.1449	0.16932	0.8553	0.4040
ECI80(-1)	-1.04712	0.2949	-3.5505	0.0025
PCGDPG	0.6314	0.2546	2.479	0.0239
HDI(-1)	0.3201	0.3182	1.0058	0.3286
ECI80(-1)*HDI(-1)	0.134188	0.10680	1.2564	0.2260
D(ECI80(-1))	0.3822	0.2190	1.74464	.0991
D(ECI80(-2))	0.3875	0.2432	1.5933	0.125
D(ECI80(-3))	0.5030	0.2253	2.3225	0.0393
D(HDI)	-7.7141	4.1750	-1.8446	0.0820
D(HDI(-1))	-9.5902	4.368	-2.1954	0.0423
D(HDI(-2))	11.05046	5.3201	2.077	0.0533
D(HDI(-3))	-9.5310	6.0623	-1.5644	0.1361
D(ECI’HDI)	0.0975	0.073469	1.327	0.2017
D(ECI)(-1)’HDI(-1))	0.0707	0.06069	1.1662	0.2569
FDIP	-0.0882	0.9149	-0.0694	0.924
TOP	-0.0637	0.194830	-0.3272	0.7475
GCFP	0.4957	0.5695	0.8704	0.3962
Variable	Coefficient	Std.Error	t-Statistic	Prob
PCGDPG	0.6030	0.222663	2.70958	0.0149
HDI	0.3057	0.28721	1.064423	0.3020
HDI’ECI80	0.12814	0.07880	1.26166	0.1223
C	0.13839	0.10556	1.310973	0.2073
EC = ECI80– (0.6031*PCGDPG + 0.3057*HDI-0.1281’HDI*ECI+0.1384)				
Test statistic	Value	Signif.	I(0)	I(1)
F-statistic	3.703349	10%	2.37	3.2
K	3	5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66
Actual sample size	34	Final Sample: n=35		
		10%	2.618	3.532
		5%	3.164	4.194
		1%	4.428	5.816
		Final sample: n =30		
		10%	2.676	3.586
		5%	3.272	4.306
		1%	4.614	5.966

Table 10: ARDL long run form and bounds test (2,0,2,0)

condition error correction regression

Variable	Coefficient	Std.Error	t-Statistic	Prob
C	0.01116	0.007114	1.56899	0.1293
HDI(-1)	0.002737	0.010889	0.2513	0.8036
PCGDPG	0.02096	0.010369	2.02210	0.0540
ECI80(-1)	-0.02892	0.010485	-2.75850	0.0107
HDI'ECI	-0.00100	0.002357	-0.425375	0.6742
D(HDI)(-1))	-0.23684	0.201527	-1.17524	0.2510
D(ECI80)	-0.02544	0.006260	-4.065091	0.0004
D(ECI80(-1))	0.00205	0.00795	0.258352	0.7983
FDIP	-0.02804	0.03465	-0.800978	0.4257
TOP	-0.003617	0.008460	-0.427525	0.6724
GCFP	0.03529	0.017761	1.9847	0.0579
Variable	Coefficient	Std.Error	t-Statistic	Prob
PCGDPG	0.6030	0.222663	2.70958	0.0149
HDI	0.3057	0.28721	1.064423	0.3020
HDI'ECI80	0.12814	0.07880	1.26166	0.1223
C	0.13839	0.10556	1.310973	0.2073
EC = HDI– (-7.6606*PCGDPG + 10.5680*ECI80+0.3664*HDI*ECI-4.0774)				
Test statistic	Value	Signif.	I(0)	I(1)
F-statistic	2.239558	10%	2.37	3.2
K	3	5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66
Actual sample size	36	Final Sample: n=40		
		10%	2.592	3.532
		5%	3.1	4.194
		1%	4.431	5.816
		Final sample: n =35		
		10%	2.618	3.532
		5%	3.164	4.194
		1%	4.428	5.816

Table 11: ARDL long run form and bounds test (2,4,4,4)

condition error correction regression				
Variable	Coefficient	Std.Error	t-Statistic	Prob
C	0.080658	0.075823	1.063778	0.3084
ECI80(-1)'HDI(-1)	0.518463	0.322816	1.606061	0.1342
PCGDPG(-1)	-0.105110	0.038043	-2.762956	0.0172
ECI80(-1)	-0.320036	0.249336	-1.283554	0.2235
HDI(-1)	-0.120115	0.096773	-1.241209	0.2382
D(ECI80(-1)'HDI(-1))	-0.781522	0.230062	-3.397008	0.0053
D(PCGDPG)	-0.054914	0.024097	-2.278647	0.0418
D(PCGDPG(-1))	-0.001010	0.024364	-0.041448	0.9676
D(PCGDPG(-2))	0.016861	0.018324	0.92146	0.3756
D(PCGDPG(-3))	0.033323	0.012171	2.737966	0.0180
D(ECI80)	0.744980	0.018549	40.1691	0.0000
D(ECI80(-1))	0.539969	0.160406	3.366277	0.0056
D(ECI80(-2))	-0.003162	0.020474	-0.154427	0.8798
D(ECI80(-3))	-0.019571	0.016475	-1.187940	0.2578
D(HDI)	-0.249724	0.355124	-0.76890	0.4573
D(HDI)(-1))	0.491384	0.451308	1.088798	0.2976
D(HDI)(-2))	0.922884	0.409220	2.25310	0.0437
D(HDI)(-3))	-2.970396	0.32.340	-4.544867	0.0007
FDIP	-0.214178	0.067828	-3.157668	0.0083
TOP	0.006659	0.013894	0.479221	0.6404
GCFP	0.030113	0.046385	0.649193	0.5284
Variable	Coefficien0.006659t	Std.Error	t-Statistic	Prob
PCGDPG	0.202733	0.204321	0.992231	0.3407
ECI80	0.617278	0.172594	3.576475	0.0038
HDI	0.231676	0.060236	3.846117	0.0023
C	-0.155572	0.078678	-1.977331	0.0714
EC = HDI*ECI80-(0.2027*PCGDPG + 0.6173*ECI80+0.2317*HDI-0.1556)				
Test statistic	Value	Signif.	I(0)	I(1)
F-statistic	2.485131	10%	2.37	3.2
K	3	5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66
Actual sample size	33	Final Sample: n=35		
		10%	2.618	3.532
		5%	3.164	4.194
		1%	4.428	5.816
		Final sample: n =35		
		10%	2.618	3.532
		5%	3.164	4.194
		1%	4.428	5.816

Bounds tests indicate that there exists a cointegration relationship between the four variables, only when the regression is normalized on PCGDPG or on the combination of economic complexity and human development. In these cases, the calculated F-statistic is higher than the upper value implying a long-run relationship between economic growth, economic complexity, and human development and the combination of the two latter variables. When the regression is normalized on the human development index the null hypothesis of no cointegration is accepted. The bounds test is inconclusive when the regression is normalized on the economic complexity index. These results are helpful to detect short and long-run causality relationships and their directions.

Once the cointegration relationship is established through the bounds test we perform an ARDL long run form and estimate a conditional error correction regression. Results of table 12 show that estimation of the long-run coefficient of the economic complexity index is positive and significant while that of the human development index is positive but not significant. On the contrary, the estimated coefficient of their combined effect through the variable (hdi*eci) is negative but not significant.

These results indicate that the engagement of Saudi Arabia in the process of diversification and sophistication of its produced and exported products during the past years begin to bring its effects on economic growth.

Table 12: ARDL long-run coefficient

condition error correction regression				
Variable	Coefficient	Std.Error	t-Statistic	Prob
C	-1.3400	1.0698	-1.2525	0.2389
PCGDPG(-1)	-1.9161	0.3822	-5.0133	0.0005
ECI80(-1)	4.6297	3.7348	1.2236	0.2491
HDI(-1)	1.6715	1.4425	1.1573	0.2740
ECI80(-1)*HDI(-1)	-6.656	5.4496	-1.2213	0.2500
D(PCGDPG(-1))	0.2863	0.2892	0.9898	0.3456
D(PCGDPG(-2))	0.1859	0.1716	1.0829	0.3043
D(PCGDPG(-3))	0.2469	0.1201	2.0453	0.0680
D(ECI80)	3.46100	1.6457	2.1029	0.0618
D(ECI80(-1))	-3.8864	3.64612	-1.0659	0.3115
D(ECI80(-2))	-4.7079	3.00093	-1.5644	0.1488
D(ECI80(-3))	-5.3357	2.3429	-2.2773	0.0460
D(HDI)	-1.5676	3.4060	-0.4902	0.662
D(HDI(-1))	3.2196	4.1614	0.7736	0.4570
D(HDI(-2))	-1.676	5.73911	-0.2920	0.7762
D(HDI(-3))	-17.46388	9.1470	-1.9094	0.0853
D(ECI80*HDI))	-4.1016	2.2804	-1.7985	0.1023
D(ECI80(-1)*HDI(-1))	6.1762	5.50700	1.1215	0.2858
D(ECI80(-2)*HDI(-2))	7.1780	4.5638	1.572	0.1468
D(ECI80(-3)*HDI(-3))	7.6795	3.5560	2.1595	0.0562
FDP	-1.2179	0.76733	-1.58728	0.10435
TOP	0.2558	0.11385	2.2468	0.0484
GCFP	0.58744	0.5708	1.02914	0.3277
Variable	Coefficient	Std.Error	t-Statistic	Prob
ECI80	2.416186	1.2564	1.9228	0.0834
HDI	0.87233	0.55222	1.57966	0.1453
HDI'ECI80	-3.473499	1.932223	-1.79766	0.1024
C	-0.69934	0.36176	-1.93313	0.0820
EC = PCGDPG – (2.4162*ECI80 + 0.8723*HDI-3.4735*HDI*ECI80-0.6993)				
Test statistic	Value	Signif.	I(0)	I(1)
F-statistic	7.705195	10%	2.37	3.2
K	3	5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66
Actual sample size	33	Final Sample: n=35		
		10%	2.618	3.532
		5%	3.164	4.194
		1%	4.428	5.816
		Final sample: n =30		
		10%	2.676	3.586
		5%	3.272	4.306
		1%	4.614	5.966

Source: Authors' calculation

Results of table 13 show that the error correction term (ECT) is as expected negative and its coefficient is highly significant. This indicates that the speed of correction between the short and long term is relatively significant. In addition, a coefficient of -1.916 implies that the model converges in a fluctuating manner to equilibrium and that the deviation from long-term is corrected by 1.916% each year.

Table 13: ARDL-ECM and Short-run dynamics

condition error correction regression

Variable	Coefficient	Std.Error	t-Statistic	Prob
D(PCGDPG(-1))	0.286355	0.18466	1.5507	0.1520
D(PCGDPG(-2))	0.185933	0.136013	1.3670	0.2016
D(PCGDPG(-3))	0.2469	0.090161	2.738	0.0209
D(ECI80)	3.46100	1.175193	2.9450	0.0147
D(ECI80(-1))	-3.886472	0.94143	-4.2505	0.0017
D(ECI80(-2))	-4.7079	1.678155	-2.8054	0.0186
D(ECI80(-3))	-5.335717	1.369201	-3.8969	0.0030
D(HDI)	-1.567602	2.661606	-0.5889	0.689
D(HDI)(-1))	3.2196	2.839905	1.337	0.234
D(HDI)(-2))	-1.676084	3.7435	-0.4477	0.663
D(HDI)(-3))	-17.46388	6.40155	-2.7280	0.0213
D(ECI80'HDI)	-4.101634	1.5814	-2.59	0.0268
D(ECI80(-1)*HDI(-1))	6.1762	1.32022	4.678	0.009
D(ECI80(-2)*HDI(-2))	7.178015	2.51154	2.85800	0.0170
D(ECI80(-3)*HDI(-3))	7.679538	2.05377	3.73922	0.0039
FDIP	-1.217977	0.53636	-2.2708	0.0465
TOP	0.255818	0.05900	4.335	0.0015
GCFP	0.587447	0.3187	1.8429	0.0951
ECT(-1)	-1.916150	0.26090	-7.344	0.0000
R-squared	0.945600	Mean dependent Var	0.0022	
Adjusted R squared	0.875658	S.D. dependent Var	0.091355	
S.E. of regression	0.032214	Akaike info criterion	-3.738	
Sum squared resid	0.014528	Schwarz criterion	-2.877	
Log likelihood	80.68954	Hannan –Quinn	-3.4488	
Durbin-Watson stat	2.056			

Test statistic	Value	Signif.	I(0)	I(1)
F-statistic	7.705195	10%	2.37	3.2
K	3	5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66

4-5 Stability and Robustness Check

In order to check the robustness and stability of the estimated ARDL model, we proceed in two ways. First, we perform a set of diagnostic tests relative to the stability of model coefficients such as CUSUM and CUSUM SQUARES and relative to the good fitness of the model such as error autocorrelation or heteroskedasticity and normality tests. Second, we introduce control variables (exogenous variables) that could influence the economic growth-economic complexity nexus.

Diagnostic tests

Table 14 presents diagnostic tests for serial correlation, functional form, normality, and heteroskedasticity of the ARDL model. We can observe that the model has a correct functional form and residuals are serially uncorrelated and homoscedastic. However, the model suffers from the normality of errors. Therefore, the results are globally valid for meaningful interpretation.

Table 14: Diagnostic tests

Test	F-statistic	p-value
Serial correlation[a]	0.418	0.6719
Normality[b]	13.17	0.0013
Heteroskedasticity[c]	0.166	0.9998
Model specification[d]	2.339	0.1585

Note: [a] Lagrange multiplier (LM) test of residual serial correlation; [b] Jarque-Bera test; [c] Harvey test for heteroscedasticity.; [d] Ramsey's RESET test.

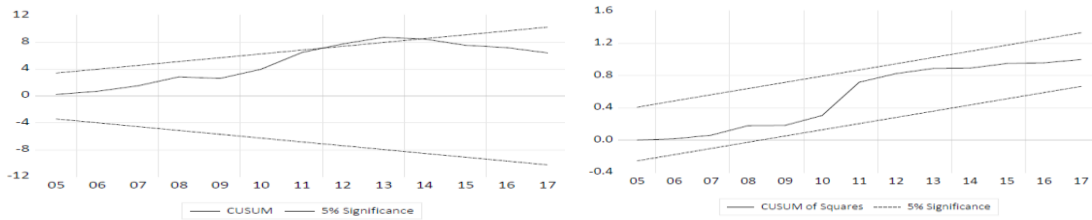
Stability tests

The cumulative sum (CUSUM) test identifies systematic changes in the regression coefficients, while the cumulative sum of squares (CUSUMSQ) test detects sudden changes from the constancy of the regression coefficients. Results of Figure 5 indicate the absence of any instability of the coefficients because the plots of the CUSUM and CUSUMSQ statistics fall inside the critical bands of the 5 percent confidence intervals of parameter stability[13]. Moreover, recursive residual graphics confirm this result. Therefore,

[13] CUSUM is outside the critical band only for the [12,14] period.

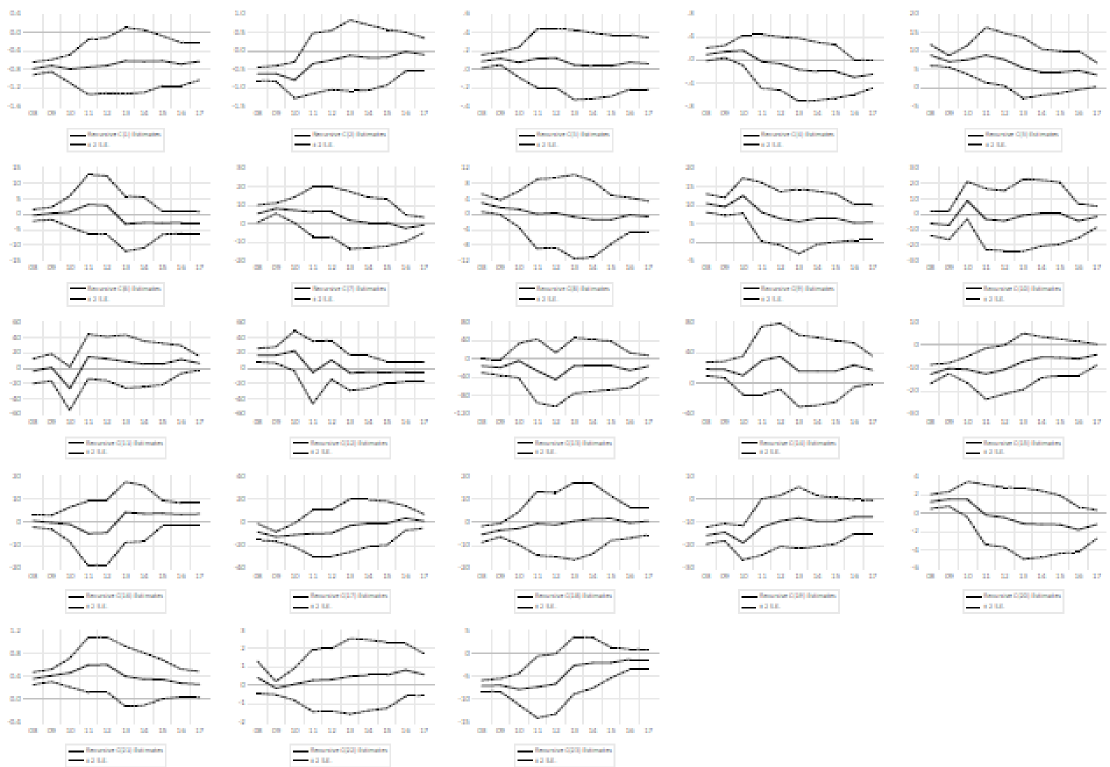
the coefficients are stable over the sample period. These results are corroborated by the Ramsey RESET test in figures 15-a and 15-b.

Figure 15-a: Stability tests, CUSUM and CUSUM of squares



Source: Authors' calculation.

Figure 15-b: Stability tests, recursive residuals



Source: Authors' calculation.

Control variables

As it has been developed in subsection 4-3 that the economic growth-economic complexity nexus literature recognizes that many variables could condition such relationship, such as gross capital formation (GDF) as an indicator of domestic investment, education or human development index (HDI), trade openness (TO), foreign direct investment (FDI) and institutional quality (IQ) (see for example Zhu and Li (2016), and Khan et al.(2020)).

Results of the ARDL model with control (exogenous) variables are presented in table 15 for the whole sample and in table 16 and table 17 on the sub-sample 1996-2019 when introducing the institutional quality variable. From table 15, we depict that trade openness has a moderate effect while foreign direct investment has an adverse effect and the coefficient of gross capital formation is not significant. The F-statistic reveals that the model is accepted at the 5% level. When introducing the institutional quality variable (IQ), the model is rejected due essentially to the low number of observations (25). When IQ is the only control variable, the quality of the model is improved but it is rejected at the 10% level.

Table 15: Economic growth, economic complexity and control variables

Variable	Coefficient	Std.Error	t-Statistic	Prob
PCGDPG(-1)	-0.629	0.12790	-4.924	0.0006
PCGDPG(-2)	0.100422	0.2230	-0.4502	0.6621
PCGDPG(-3)	0.0699	0.138415	0.440660	0.6688
PCGDPG(-4)	-0.2469	0.07113	-3.47115	0.0060
ECI80	3.46100	1.1050	3.1318	0.0107
ECI80(-1)	-2.7177	1.323	-2.0575	0.0672
ECI80(-2)	-0.82144	1.6923	-00.48539	0.6376
ECI80(-3)	-0.6277	2.5808	-0.2432	0.8127
ECI80(-4)	5.3357	2.3014	2.31838	0.0429
HDI	-1.56760	4.4654	-0.34877	0.7345
HDI(-1)	6.45877	3.607046	1.7548	0.1095
HDI(-2)	-4.8957	7.04613	-0.6948	0.5030
HDI(-3)	-15.787	8.436	-1.8714	0.09080
HDI(-4)	17.46388	79644	2.1927	0.0531
HDI*ECI80	-4.1016	1.519	-2.6988	0.0224
HDI(-1)*ECI80(-1)	3.62216	1.850	1.9531	0.0788
HDI(-2)*ECI80(-2)	1.001738	2.407	0.416069	0.6861
HDI(-3)*ECI80(-3)	0.501523	4.10047	0.12230	0.9051
HDI(-4)*ECI80(-4)	-7.679	3.5224	-2.1767	0.0545
FDIP	-1.2179	0.6320	-1.9244	0.0832
TOP	0.255	0.13903	1.8399	0.0956
GCFP	0.587	0.517399	1.1353	0.2827
C	-1.340	0.873465	-1.534	0.1560

R-squared	0.8678	**Mean dependent var**	0.0050
Adjusted R squared	0.5772	**S.D. dependent var**	0.058619
S.E. of regression	0.03811	**Akaike info criterion**	-3.4963
Sum squared resid	0.01452	**Schwarz criterion**	-2.45334
Log likelihood	80.6894	**Hannan –Quinn criter**	-3.1454
F-statistic	2.9857	**Durbin-Watson stat**	2.056
Prob(F-statistic)	0.03846		

Table 16: Economic growth, economic complexity and control variables with institutional quality

Variable	Coefficient	Std.Error	t-Statistic	Prob
PCGDPG(-1)	-0.8410	0.2617	-3.21354	0.0847
PCGDPG(-2)	-1.1300	0.3436	-3.2882	0.0814
PCGDPG(-3)	-0.7930	0.3111	-2.5489	0.1256
ECI80	3.4377	4.497	0.76442	0.5245
ECI80(-1)	9.9398	3.394	2.92844	0.099
ECI80(-2)	5.0725	6.6477	0.7630	0.255
ECI80(-3)	15.7613	8.8920	1.7725	0.2183
HDI	14.56620	5.439	2.6780	0.1157
HDI(-1)	5.935	3.635	1.63429	0.2438
HDI(-2)	-31.9044	8.5664	-3.40136	0.0651
HDI(-3)	26.0899	9.7253	2.6828	0.1154
HDI*ECI80	-3.4967	5.228	-0.6688	0.5725
HDI(-1)*ECI80(-1)	-11.595	3.971	-2.1716	0.100
HDI(-2)*ECI80(-2)	-6.3838	8.2907	-0.7700	0.5218
HDI(-3)*ECI80(-3)	-20.988	11.544	-1.81800	0.2107
FDIP	3.364	1.18429	2.8406	0.1048
TOP	-0.61491	0.332	-1.1848	0.20574
GCFP	-3.632	1.03909	-3.4956	0.0730
IQ	0.457	0.164890	2.77	0.1090
C	-10.44	5.5347	-1.8876	0.1997

R-squared	0.9505	**Mean dependent var**	0.005129
Adjusted R squared	0.4811	**S.D. dependent var**	0.03629
S.E. of regression	0.02614	**Akaike info criterion**	-5.0299
Sum squared resid	0.001367	**Schwarz criterion**	-4.03812
Log likelihood	75.32	**Hannan –Quinn criter**	-4.796
F-statistic	2.024	**Durbin-Watson stat**	3.177
Prob(F-statistic)	0.03821		

Table 17: Economic growth, economic complexity and institutional quality

Variable	Coefficient	Std.Error	t-Statistic	Prob
PCGDPG(-1)	-1.0513	0.0936	-11.22	0.0566
PCGDPG(-2)	-2.1058	0.3370	-6.24	0.1010
PCGDPG(-3)	-1.9690	0.39160	-5.007	0.1255
PCGDPG(-4)	-1.5032	0.27184	-5.5296	0.1139
ECI80	14.8463	4.3672	3.399	0.1821
ECI80(-1)	14.34260	3.0873	4.6456	0.1350
ECI80(-2)	18.818	3.8812	4.847	0.1295
ECI80(-3)	21.5925	2.9326	7.3626	0.0859
ECI80(-4)	8.457	1.1588	7.2986	0.086
HDI	10.329	2.5727	4.01500	0.1554
HDI(-1)	10.717	1.4504	7.3885	0.0856
HDI(-2)	-25.58	2.29315	-11.1577	0.0569
HDI(-3)	34.810	8.54155	4.0753	0.1532
HDI(-4)	-4.245	5.5010	-0.7723	0.5813
HDI*ECI80	-16.089	4.927	-3.264	0.1892
HDI(-1)*ECI80(-1)	-17.3639	3.822	-4.5425	0.1379
HDI(-2)*ECI80(-2)	-23.7788	4.7836	-4.975	0.1264
HDI(-3)*ECI80(-3)	26.8403	3.4129	-7.8624	0.0805
HDI(-4)*ECI80(-4)	-12.55391	1.5665	-8.0173	0.0790
IQ	0.668	0.119	5.235	0.1131
C	-20.9866	3.7675	-5.570	0.1131
R-squared	0.9987		**Mean dependent var**	0.00512
Adjusted R squared	0.97360		**S.D. dependent var**	0.0362
S.E. of regression	0.00589		**Akaike info criterion**	-8.610
Sum squared resid	3.48E-05		**Schwarz criterion**	-7.569
Log likelihood	115.7172		**Hannan –Quinn criter**	-8.365
F-statistic	39.729		**Durbin-Watson stat**	3.8177
Prob(F-statistic)	0.1244			

4-6 Causality relationships between economic growth, economic complexity, and their determinants

Traditional sequential Granger causality tests face many shortages, especially in finite samples. First, Granger causality tests are conducted only on stationary series. However, unit root tests are less efficient on a small sample and are not always unbiased. Second, by transforming the series in first difference for the sake of stationary or cointegration relationship, we obtain good statistical proprieties while losing information on the level of the series which is important to explain the dynamics of the model. These weaknesses and others lead Toda and Yamamoto (1995) to propose a non-sequential procedure to test Granger causality where variables could have different levels of integration. They propose to estimate an augmented VAR $(k + d_{max})$ in level which could integrate probable potential cointegration between the series. One of the main advantages of Tostada and Yamamoto procedure is that we do not have to test cointegration or transform VAR into VECM. Granger causality procedure of Toda and Yamamoto is based on a modified Wald test which follows a $\chi^2(k + d_{max})$ where $(k + d_{max})$ is the degree of freedom which is equal to the number of lags in the augmented VAR. We can summarize Toda and Yamamoto procedure in the following steps:

- We construct and estimate VAR(k) model on series levels regardless of their integration order, where k is lag length taken from an information criterion (AIC, SIC).
- We construct and estimate the augmented $VAR(k + d_{max})$, where d_{max} is the maximum order of integration among series, and test if it's correctly specified.
- We use the modified Wald (MWald) statistic to test for Granger causality in the sense of Toda and Yamamoto.

In what follows we implement the Toda-Yamamoto methodology to test Granger causality relationships between economic growth, economic complexity, and human development. We also test for causality between economic growth and the combined effect of economic complexity and human development. For each pair of variables, we estimate the following augmented $VAR(k + d_{max})$ and calculate MWald statistics.

$$y_t = \mu + \sum_{i=1}^{k} \alpha_{1i} y_{t-i} + \sum_{i=k+1}^{d_{max}} \alpha_{2i} y_{t-i} + \sum_{j=1}^{k} \beta_{1j} x_{t-j} + \sum_{j=k+1}^{d_{max}} \beta_{2j} x_{t-j} + \varepsilon_{1t} \qquad (8)$$

$$x_t = \vartheta + \sum_{j=1}^{k} \gamma_{1j} x_{t-j} + \sum_{i=k+1}^{d_{max}} \gamma_{2j} x_{t-j} + \sum_{i=1}^{k} \delta_{1i} y_{t-i} + \sum_{i=k+1}^{d_{max}} \delta_{2i} y_{t-i} + \varepsilon_{2t} \qquad (9)$$

The test is conducted on the k first coefficients. The null hypothesis is:

In equation (8) H_0: $\beta_{1j} = 0$: x_t does not Granger cause y_t

In equation (9) H_0: $\delta_{1i} = 0$: y_t does not Granger cause x_t

The empirical results of the Granger Causality test based on Toda and Yamamoto's (1995) methodology are reported in Table 18. The MWALD test, which follows a chi-squared distribution with n degree of freedom equal to the number of restrictions in the estimated VAR[14], shows that both economic complexity index and human development index and their combined effect cause real per capita GDP growth. Moreover, causality runs also from the human development index to the economic complexity index. These results are in concordance with new economic growth and economic development theories as developed by Haussmann and Hidalgo.

Table 18: Toda-Yamamoto causality (MWald) test results

Null Hypothesis	χ^2_n	P-value	Granger causality
ECI does not Granger cause PCGDPG	**9.47569**	**0.0502**	ECI → PCGDPG
PCGDPG does not Granger cause ECI	2.606754	0.2656	
ECI does not Granger cause HDI	5.089119	0.2783	
HDI does not Granger cause ECI	**15.14689**	**0.0044**	HDI → ECI
PCGDPG does not Granger cause HDI	0.001597	0.9681	
HDI does not Granger cause PCGDPG	**2.813427**	**0.0935**	HDI → PCGDPG
PCGDPG does not Granger cause ECI*HDI	4.210474	0.3783	HDI*ECI →
HDI*ECI does not Granger cause PCGDPG	**7.928347**	**0.0942**	PCGDPG

Source: Author's calculation.

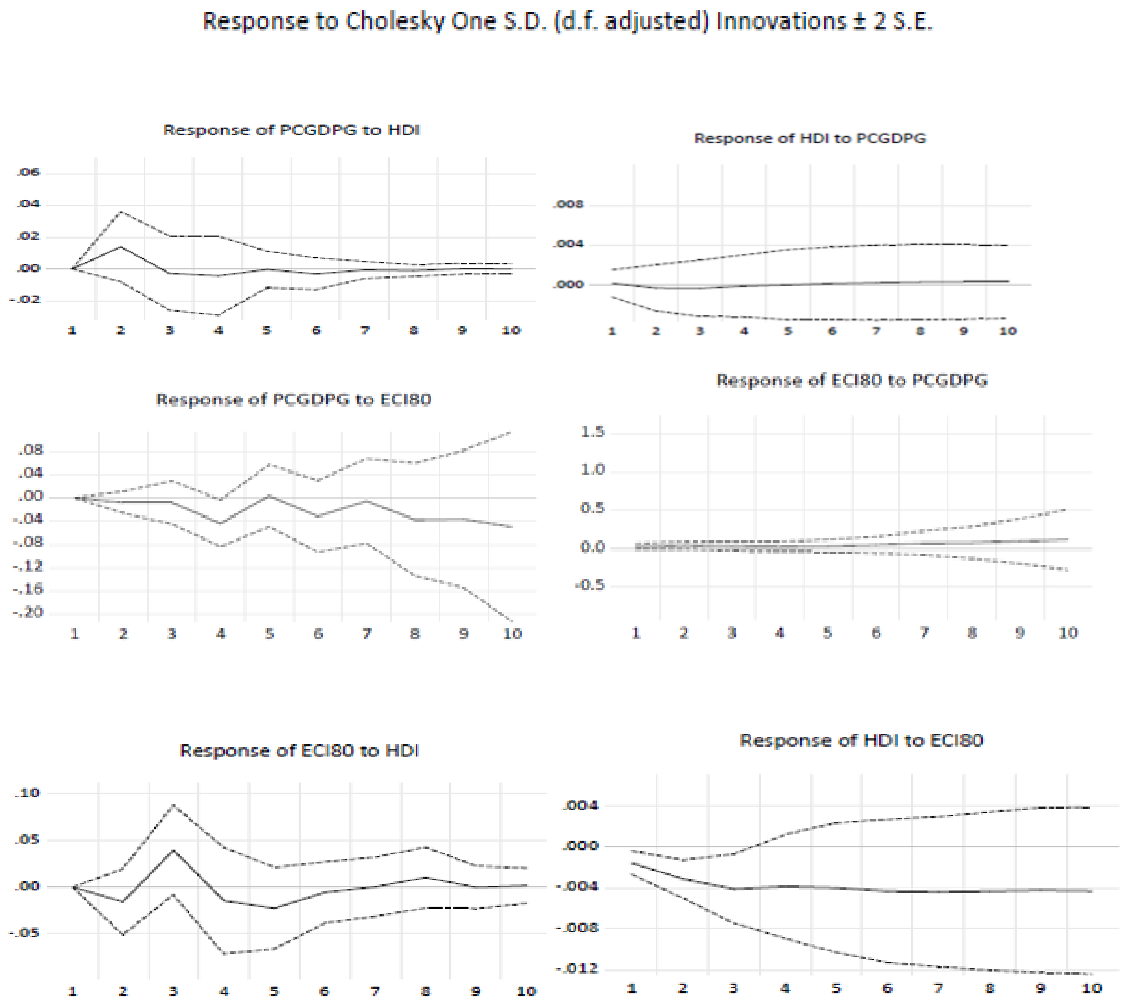
Impulse response functions

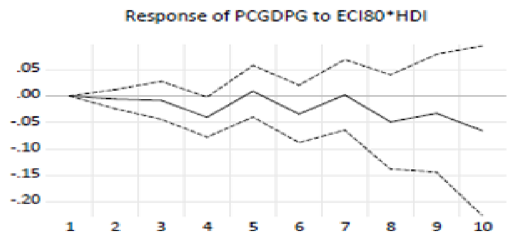
The ARDL-ECM and Toda-Yamamoto Granger-causality tests developed in the previous sections don't give information on the instant reaction of the variables of the model to a shock in one of them. Impulse-response functions are a tool to trace the effects of a one-time shock to one of the innovations on the current and future values of all the endogenous variables of the model. A shock on one variable not only affects the variable itself but also transfers its impact to all other endogenous variables via the dynamic lag structure of the model. In order to depict the outcomes of impulse-response on the variables under consideration, we reproduce the graphics of the response to one-time shock (figure 16). We can observe that when per capita GDP is the impulse; the response of ECI is almost null during the six-seven first years following the shock and becomes positive during the rest

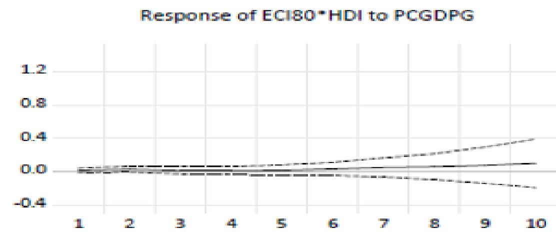
[14] As mentioned by Toda and Yamamoto this test is independent of the order of integration of the series and of the cointegration relationships.

of the propagation period while the response of HDI is quasi-null during all the period. The response of the combined effect of economic complexity and human development to per capita GDP shock follows the same pattern. The reaction of per capita GDP to an impulse in ECI is quasi-null during the three-first years and oscillates around a small negative value during the rest of the period. Per capita GDP reacts positively during the three first years to a shock in HDI and the effect attenuates to become nearly zero during the rest of the period. Finally, the analysis of the confidence intervals indicates that all individual impulse responses coefficients are significant at 95%.

Figure 16: One time chock impulse-response between PCGDPC, ECI and HDI







5. Summary and policy recommendations

New development economic theory emphasizes the role of know-how and economic complexity to explain the economic performance of countries. Hidalgo et al. (2009) and Hausmann et.al (2011), among others, argued that net differences in income levels between countries are mainly due to differences in productive knowledge, and the reason behind these differences lies in the diversity of production structures. The advantage of economic complexity theory is that it suggests specific ways for each country to reach higher growth rates and a higher level of development depending on its capabilities and productive knowledge.

Within this context, the main motivation of this work was to study the state of sophistication and complexity of the Saudi economy through economic complexity index and product space and to inspect the implications of economic complexity on economic growth. The inspection of economic complexity ranking and the evolution of the product space of Saudi Arabia during the past decades shows that the country is becoming one of the thirty-first more complex economies in the world. This improvement has been driven by the diversification of exports leading to denser product space. In this regard, during the last five years, Saudi Arabia has multiplied by more than two the number of exported products with revealed comparative advantage greater than one. This dynamism is the consequence of the new investment policy and economic reforms the country has launched in 2016 making part of vision 2030 which aims to transform the economy and the society in multiple dimensions.

By diversifying its production, Saudi Arabia can avoid the impairing effects of non-diversified economies revealed by the famous English saying “Putting all of one’s eggs in one basket”. Countries that rely significantly on one or few products can face harmful consequences, especially in export revenues and terms of trade, if unexpected shocks come to international prices of such products. In Saudi Arabia, oil is the main exported product, which is an exhaustible resource. If oil revenues decrease, Governments' capacity to support economic growth will be impaired because of resource shortage. In order to improve its economic performance and assess sustainable growth, Saudi authorities should develop new sectors and provide alternative sources of revenues. New development strategies should raise non-oil production, enhance the role of private sector investment and encourage foreign direct investment. These investments should be directed to value-added industrial activities that will lead to export diversification and more economic complexity.

Econometric results based on ARDL methodology have shown that economic complexity, human development index, and economic growth are cointegrated in Saudi Arabia. Moreover, using Toda and Yamamoto approach empirical findings show that both economic complexity and human development index Granger cause economic growth. This result implies that sustainable economic growth is mainly induced by economic sophistication which relies on the development of the county's capabilities and know-how. Increasing economic complexity, not only allows Saudi Authorities to attain their main goals in terms of social and economic development, macroeconomic equilibrium, and job creation, but also to protect the country from unfavorable effects of output volatility.

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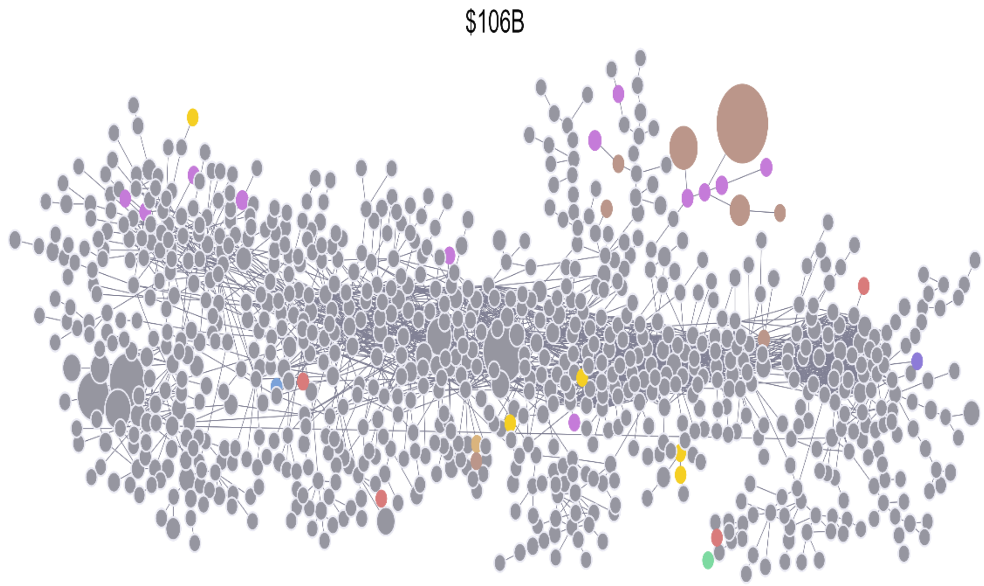
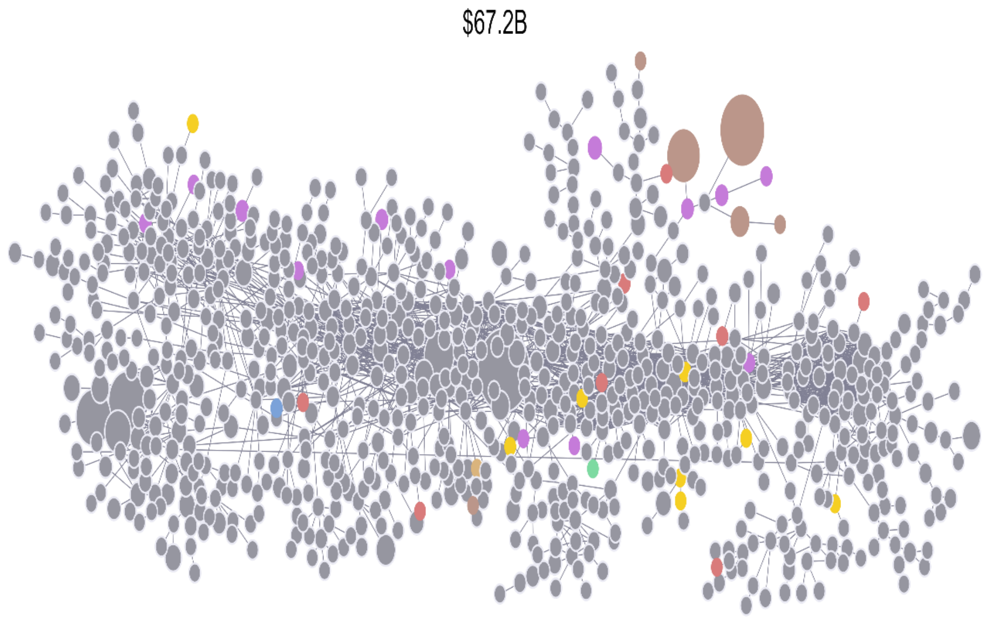
Appendix

Product space 2000 of Saudi Arabia



Product space 1995 of Saudi Arabia



Descriptive statistics

Date: 05/17/21 Time: 21:31
Sample: 1980 2019

	PCGDPG	ECI80	HDI	ECI80*HDI	FDIP	TOP	GCFP
Mean	-0.020864	0.334612	0.732283	0.256520	0.016355	0.741644	0.238336
Median	-0.004842	0.305181	0.739900	0.219134	0.010437	0.714141	0.225623
Maximum	0.113127	1.002000	0.859000	0.855708	0.084964	0.961026	0.343505
Minimum	-0.382104	-0.081941	0.583000	-0.047772	-0.019401	0.560884	0.156841
Std. Dev.	0.096355	0.210647	0.087074	0.184936	0.025947	0.111202	0.049674
Skewness	-1.722659	1.466224	-0.084906	1.780878	1.069807	0.396269	0.592151
Kurtosis	7.035454	6.091250	1.754669	6.388837	3.337992	1.968621	2.249349
Jarque-Bera	46.92517	30.25846	2.632810	40.28387	7.820311	2.819766	3.276746
Probability	0.000000	0.000000	0.268097	0.000000	0.020037	0.244172	0.194296
Sum	-0.834570	13.38449	29.29130	10.26078	0.654195	29.66575	9.533423
Sum Sq. Dev.	0.362090	1.730513	0.295693	1.333848	0.026257	0.482266	0.096232
Observations	40	40	40	40	40	40	40

Correlation matrix

Correlation

	PCGDPG	ECI80	HDI	ECI80*HDI	FDIP	TOP	GCFP
PCGDPG	1.000000	0.357493	0.438624	0.319846	-0.057171	-0.259440	-0.229582
ECI80	0.357493	1.000000	0.642433	0.990467	-0.112940	-0.365974	0.283037
HDI	0.438624	0.642433	1.000000	0.702400	0.112356	-0.040609	0.397616
ECI80*	0.319846	0.990467	0.702400	1.000000	-0.092722	-0.313630	0.327024
FDIP	-0.057171	-0.112940	0.112356	-0.092722	1.000000	0.643962	0.507259
TOP	-0.259440	-0.365974	-0.040609	-0.313630	0.643962	1.000000	0.352771
GCFP	-0.229582	0.283037	0.397616	0.327024	0.507259	0.352771	1.000000

Optimal ARDL(4,4,4,4) estimation

Dependent Variable: PCGDPG
Method: ARDL
Date: 05/16/21 Time: 00:08
Sample (adjusted): 1985 2017
Included observations: 33 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): ECI80 HDI HDI*ECI80
Fixed regressors: C
Number of models evalulated: 500
Selected Model: ARDL(4, 4, 4, 4)
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
PCGDPG(-1)	-0.456152	0.129379	-3.525690	0.0037
PCGDPG(-2)	-0.097279	0.226711	-0.429089	0.6749
PCGDPG(-3)	0.049239	0.133317	0.369339	0.7178
PCGDPG(-4)	-0.245364	0.080283	-3.056225	0.0092
ECI80	3.161428	1.012006	3.123921	0.0081
ECI80(-1)	-1.649110	1.371237	-1.202644	0.2506
ECI80(-2)	-0.657826	1.399597	-0.470011	0.6461
ECI80(-3)	-1.139424	2.296142	-0.496234	0.6280
ECI80(-4)	4.684962	1.410885	3.320583	0.0055
HDI	0.610417	4.821043	0.126615	0.9012
HDI(-1)	6.172638	3.280094	1.881848	0.0824
HDI(-2)	-6.783963	7.310956	-0.927917	0.3704
HDI(-3)	-11.36663	7.342963	-1.547962	0.1456
HDI(-4)	13.02643	5.131079	2.538731	0.0247
HDI*ECI80	-3.677180	1.383917	-2.657081	0.0197
HDI(-1)*ECI80(-1)	2.290002	1.764341	1.297936	0.2169
HDI(-2)*ECI80(-2)	0.912429	1.948211	0.468342	0.6473
HDI(-3)*ECI80(-3)	1.246872	3.651768	0.341443	0.7382
HDI(-4)*ECI80(-4)	-6.636480	2.138656	-3.103107	0.0084
C	-1.191842	1.106012	-1.077604	0.3008

R-squared	0.785726	Mean dependent var	0.005035
Adjusted R-squared	0.472556	S.D. dependent var	0.058619
S.E. of regression	0.042572	Akaike info criterion	-3.194662
Sum squared resid	0.023561	Schwarz criterion	-2.287687
Log likelihood	72.71192	Hannan-Quinn criter.	-2.889492
F-statistic	2.508943	Durbin-Watson stat	1.403421
Prob(F-statistic)	0.047298		

*Note: p-values and any subsequent tests do not account for model selection.

ARDL long run form and bounds test (4,4,4,4)

ARDL Long Run Form and Bounds Test
Dependent Variable: D(PCGDPG)
Selected Model: ARDL(4, 4, 4, 4)
Case 2: Restricted Constant and No Trend
Date: 05/14/21 Time: 21:50
Sample: 1980 2019
Included observations: 33

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.340048	1.069887	-1.252514	0.2389
PCGDPG(-1)*	-1.916150	0.382208	-5.013370	0.0005
ECI80(-1)	4.629774	3.783486	1.223679	0.2491
HDI(-1)	1.671517	1.444250	1.157360	0.2740
ECI80(-1)*HDI(-1)	-6.655745	5.449655	-1.221315	0.2500
D(PCGDPG(-1))	0.286355	0.289288	0.989862	0.3456
D(PCGDPG(-2))	0.185933	0.171699	1.082904	0.3043
D(PCGDPG(-3))	0.246927	0.120726	2.045353	0.0680
D(ECI80)	3.461002	1.645784	2.102950	0.0618
D(ECI80(-1))	-3.886472	3.646127	-1.065918	0.3115
D(ECI80(-2))	-4.707920	3.009334	-1.564439	0.1488
D(ECI80(-3))	-5.335717	2.342901	-2.277398	0.0460
D(HDI)	-1.567602	3.406053	-0.460240	0.6552
D(HDI(-1))	3.219651	4.161467	0.773682	0.4570
D(HDI(-2))	-1.676084	5.739117	-0.292046	0.7762
D(HDI(-3))	-17.46388	9.147012	-1.909244	0.0853
D(ECI80*HDI)	-4.101634	2.280433	-1.798621	0.1023
D(ECI80(-1)*HDI(-1))	6.176276	5.507001	1.121532	0.2883
D(ECI80(-2)*HDI(-2))	7.178015	4.563962	1.572759	0.1468
D(ECI80(-3)*HDI(-3))	7.679538	3.556074	2.159555	0.0562
FDIP	-1.217977	0.767333	-1.587287	0.1435
TOP	0.255818	0.113857	2.246828	0.0484
GCFP	0.587447	0.570813	1.029141	0.3277

* p-value incompatible with t-Bounds distribution.

Levels Equation
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ECI80	2.416186	1.256475	1.922988	0.0834
HDI	0.872331	0.552225	1.579667	0.1453
HDI*ECI80	-3.473499	1.932232	-1.797662	0.1024
C	-0.699344	0.361767	-1.933132	0.0820

EC = PCGDPG - (2.4162*ECI80 + 0.8723*HDI -3.4735*HDI*ECI80 - 0.6993)

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	7.705195	10%	2.37	3.2
k	3	5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66
Actual Sample Size	33		Finite Sample: n=35	
		10%	2.618	3.532

ARDL long run form and bounds test (4,0,4,2)

ARDL Long Run Form and Bounds Test
Dependent Variable: D(ECI80)
Selected Model: ARDL(4, 0, 4, 2)
Case 2: Restricted Constant and No Trend
Date: 05/15/21 Time: 15:31
Sample: 1980 2019
Included observations: 34

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.144915	0.169328	0.855827	0.4040
ECI80(-1)*	-1.047121	0.294917	-3.550557	0.0025
PCGDPG**	0.631471	0.254692	2.479346	0.0239
HDI(-1)	0.320126	0.318272	1.005824	0.3286
ECI(-1)*HDI(-1)	0.134188	0.106803	1.256402	0.2260
D(ECI80(-1))	0.382210	0.219077	1.744641	0.0991
D(ECI80(-2))	0.387584	0.243244	1.593398	0.1295
D(ECI80(-3))	0.503071	0.225335	2.232548	0.0393
D(HDI)	-7.717479	4.175028	-1.848486	0.0820
D(HDI(-1))	-9.590291	4.368204	-2.195477	0.0423
D(HDI(-2))	11.05046	5.320139	2.077099	0.0533
D(HDI(-3))	-9.531066	6.092324	-1.564438	0.1361
D(ECI*HDI)	0.097528	0.073469	1.327478	0.2019
D(ECI(-1)*HDI(-1))	0.070785	0.060696	1.166222	0.2596
FDIP	-0.088280	0.914949	-0.096486	0.9243
TOP	-0.063747	0.194830	-0.327191	0.7475
GCFP	0.495750	0.569507	0.870491	0.3962

* p-value incompatible with t-Bounds distribution.
** Variable interpreted as Z = Z(-1) + D(Z).

Levels Equation
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
PCGDPG	0.603054	0.222563	2.709588	0.0149
HDI	0.305720	0.287217	1.064423	0.3020
HDI*ECI	0.128149	0.078805	1.626166	0.1223
C	0.138394	0.105566	1.310973	0.2073

EC = ECI80 - (0.6031*PCGDPG + 0.3057*HDI + 0.1281*HDI*ECI + 0.1384)

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	3.703349	10%	2.37	3.2
k	3	5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66
Actual Sample Size	34		Finite Sample: n=35	
		10%	2.618	3.532
		5%	3.164	4.194
		1%	4.428	5.816
			Finite Sample: n=30	
		10%	2.676	3.586

ARDL long run form and bounds test (2,0,2,0)

ARDL Long Run Form and Bounds Test
Dependent Variable: D(HDI)
Selected Model: ARDL(2, 0, 2, 0)
Case 2: Restricted Constant and No Trend
Date: 05/15/21 Time: 15:36
Sample: 1980 2019
Included observations: 36

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.011160	0.007114	1.568599	0.1293
HDI(-1)*	0.002737	0.010889	0.251356	0.8036
PCGDPG**	0.020967	0.010369	2.022101	0.0540
ECI80(-1)	-0.028924	0.010485	-2.758509	0.0107
HDI*ECI**	-0.001003	0.002357	-0.425373	0.6742
D(HDI(-1))	-0.236844	0.201527	-1.175246	0.2510
D(ECI80)	-0.025447	0.006260	-4.065091	0.0004
D(ECI80(-1))	0.002056	0.007958	0.258352	0.7983
FDIP	-0.028047	0.034636	-0.809787	0.4257
TOP	-0.003617	0.008460	-0.427525	0.6727
GCFP	0.035298	0.017761	1.987404	0.0579

* p-value incompatible with t-Bounds distribution.
** Variable interpreted as Z = Z(-1) + D(Z).

Levels Equation
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
PCGDPG	-7.660579	25.55930	-0.299718	0.7669
ECI80	10.56800	34.03193	0.310532	0.7587
HDI*ECI	0.366350	1.209029	0.303012	0.7644
C	-4.077414	15.03302	-0.271231	0.7884

EC = HDI - (-7.6606*PCGDPG + 10.5680*ECI80 + 0.3664*HDI*ECI - 4.0774)

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	2.239558	10%	2.37	3.2
k	3	5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66
Actual Sample Size	36		Finite Sample: n=40	
		10%	2.592	3.454
		5%	3.1	4.088
		1%	4.31	5.544
			Finite Sample: n=35	
		10%	2.618	3.532
		5%	3.164	4.194
		1%	4.428	5.816

ARDL long run form and bounds test (2,4,4,4)

ARDL Long Run Form and Bounds Test
Dependent Variable: D(ECI80*HDI)
Selected Model: ARDL(2, 4, 4, 4)
Case 2: Restricted Constant and No Trend
Date: 05/15/21 Time: 15:46
Sample: 1980 2019
Included observations: 33

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.080658	0.075823	1.063778	0.3084
ECI80(-1)*HDI(-1)*	0.518463	0.322816	1.606061	0.1342
PCGDPG(-1)	-0.105110	0.038043	-2.762956	0.0172
ECI80(-1)	-0.320036	0.249336	-1.283554	0.2235
HDI(-1)	-0.120115	0.096773	-1.241209	0.2382
D(ECI80(-1)*HDI(-1))	-0.781522	0.230062	-3.397008	0.0053
D(PCGDPG)	-0.054914	0.024097	-2.278847	0.0418
D(PCGDPG(-1))	-0.001010	0.024364	-0.041448	0.9676
D(PCGDPG(-2))	0.016861	0.018324	0.920146	0.3756
D(PCGDPG(-3))	0.033323	0.012171	2.737966	0.0180
D(ECI80)	0.744980	0.018549	40.16191	0.0000
D(ECI80(-1))	0.539969	0.160406	3.366277	0.0056
D(ECI80(-2))	-0.003162	0.020474	-0.154427	0.8798
D(ECI80(-3))	-0.019571	0.016475	-1.187940	0.2578
D(HDI)	-0.249724	0.325124	-0.768090	0.4573
D(HDI(-1))	0.491384	0.451308	1.088798	0.2976
D(HDI(-2))	0.922884	0.409550	2.253410	0.0437
D(HDI(-3))	-2.970396	0.653572	-4.544867	0.0007
FDIP	-0.214178	0.067828	-3.157688	0.0083
TOP	0.006659	0.013894	0.479221	0.6404
GCFP	0.030113	0.046385	0.649193	0.5284

* p-value incompatible with t-Bounds distribution.

Levels Equation
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
PCGDPG	0.202733	0.204321	0.992231	0.3407
ECI80	0.617278	0.172594	3.576475	0.0038
HDI	0.231676	0.060236	3.846117	0.0023
C	-0.155572	0.078678	-1.977331	0.0714

EC = HDI*ECI80 - (0.2027*PCGDPG + 0.6173*ECI80 + 0.2317*HDI - 0.1556)

F-Bounds Test Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	3.485131	10%	2.37	3.2
k	3	5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66
Actual Sample Size	33		Finite Sample: n=35	
		10%	2.618	3.532
		5%	3.164	4.194
		1%	4.428	5.816

ARDL long-run coefficient

ARDL Long Run Form and Bounds Test
Dependent Variable: D(PCGDPG)
Selected Model: ARDL(4, 4, 4, 4)
Case 2: Restricted Constant and No Trend
Date: 05/14/21 Time: 21:50
Sample: 1980 2019
Included observations: 33

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.340048	1.069887	-1.252514	0.2389
PCGDPG(-1)*	-1.916150	0.382208	-5.013370	0.0005
ECI80(-1)	4.629774	3.783486	1.223679	0.2491
HDI(-1)	1.671517	1.444250	1.157360	0.2740
ECI80(-1)*HDI(-1)	-6.655745	5.449655	-1.221315	0.2500
D(PCGDPG(-1))	0.286355	0.289288	0.989862	0.3456
D(PCGDPG(-2))	0.185933	0.171699	1.082904	0.3043
D(PCGDPG(-3))	0.246927	0.120726	2.045353	0.0680
D(ECI80)	3.461002	1.645784	2.102950	0.0618
D(ECI80(-1))	-3.886472	3.646127	-1.065918	0.3115
D(ECI80(-2))	-4.707920	3.009334	-1.564439	0.1488
D(ECI80(-3))	-5.335717	2.342901	-2.277398	0.0460
D(HDI)	-1.567602	3.406053	-0.460240	0.6552
D(HDI(-1))	3.219651	4.161467	0.773682	0.4570
D(HDI(-2))	-1.676084	5.739117	-0.292046	0.7762
D(HDI(-3))	-17.46388	9.147012	-1.909244	0.0853
D(ECI80*HDI)	-4.101634	2.280433	-1.798621	0.1023
D(ECI80(-1)*HDI(-1))	6.176276	5.507001	1.121532	0.2883
D(ECI80(-2)*HDI(-2))	7.178015	4.563962	1.572759	0.1468
D(ECI80(-3)*HDI(-3))	7.679538	3.556074	2.159555	0.0562
FDIP	-1.217977	0.767333	-1.587287	0.1435
TOP	0.255818	0.113857	2.246828	0.0484
GCFP	0.587447	0.570813	1.029141	0.3277

* p-value incompatible with t-Bounds distribution.

Levels Equation
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ECI80	2.416186	1.256475	1.922988	0.0834
HDI	0.872331	0.552225	1.579667	0.1453
HDI*ECI80	-3.473499	1.932232	-1.797662	0.1024
C	-0.699344	0.361767	-1.933132	0.0820

EC = PCGDPG - (2.4162*ECI80 + 0.8723*HDI -3.4735*HDI*ECI80 - 0.6993)

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	7.705195	10%	2.37	3.2
k	3	5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66
Actual Sample Size	33		Finite Sample: n=35	
		10%	2.618	3.532

ARDL-ECM and Short-run dynamics

ARDL Error Correction Regression
Dependent Variable: D(PCGDPG)
Selected Model: ARDL(4, 4, 4, 4)
Case 2: Restricted Constant and No Trend
Date: 05/14/21 Time: 21:51
Sample: 1980 2019
Included observations: 33

ECM Regression
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(PCGDPG(-1))	0.286355	0.184661	1.550702	0.1520
D(PCGDPG(-2))	0.185933	0.136013	1.367023	0.2016
D(PCGDPG(-3))	0.246927	0.090161	2.738724	0.0209
D(ECI80)	3.461002	1.175193	2.945049	0.0147
D(ECI80(-1))	-3.886472	0.914343	-4.250561	0.0017
D(ECI80(-2))	-4.707920	1.678155	-2.805414	0.0186
D(ECI80(-3))	-5.335717	1.369201	-3.896956	0.0030
D(HDI)	-1.567602	2.661606	-0.588969	0.5689
D(HDI(-1))	3.219651	2.839905	1.133718	0.2834
D(HDI(-2))	-1.676084	3.743549	-0.447726	0.6639
D(HDI(-3))	-17.46388	6.401554	-2.728069	0.0213
D(ECI80*HDI)	-4.101634	1.581427	-2.593629	0.0268
D(ECI80(-1)*HDI(-1))	6.176276	1.320222	4.678209	0.0009
D(ECI80(-2)*HDI(-2))	7.178015	2.511549	2.858003	0.0170
D(ECI80(-3)*HDI(-3))	7.679538	2.053776	3.739228	0.0039
FDIP	-1.217977	0.536354	-2.270846	0.0465
TOP	0.255818	0.059005	4.335512	0.0015
GCFP	0.587447	0.318762	1.842902	0.0951
CointEq(-1)*	-1.916150	0.260909	-7.344138	0.0000

R-squared	0.945600	Mean dependent var	0.002261
Adjusted R-squared	0.875658	S.D. dependent var	0.091355
S.E. of regression	0.032214	Akaike info criterion	-3.738778
Sum squared resid	0.014528	Schwarz criterion	-2.877153
Log likelihood	80.68984	Hannan-Quinn criter.	-3.448868
Durbin-Watson stat	2.056703		

* p-value incompatible with t-Bounds distribution.

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	7.705195	10%	2.37	3.2
k	3	5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66

Economic growth, economic complexity and control variables

Dependent Variable: PCGDPG
Method: ARDL
Date: 05/14/21 Time: 21:45
Sample (adjusted): 1985 2017
Included observations: 33 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): ECI80 HDI HDI*ECI80
Fixed regressors: FDIP TOP GCFP C
Number of models evalulated: 500
Selected Model: ARDL(4, 4, 4, 4)
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
PCGDPG(-1)	-0.629795	0.127902	-4.924040	0.0006
PCGDPG(-2)	-0.100422	0.223043	-0.450234	0.6621
PCGDPG(-3)	0.060994	0.138415	0.440660	0.6688
PCGDPG(-4)	-0.246927	0.071137	-3.471151	0.0060
ECI80	3.461002	1.105092	3.131868	0.0107
ECI80(-1)	-2.717700	1.323929	-2.052754	0.0672
ECI80(-2)	-0.821448	1.692317	-0.485398	0.6379
ECI80(-3)	-0.627797	2.580827	-0.243254	0.8127
ECI80(-4)	5.335717	2.301485	2.318380	0.0429
HDI	-1.567602	4.494543	-0.348779	0.7345
HDI(-1)	6.458770	3.680601	1.754814	0.1098
HDI(-2)	-4.895735	7.046139	-0.694811	0.5030
HDI(-3)	-15.78780	8.436219	-1.871431	0.0908
HDI(-4)	17.46388	7.964455	2.192728	0.0531
HDI*ECI80	-4.101634	1.519760	-2.698870	0.0224
HDI(-1)*ECI80(-1)	3.622165	1.850582	1.957311	0.0788
HDI(-2)*ECI80(-2)	1.001738	2.407625	0.416069	0.6861
HDI(-3)*ECI80(-3)	0.501523	4.100474	0.122309	0.9051
HDI(-4)*ECI80(-4)	-7.679538	3.527976	-2.176755	0.0545
FDIP	-1.217977	0.632903	-1.924428	0.0832
TOP	0.255818	0.139035	1.839945	0.0956
GCFP	0.587447	0.517399	1.135385	0.2827
C	-1.340048	0.873465	-1.534175	0.1560

R-squared	0.867875	Mean dependent var	0.005035
Adjusted R-squared	0.577201	S.D. dependent var	0.058619
S.E. of regression	0.038116	Akaike info criterion	-3.496354
Sum squared resid	0.014528	Schwarz criterion	-2.453334
Log likelihood	80.68984	Hannan-Quinn criter.	-3.145410
F-statistic	2.985731	Durbin-Watson stat	2.056703
Prob(F-statistic)	0.038456		

*Note: p-values and any subsequent tests do not account for model selection.

Economic growth, economic complexity and control variables with institutional quality

Dependent Variable: PCGDPG
Method: ARDL
Date: 05/18/21 Time: 16:29
Sample (adjusted): 1996 2017
Included observations: 22 after adjustments
Maximum dependent lags: 3 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (3 lags, automatic): ECI80 HDI HDI*ECI80
Fixed regressors: FDIP TOP GCFP IQ C
Number of models evalulated: 192
Selected Model: ARDL(3, 3, 3, 3)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
PCGDPG(-1)	-0.841067	0.261726	-3.213544	0.0847
PCGDPG(-2)	-1.130024	0.343658	-3.288221	0.0814
PCGDPG(-3)	-0.793012	0.311119	-2.548907	0.1256
ECI80	3.437755	4.497156	0.764429	0.5245
ECI80(-1)	9.939809	3.394229	2.928444	0.0995
ECI80(-2)	5.072599	6.647734	0.763057	0.5251
ECI80(-3)	15.76131	8.892003	1.772526	0.2183
HDI	14.56620	5.439156	2.678025	0.1157
HDI(-1)	5.935736	3.631995	1.634291	0.2438
HDI(-2)	-31.90447	8.566416	-3.724366	0.0651
HDI(-3)	26.08993	9.725319	2.682682	0.1154
HDI*ECI80	-3.496737	5.228348	-0.668803	0.5725
HDI(-1)*ECI80(-1)	-11.59528	3.974851	-2.917162	0.1002
HDI(-2)*ECI80(-2)	-6.383852	8.290710	-0.770001	0.5218
HDI(-3)*ECI80(-3)	-20.98841	11.54475	-1.818005	0.2107
FDIP	3.364132	1.184298	2.840612	0.1048
TOP	-0.614914	0.332582	-1.848908	0.2057
GCFP	-3.632310	1.039093	-3.495654	0.0730
IQ	0.457611	0.164890	2.775251	0.1090
C	-10.44760	5.534709	-1.887651	0.1997

R-squared	0.950584	Mean dependent var	0.005129
Adjusted R-squared	0.481136	S.D. dependent var	0.036297
S.E. of regression	0.026146	Akaike info criterion	-5.029979
Sum squared resid	0.001367	Schwarz criterion	-4.038122
Log likelihood	75.32977	Hannan-Quinn criter.	-4.796327
F-statistic	2.024895	Durbin-Watson stat	3.177308
Prob(F-statistic)	0.382110		

*Note: p-values and any subsequent tests do not account for model selection.

Economic growth, economic complexity and institutional quality

Dependent Variable: PCGDPG
Method: ARDL
Date: 05/18/21 Time: 16:50
Sample (adjusted): 1996 2017
Included observations: 22 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): ECI80 HDI HDI*ECI80
Fixed regressors: IQ C
Number of models evalulated: 500
Selected Model: ARDL(4, 4, 4, 4)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
PCGDPG(-1)	-1.051302	0.093693	-11.22069	0.0566
PCGDPG(-2)	-2.105869	0.337024	-6.248429	0.1010
PCGDPG(-3)	-1.960960	0.391609	-5.007449	0.1255
PCGDPG(-4)	-1.503213	0.271844	-5.529687	0.1139
ECI80	14.84634	4.367640	3.399167	0.1821
ECI80(-1)	14.34260	3.087319	4.645648	0.1350
ECI80(-2)	18.81836	3.882293	4.847230	0.1295
ECI80(-3)	21.59253	2.932698	7.362684	0.0859
ECI80(-4)	8.457823	1.158822	7.298637	0.0867
HDI	10.32977	2.572791	4.015005	0.1554
HDI(-1)	10.71708	1.450490	7.388593	0.0856
HDI(-2)	-25.58644	2.293156	-11.15774	0.0569
HDI(-3)	34.81017	8.541558	4.075388	0.1532
HDI(-4)	-4.248540	5.501056	-0.772314	0.5813
HDI*ECI80	-16.08932	4.927828	-3.264992	0.1892
HDI(-1)*ECI80(-1)	-17.36395	3.822503	-4.542561	0.1379
HDI(-2)*ECI80(-2)	-23.77889	4.783966	-4.970540	0.1264
HDI(-3)*ECI80(-3)	-26.84036	3.412956	-7.864256	0.0805
HDI(-4)*ECI80(-4)	-12.55931	1.566510	-8.017384	0.0790
IQ	0.668026	0.119972	5.568169	0.1131
C	-20.98665	3.767545	-5.570378	0.1131

R-squared	0.998743	Mean dependent var	0.005129
Adjusted R-squared	0.973604	S.D. dependent var	0.036297
S.E. of regression	0.005897	Akaike info criterion	-8.610657
Sum squared resid	3.48E-05	Schwarz criterion	-7.569207
Log likelihood	115.7172	Hannan-Quinn criter.	-8.365323
F-statistic	39.72914	Durbin-Watson stat	3.817736
Prob(F-statistic)	0.124466		

*Note: p-values and any subsequent tests do not account for model selection.