UCLouvain

UNIVERSITÉ DE NAMUR

Economics School of Louvain - ESL

Economics School of Namur - ESN

Capabilities, Opportunity Costs, and Knowledge Spillovers

A Dynamic Decomposition of Export Complexity and a Shift-Share Research Design

Author : Bastien LATOUR

Thesis Director : Gonzague VANNOORENBERGUE

Thesis Reader : Lorenzo TRIMARCHI

Academic Year 2024-2025

Master in Economics – 120 credits – Focus : Professional focus

Université catholique de Louvain - Economics School of Louvain - Place Montesquieu 3, 1348 Louvain-La-Neuve
Université de Namur – Economics School of Namur – Rempart de la Vierge 8, 5000 Namur

Abstract:

This paper develops a decomposition framework inspired by Griliches and Regev (1995) to assess the sources of weighted export complexity changes across 124 countries between 1998 and 2023. The findings highlight the role of between-sector reallocation in enabling less complex economies to increase the sophistication of their exports. By contrast, within-sector specialisation and changes in product complexity over time reveal divergent patterns, casting doubts on the prospects for convergence across countries. Moreover, the results suggest that advanced economies face opportunity costs that limit their ability to sustain entries into simpler products. Taken together, these findings provide a cautionary message: policymakers should carefully balance objectives of (re-)industrialisation against the need to develop (preserve) long-term innovation capacities. In a complementary analysis on the role of foreign direct investments as a channel for capability acquisition, a positive correlation between FDI complexity and export complexity is observed. However, the attempts to establish causality using a shift-share instrumental variable strategy yield inconclusive results, largely due to the limited availability of granular data.

Acknowledgements:

I want to express my deepest gratitude to my promotor, Prof. Vannoorenbergue, for his invaluable guidance, support and availability throughout the completion of this work. granted me. I am equally grateful to the university for the opportunity it has provided and to the many professors whose teaching and passion have profoundly inspired my academic journey. I owe special thanks to my family for their support, care, and encouragements whose severed me as a constant source of strengths and motivation.

Content Table:

1. Introduction

Recent geo-economic tensions have heightened concerns about dependence on foreign technologies and the risk of falling behind in critical sectors. This is exemplified by the intense global competition in highly technological industries such for semiconductors, artificial intelligence, electric vehicles, and 5G technologies. The ability to remain competitive in these knowledge-intensive domains is increasingly regarded as critical for safeguarding countries' sovereignty, which was acknowledged, for instance, in the European Parliaments' report on European technological sovereignty and digital infrastructure (European Parliament).

These concerns lie at the intersection of international trade, industrial organisation and development economic. The processes through which countries and firms develop, and sustain productive capacities over time, their implication for long-term growth trajectories in a globalised world have been the subject of considerable scholarly attention.

Traditional trade theories highlight the gains from specialization based on comparative advantages, typically defined by exogenous factors such as relative productivity (Ricardian model) or factor endowments (Heckscher-Ohlin model). Endogenous growth theories contribute by showing how comparative advantages and specialisation may evolve through innovation, human capital, and knowledge spillovers (Romer, 1986; Krugman 1987; Lucas, 1988, 1993; Aghion and Howitt, 1992; Grossman and Helpman, 1991; Redding, 1999). This notion of dynamic comparative advantage underscores the importance of policies that foster knowledge- and technology-intensive activities, therefore generating positive externalities for the wider economy and sustaining long-term growth.

It thus becomes crucial to identify which economic activities should be supported. The literature on economic complexity contributes to this question by developing indices of economic sophistication, most notably are those based on the implied productivity of product (PRODY, Hausmann, Hwang and Rodrik, 2007) or on the underlying diversity and rarity of capabilities they require (PCI, Hidalgo and Hausmann, 2009). In both cases, these approaches find that the ability to produce complex products correlates strongly with income and could serve as predictor of future growth.

Since richer countries possess a broader set of capabilities than poorer ones, specialisation would theoretically predict divergent equilibria. In practice, however developed countries export both complex and simple products by climbing the quality ladder (Schott, 2004; Hummels and Klenow, 2005; Schetter, 2024). Nevertheless, as wages rise, so do opportunity costs, leading to a re-concentration of products around a narrower set of complex products (Dornbusch et al., 1977; Imbs and Wacziarg, 2003; Cadot et al., 2011;Van Dam and Frenken, 2022). Moreover, as income increases, the share of exports accounted for by simple products tends to decline, while that of complex products rises (Felipe et al., 2012). Understanding the drivers of concentration in simple products, diversification away from them, and ultimately re-concentration in complex products, is therefore essential for policymakers seeking to design effective industrial and trade policies.

This paper contributes by proposing a dynamic hierarchical decomposition, inspired by Griliches and Regev (1995), to assess how changes in export shares shape the weighted export complexity over time and across countries. Specifically, it addresses three questions: (i) what effect primarily drives changes in export complexity from between sector reallocations or within-sector specialisation? (ii) what is the relative importance of entries and exits at each level? and (iii) to what extent do these trends vary conditional on countries' level of economic complexity?

The results are consistent with the development economics narrative that the least developed countries must undergo structural shifts between sectors towards complex ones to change their development path. Furthermore, within-sector specialisation appears to have opposite effects depending on the level of economic complexity: developed countries tend to complexify by entering in relatively more complex products and exiting simpler ones, while less complex economies move in the reverse direction, entering in relatively simpler products and exiting more complex ones. This reaffirms the idea that the nature of sectors and products matters for long-term technological trajectories, a dynamic is further reinforced by a technological cycle whereby changes in PCI increasingly favour developed economies while disadvantaging less complex ones. Finally, the analysis shows that complex economies do not only re-concentrate the towards complex products but also face a barrier to entering simple products explained by an opportunity cost of diverting resources away from high-value activities.

A subsequent section of the paper examines the role of foreign direct investments (FDI) as a potential channel for capability acquisition. The product complexity index builds on the idea that complex products require a larger and rarer set of local capabilities, thus explaining persistent differences across countries. The literature on idea transmission and growth determinants has highlighted the role of FDI (Romer, 1992; Almfraji and Almsafir, 2013; Mahembe and Odhiambo, 2014), and a nascent strand explores its effect on the acquisitions of capabilities proxied by the economic complexity index (Javorcik, Turco and Maggioni, 2018; Khan, Khan and Khan, 2020; Antonietti and Franco, 2021) and the reverse impact of complexity on FDI attraction (Sadeghi, Shahrestani, Kiani and Torabi, 2020). In this work, I test the causal impact of FDI on the share of complex exports using a shift-share instrumental variable strategy built on (Borusyak, Hull, and Jaravel, 2020). While weighted export complexity and weighted FDI complexity are correlated, no significant effect was found between the FDI stock growth and export complexity growth. This absence of results may be attributed to limited country coverages and a short time span of the data.

To address these two main inquiries, I use trade data from BACI, complexity indices from the Observatory of Economic Complexity, FDI data per country and industries from the OECD, and control variables drawn from both the OECD and the World Bank Group.

The remainder of the paper is organised as follows. Section 2 reviews the selected literature. Section 3 describes the data. Section 4 explores the structural evolution of export complexity, highlighting the roles of within-sector specialisation, between-sector reallocation, their subcomponents (continuity, entries and exits), and PCI changes in shaping upgrading and downgrading trajectories over time. Section 5 tests the relationship between FDI and export complexity. Sections 6, eventually, concludes and discusses policy implications.

2. Selected literature

2.1. International trade, endogenous growth, and dynamic comparative advantage

In the international trade literature, foundational models like the Ricardian model, the Hecksher-Ohlin model, or the New Trade Theory models, generally treat goods as symmetrical or neutral, meaning that there are no dynamic gains differences from exporting one type over another. In the Ricardian model, trade patterns are driven by comparative advantage exogenously determined by differences in labour productivity across countries. Countries gain from trade by exporting goods they are relatively more efficient at producing and maximize their welfare by importing others. Only the allocation of labour in sectors with a comparative advantage explains differences of prosperity among countries, not the type of products exported. The Hecksher-Ohlin (HO) model explains trade patterns based on relative factor endowments. Like the Ricardian model, the goods are not differentiated. Finally, New Trade Theory, which introduce increasing returns to scale and product differentiation, accounts for intra-industry trade and the role of the preference for variety by consumers. While allowing firm-level heterogeneity, productivity differences are modelled as exogenous and randomly assigned, and no developmental or growth implications are given to the type of products exported. For all tree models, there is no long-term implication for growth for the nature of goods exported, the gains from trade emerge from the efficient allocation towards sectors with a comparative advantage (Ricardian and HO models), the increase in the number of accessible varieties (Krugman, 1979), or the market share reallocation to more productive firms (Melitz, 2003).

The exogeneity assumption of technological differences in the above static trade models contrasts with endogenous growth theories, which seek to explain persistent cross-country divergence by emphasizing the role of dynamic, self-reinforcing nature of innovation on productivity. Romer (1986) finds that when profit-maximizing firms invest in R&D, productivity gains can generate sustained and even rising growth rates making the initial conditions crucial for long-run growth performance implying that less developed countries may see persistently lower growth rates. Lucas (1988; 1993) recasts growth as an accumulation process of human capital, which raises labour's productivity and, through externalities, benefits the entire economy. Finally, Aghion and Howitt (1992) developed a Schumpeterian model of creative destruction in which waves of quality-ladder (vertical) innovation drive long-term growth.

Following the insights that endogenous innovation can explain sustained growth differences between countries and the lack of convergence, Grossman and Helpman (1991) integrate international trade to growth process by explicitly linking long-run-growth to trade performance. In their book, profit-maximizing firms allocates resources to research in response to market incentives, which returns are twofold. First, private (direct) returns take the form of higher profits earned from producing more advance and differentiated goods. Second, social (indirect) returns emerge from knowledge produced by firms spreading in the economy, which are productivity-enhancing for other firms and sectors. The nature of the technology as a nonrival, partially excludable good allows for this knowledge spillover, in other words, technology can be used by many at the same time, and firms cannot fully prevent other firms from using it. As a result, investments remain below the socially optimal level because firms do not internalize the spillovers (positive externality) generated by their innovation. At the same time, future private returns from research decline over time as competing firms adopt the new technology, eroding the initial innovator's advantage.

Furthermore, Grossman and Helpman emphasize that innovation is a self-reinforcing dynamic: countries with a larger stock of resources and knowledge are better positioned to produce new ideas, which in turn further raise their productivity as long as the private incentives remain high enough to maintain the process. This dynamic reflects the importance of prior knowledge and its diversity to shape future innovation performance by countries (Weitzman 1998, Fleming & Sorenson 2001). Cohen and Levinthal (1990) describe this as absorptive capacity. Firms with past investments in R&D find themselves better at recognizing and assimilating external ideas making them to learn faster and creates path-dependent innovative performances.

Moreover, when productivity dependents on past cumulative experience, the specialization becomes dynamic, as notes Krugman (1987), and the pattern can deepen via learning by doing once a country specialize in a sector as productivity is raised by the learning effect, further locking the specialization pattern. He argues in particular that a comparative advantage can be lost via changes in real exchange rates (Dutch diseases) or possibly gained with an infant industry policy.

Grossman and Helpman (1991) build a model of "dynamic comparative advantage" that captures this mechanism applied to impact of innovation. They show that whether investments in R&D shape or reverse comparative advantage in the long run depends on the extent of knowledge spillovers. They find that in a model where the knowledge produced flows into a worldwide pool, the ultimate determinant of comparative advantage and growth remain relative endowments (Chap. 7). However, if technological spillovers are localized within countries, then innovation can alter the long-run path of specialization and growth (Chap. 8). In such cases, they argue that a lagging country can even catch up by implementing a temporary push policy to promote local research to initiate a self-sustained innovation process through feedback loops. Ultimately, they acknowledge that the reality lies between the two extremes, meaning that knowledge spillovers are easier within countries, but not impossible between them, and that both history and comparative advantage based on relative factors endowments have a role to play in determining trade patterns and growth outcomes (p. 233).

Building on this framework, Redding (1999) explores whether countries should specialize in sectors where they currently have a comparative advantage or instead attempt to develop a new one. He argues that this question is particularly important for developing countries which usually specialize in low-technology, and low-growth sectors. The model used shows that under certain conditions, developing new comparative advantages in knowledge-intensive industries can yield welfare gains for the home country and the trade partner.

2.2. Sophistication and complexity index

The idea that comparative advantage can change over time because of innovation and that cumulative knowledge shape countries' productivity as led to see exports as not only reflecting endowments, but also the result of a dynamic process of capability-building. Questions emerged regarding which sectors and goods were the most revealing in terms of underlying capabilities presence and rarity and which of them were the most conductive to learning, spillovers and long-term growth than others. Two widely known measures of product sophistication have been developed: the PRODY (Hausmann, Hwang and Rodrik, 2007) and the Product Complexity Index (PCI) (Hidalgo and Hausmann, 2009).

First, Hausmann, Hwang and Rodrik (2007), in their seminal paper *"What you export matters"*, calculate the PRODY index for each good based the per capita income of countries that export it. The index consists of a weighted average of per capita income where the weighted are the revealed comparative advantage of countries exporting the good in question. This method allows to associate each product with a level of productivity. In other words, if rich countries export a product with an important RCA compared to poor countries, the associated productivity level, which result in a higher income, will be bigger than for products exported by poor countries.

Following this measure, the EXPY index of a country is determined by the export weighted average of the PRODY. Countries with a high EXPY was found to have high per capita GDP and to be a good predictor of future economic growth. Simply put, for a country to be richer, it must produce rich countries' goods (Hausmann, Hwang and Rodrik, 2007)

Second, in their seminal paper *"The building blocks of economic complexity"*, Hidalgo and Hausmann (2009) introduce a new metric that quantifies the complexity of a country's economy, which is built based on the view of Adam Smith on the wealth of nations as originating from the division of labour. Specialization by workers and firms into different activities brings efficiency gains and thus economic prosperity for all, suggesting that economic development is the result of interactions between increasingly numerous and specialised individuals leading to a greater complexity. The authors note that with international trade, we should be able to exploit division of labour at the global scale and ultimately see convergences in per capita GDP.

However, the great divergence in income observed (Pritchett 1997) seem to go against this narrative. To explain this puzzling information, Hidalgo and Hausmann suggest that some activities that emerged from the division of labour are not exportable and need to be locally present to produce certain types of products. These "nontradable capabilities" can include institutions that insure property rights, create regulations, control corruption, enforce contracts, or access to physical inputs, capital, labour, skills, technology, infrastructure and so on. Then, a greater diversity of available capabilities can explain differences in productivity. Therefore, income differences between countries can be seen as the result of differences in economic complexity, which is understood as the diversity of capabilities locally available and their interactions.

To proxy the presence of capabilities locally available, which are difficulty and often only partially observed, the authors linked countries to the products they competitively exports. They argue that the tripartite network *products-capabilities-countries* can be characterized by a bipartite network *products-countries* as competitive exports are revealing of capabilities locally available.

The authors built an adjacency matrix where its elements equal to one if a country has a comparative advantage (RCA>1) in a product and zero otherwise, thus, linking countries to products. Initially, they use the "method of reflexion" which iteratively compute the mean of goods and countries properties, which are initially the ubiquity and diversity. Eventually, the method finds the ECI and PCI after successively repeating the iteration. The ECI, then, can be reduced to the simple mean of the products' PCI the country is able to export, and inversely, the PCI equal the average ECI of countries that export the product. It was later shown that both indices could be extracted from the second largest eigen values of normalized similarity matrices. Both methods are developed in further detailed in the Annex A1 (Hidalgo and Hausmann, 2007; Hausmann et al., 2013).

The ECI metrics, as for the EXPY, was found to be highly correlated to per capita income, especially when controlling for natural resources wealth. In addition, deviations of the per capita income with respect to its predicted value given the ECI is predictive of future growth (Hidalgo and Hausmann, 2009). Recently, numerous papers have delved into the relationship between the economic complexity of a country and variables about inequality and environment (see Balland et al. 2022), that "co-evolve with a country's mix of exported products and with the inclusiveness of its economy" (Hartmann et al. 2017).

2.3. Specialization, net extensive margin, and transfer of knowledge

The contributions of dynamic comparative advantage, the PRODY measure, which associates a level of productivity to each product, and the PCI, which captures the number and the rarity of capabilities required for production, are valuable. Together, they connect exports structure to development potential, framing structural development as a process by which a country shifts from peripheral, low-technology goods toward central, high-technology products in the product space, which are more complex and closer to other complex products (Balland et al., 2022).

However, beyond the objective to produce goods in the centre of the product space, international trade exerts competitive pressures pushing countries (Ricardian and Hecksher-Ohlin models) and firms (Melitz, 2003; Bernard, Redding and Schott, 2006) to specialise respectively in their comparative advantage and their core competencies. Such processes incentivise poor countries to specialise in simple goods (development trap) and rich countries to specialise in complex ones.

Yet, a puzzle emerges: despite the predicted specialization of developed countries in complex goods, they continue to export simple products, leading to the well-known triangular structure of the country-product export matrix. A possible explanation is quality upgrading, whereby developed countries preserve their exports in simple products by producing them at higher quality levels, while complex products have a functional minimum quality requirement preventing less capable countries from exporting them (Schetter, 2024). Over time, however, it was shown that developing countries were less affected by this threshold allowing them to enter in new advanced markets. Empirically, Schott (2004) highlights first the increasing overlap between the export baskets of China and developed countries, then shows the price difference within products (interpreted as a proxy for quality) which is consistent with a within product specialization but reject factor proportion specialization. Further support comes from Hummels and Klenow (2005) who find that higher capital to labour ration is associated with higher quantities in developing countries but not higher prices, whereas in developed countries they raise prices but not quantities.

Quality upgrading, however, has limitations in its capacity to allow rich countries to keep exporting simple products since, as development proceeds, rising wages can offset any quality improvements. When domestic labour costs make the production of simple products, even with a better quality, inefficient, developed countries offshore such activities to lower-wage countries, which mechanism is captured by the product cycle theory (Vernon, 1966; Grossman and Helpman, 1991). Van Dam and Frenken (2022) finds that diversification increases only up to a certain point, after which developed countries start dropping simpler products. This reconcentration produces the diversification "hump" documented by Imbs and Wacziarg (2003) and Cadot et al. (2011), where the most advanced economies reduce the range of goods they export. This specialization, induce by opportunity costs, was shown by Dornbusch et al. (1977) to hold even when countries could technically and competitively produce all products.

The diversification of exports towards complex products while maintaining simple ones via quality upgrading until a certain point interacts with another structural tendency, which is the skewness in export composition with richer (poorer) countries having higher shares of their exports in complex (simple) products. Empirical work by Felipe et al. (2012) confirms this tendency by showing that roughly 63% of products have shares disproportionally concentrated either in rich countries for complex products or in poor countries for simple ones, with skewness increasing for the simplest and the most complex products. Recently, Schetter (2019) proposes a structural variant of the ECI and PCI that replaces the standard similarity matrix with one based on exports shares. Assuming log-supermodularity between countries and products (more complex (simple) countries export more of complex (simple) products), this approach captures deep underlying capabilities that allow countries to be competitive in certain types of products, which drives comparative advantages.

Understanding how diversification, quality upgrading, re-concentration, and structural skewed exports shares shape international trade patterns naturally leads to questions about the policies that can influence their underlying drivers. One category of policy interventions centres on fostering local innovation and the domestic development of capabilities. Such measures include public investments in innovation and education, targeted subsidies to sectors with high complexity potential, support for firms seeking to move up the complexity ladder and implement infant industry protection policies. A second category policies focuses on imitation and the absorption of foreign technologies, such as strategically attracting foreign direct investment, securing access to advanced technologies through technology transfer clauses in large procurement or investment agreements, or investing in foreign language learning to enhance access to global knowledge networks (Romer, 1992).

This paper focuses on the channel of knowledge transfer facilitated by foreign direct investment (FDI), defined by Eurostat as a lasting interest of an investors in a company in another country materialised by the acquisition of 10% or more of the shares, voting rights or the equivalent (Eurostat). Theoretically, the literature review by Mahembe and Odhiambo (2014) identifies two main channels through which FDI affects economic growth: first, technological spillovers that foster the adoption of new technologies, and second, the transmission of know-how, skills, and enhanced managerial practices. They further note that the impact of FDI on growth is contingent on local conditions such as the level of human capital, absorptive capacities and economic, political, social, and cultural conditions. Moreover, the FDI-growth relationship may be bidirectional, with GDP growth itself acting as an endogenous variable of FDI.

From an empirical perspective Almfraji and Almsafir (2013) report that most studies find a positive relationship between FDI and economic growth. They also highlight several influencing factors such as the level of human capital, the development of the financial markets, and trade openness tend to have a positive impact on the relationship, whereas the dependency on foreign investment and large technological gaps negatively contribute to it. However, the income level of the host country and the quality of political environment are found to be ambiguous. These observations are consistent with more recent works by Bénétrix, Pallan and Panizza (2023) and Baiashvili and Gattini (2020)

More specifically, this paper examines the nascent literature on the relationship between FDI and export complexity. Multinational corporations (MNCs), as major providers of FDI, transfer knowledge and know-how to their affiliates (Arnold and Javorcik, 2009), which tend to introduce more new products than domestic competitors (Brambilla, 2009), paying the discovery costs and thereby benefiting the economy through the social spillovers. According to Javorcik, Turco and Maggioni (2018), this can be explained by MNCs having better knowledge on production location suitability. In their study, they find that the presence of foreign firms in the downstream sector significantly increased the complexity of products produced by Turkish firms that are more likely to supply foreign affiliates, as identified by an instrumental regression with two instruments, one capturing competition from Polland and regional backwardness, and the second consisting of weighted average of outward FDI stocks of OECD countries in a given industry where the weights proxy for the information flows between each Turkish region and a given source country.

At a more aggregated level, Khan, Khan and Khan (2020) find a long-run bidirectional and short-run unidirectional causal link between economic complexity and FDI suggesting that FDI, not only have a direct effect on growth, but also an indirect one through capability accumulation, using an autoregressive distributed lag (ARDL) model. Similarly, Antonietti and Franco (2021) test for the causality between higher FDI stock and greater economic complexity using a panel vector autoregression (PVAR) model and impulse response function (IRF). They aim to explain why some countries have higher level of economic complexity than others and through which mechanisms can a country accumulate capabilities. They argue that attracting FDI facilitates the accumulation and combination of capabilities as investment is a key channel for the international diffusion of knowledge. They find that inward FDI stock Granger-causes higher economic complexity, but the effect is small and limited to countries with a high per capita GDP, advanced tertiary education systems, a high level of tertiarization and strong financial development. Moreover, the effect is present only for greenfield FDI in developed economies, and for knowledge-intensive greenfield investments in developing countries.

Finally, Sadeghi, Shahrestani, Kiani and Torabi (2020) examine the reverse relationship by testing whether higher economic complexity, as an indicator of national productive capabilities and knowledge, attracts more FDIs. Applying a dynamic panel data GMM-system estimator, they find that economic complexity is one of the main determinants in FDI inflows.

To summarise, while trade pressures influence specialization and trade patterns, the endogenous growth theories highlight the possibility to see countries' comparative advantages evolve over time emphasizing the role of knowledge and technologies and leading to the concept of dynamic comparative advantage. Measures of products complexity like the PRODY and the PCI were then developed to proxy for their implied productivity and the number and rarity of capabilities locally available to produce them. Co-existing with trade pressures, developed economies specialize within products by climbing the quality ladder to keep exporting simple products. However, we saw that despite this strategy, developed countries re-concentrate the number of products they export toward complex goods. Furthermore, structural patterns show that the export share of complex products have a positive relationship with income, while the export share of simple products is characterised by a negative relationship. Finally, focusing on the policies promoting imitation rather than local innovation, the role of the impact of FDI, both directly and indirectly through increased economic complexity, on growth was presented, showing positive results and a bidirectional property between FDI and complexity.

3. Data description

The product classification used is the Harmonized System Revision 1996 (HS96). Data for the Product Complexity Index (PCI) at the six-digit HS level come from the Observatory of Economic Complexity (OEC), which provides complexity measures for 3,276 products between 1998 and 2023, representing the longest available time span. Measures of the Economic Complexity Indec (ECI) are also sourced from the OEC and computed using HS6 products-level over the same time period.

Export data by country to rest of the world for the sample period and using the HS96 classification are taken from the BACI database maintained by CEPII. Only exports with a corresponding PCI are kept for the analysis. Additionally, population and the per capita GDP based on Purchasing Power Parity (PPP) in constant 2017 US international dollars data come from the CHELEM database (CEPII).

Since structural transformation is a long-term process, years are grouped into three-years periods, and values are transformed using the simple mean within these periods. Such aggregation is also useful to avoid noises due to yearly shocks. The PCI, per capita GDP and population observations are averaged based on available data, whereas export values are averaged including zeroes ensuring that if a country starts or stops exporting a product within the three-years period, the change is taken into account. This approach interprets and assumes that unobserved data are non-exported products.

To reduce the influence of outliers and ensure comparability, the sample consists of 124 countries[1]. They have in common a population on average greater than one million during the initial period 1998-2000 and export for more than one billion US dollars over three-years periods and arbitrarily let countries with less for maximum two periods. Excluding countries below these thresholds helps to prevent cases with high volatility due to small countries exporting a limited set of products potentially inflating some metrics. Furthermore, re-exporting activities, for which countries with small export values, could bias the results.

[1] See table A1 in the index for a complete list

Finally, for computational tractability and proper filtering, a product is considered “exported” by a country in a specific year if: the average export value exceeds $50,000 (Evenett and Venables, 2002), and the Revealed Comparative Advantage (RCA) for a product is greater than 0.5 (Schetter, 2024), where:

$$RCA_{cp} = \frac{X_{cp}/X_c}{X_p/X_w} \tag{1}$$

Here, X_{cp} is the export value of product p by country c, X_c is the total exports of country c, X_p is thet total export of product p in the world, and X_w I the total world export (Balassa, 1965). The RCA is computed including zero export values, and the product is removed if the mean RCA over the three-year period is less than or equal to 0,5. In this paper, in addition to the reasons cited before, the threshold of 0.5 for the RCA is chosen to allow the decomposition to track transitions and changes before a product becomes competitively exported.

For the causal analysis between FDI and export complexity, the data on FDI stocks disaggregated by sectors of destination are obtained from the OECD. A heatmap of data availability is provided in the Annex A8. To estimate the regressions, several control variables are included. The data on institutional quality comes from the Worldwide Governance Indicators (World Bank Group). The variable is constructed as the simple average of the six available dimensions, all expressed on a 0-100 scale: voice and accountability, political stability and absence of violence/terrorism, government effectiveness, regulatory quality, rule of law, and control of corruption. Additional controls are also drawn from the World Bank Group: gross capital formation (% of GDP) and the share of individuals using the internet (from the ICT indicators database), serving as proxy for capital accumulation and development of information and communication technologies. Finally, data on the share of the population with tertiary education, obtained from the OECD, are used as a proxy for human capital accumulation.

4. Weighted Export Complexity (WEC)

Being able to competitively export more complex products is recognised as a source of wealth and long-term prosperity for a country. The ECI literature captures this idea by focusing on the diversity of products exported and their ubiquity. After computing the ECI and the PCI, it has been highlighted that the complexity measure for a country’s economy could be reduced to the simple mean of the PCI of its competitive exports. This approach has been successful at mapping the availability of non-tradable capabilities and has led to several important insights into the relationship between economic complexity and development. Implicitly, this method weights each product equivalently in determining a complexity measure for countries.

However, this method implicitly assigns equal weights to all products, even though the economic importance of some products or sectors may greatly vary. In practice, total export values are unevenly distributed, and a small number of products often dominates. While the ECI framework may better reflect the productive capacities locally available, the role of export concentration in relatively more or less complex categories may also influence economic outcomes.

Indeed, countries often pay closer attention to their dominant export sectors given their exposure and dependence. For example, a country that exports both socks and computers should rightly be considered as more complex than a country only able to export socks. Yet, a country whose exports' value is split 50% from socks and 50% from computers may arguably be seen as in a weaker position than a country with 70% of exports in computers and 30% in socks. The dependence level on high-complexity sectors, and not just their presence, may bring greater benefits in term of knowledge specialization by creating specific clusters, influence industrial policy priorities, and impact long-term growth trajectories by feeding a positive feedback loop.

This reason, as well as the objective to see where countries see their exports' complexity change in terms of export value, motivates the use of a weighted complexity measure for countries calculated as an export weighted average of the PCI. This approach aligns with Hausmann, Hwang, and Rodrik (2007), who propose to compute the EXPY indicator for countries via an export weighted average of the PRODY. This methodology makes it possible it possible to capture the structure of specialization more accurately, consistent with the motivations of Schetter (2019), who refines the method of Hausmann et al. (2013) by accounting for structural differences in the relative dominance of goods in the export basket.

In this section, I address the following questions:

(1) Is export reallocation between sectors more important than within-sector specialization in explaining changes in export complexity, and what is the role played by product entries and exits ?

(2) Do such reallocations depend on the productive capacities already present in a country ?

(3) To what extent does the persistence of product entries vary with the distance between a product's PCI and the country's WEC ?

To address these questions, three perspectives are adopted. First, the analysis examines how much each effect account for changes in export complexity across periods. Second, a long-term perspective is taken by comparing trade data from a base period with subsequent ones, in order to assess how each effect influences the trends of export complexity over time. Third, the persistence of entries is analysed by mapping the share of new products that remain exported conditional on their distance from the WEC.

The remainder of this section is structured as follows: First, a Weighted Export Complexity (WEC) index is computed, and a hierarchical decomposition of changes in this measure is developed across HS2, HS4 and HS6 levels of product classification. Next the results are presented and analysed. Thereafter, the persistence of product entries is assessed. Finally, findings are discussed.

4.1. Methodology

To construct a structural measure of economic complexity that highlights countries' relative economic and technological strength, I use trade data at the HS6 level combined with corresponding PCI to compute a Weighted Export Complexity (WEC) index as a weighted average across all products n exported by country c at period t:

$$WEC_{c,t} = \sum_{i=1}^{n} s_{i,c,t} \times PCI_{i,t} \quad (2)$$

where, $s_{i,c,t}$ denotes the share of product i in the total exports of country c at time t. This formulation provides a straightforward way to account for deep underlying capabilities that shape structural differences, specialization paths and trade patterns. It is relatively practical since it permits decomposition and easily interpretable.

Building on this measure, I propose a decomposition inspired by Griliches and Regev (1995) (GR) who investigated whether changes in average productivity stemmed from within-firm dynamics, from the reallocation of resources between them, or from the net extensive changes (Melitz and Polanec, 2015). Analogously, changes in WEC can be decomposed into a within and between components, however, each of these, int turn, can be further separated into three effects: reallocation among surviving exports (at the sector or product level), the entry of new products (or sectors), and the exit of products (or sectors). This is made possible because sectoral complexity is itself computed as a weighted average of the complexity of its constituents. Conceptually, this would correspond in the GR framework to having data, not only at the firm level, but also on the range of products and activities undertaken within firms.

Formally, the weighted measure of complexity, can be expressed hierarchically as:

$$WEC_{c,t} = \sum_{k}^{n} s_{k,c,t} \sum_{j\in k}^{m_k} s_{j,t} \sum_{i\in j}^{l_j} s_{i,t} \times PCI_{i,t} \tag{3}$$

where sectors at the HS2 level are indexed by *k*, industries at the HS4 level by *j*, and products at the HS6 level by *i*. Each country *c* is present in *n* sectors, *m* industries per sectors, and *l* products per industries. This decomposition makes it possible to compute the average complexity of each HS4 industry as the sum of the product level shares multiplied by their PCI, where the shares are defined as the export value of product *i* divided by the total export value of industry *j*. Similarly, the average export complexity of each sector *k* can be estimated as a weighted sum of the complexity of the HS4 industries it contains. Finally, the WEC of country *c* at time *t* can be estimated as the weighted sum of its sectors' complexity levels. It follows directly that both the simple weighted average (equation 2) and the hierarchical decomposition (equation 3) yield equivalent results.

Applying the GR decomposition first to products at the HS6 level for illustration, we obtain:

$$\Delta WEC_c = \underbrace{\sum_{i}^{l} \Delta s_i \times (\overline{PCI_i} - \overline{WEC_c})}_{Between\ Effect} + \underbrace{\sum_{i}^{l} \Delta PCI_i \times \overline{s_i}}_{Within\ Effect} + \underbrace{\sum_{i\in\mathcal{N}}^{\mathcal{N}} s_{i,t} \times \left(PCI_{i,t} - \overline{WEC_c}\right) - \sum_{i\in\mathcal{D}}^{\mathcal{D}} s_{i,t-1} \times \left(PCI_{i,t-1} - \overline{WEC_c}\right)}_{Net\ Extensive\ Effect} \tag{4}$$

Where ΔWEC_c is the difference in WEC between two time periods for country *c*. The set $\mathcal{N}$ denotes new products exported at time *t* but not at *t-1*, while $\mathcal{D}$ is the set of products dropped exported at *t-1*, but not at *t*. Using midpoint values, the equation fully catches the change in export complexity and do not favour a period over another one. On the right-hand side lies first a between effect capturing the reallocation for export shares among products weighted by the difference between each product's complexity and the country's WEC, both meaned over the two periods (midpoint). This term is positive when exports shift towards relatively more complex products and negative when they shift towards simpler ones. The second element is the within effect and reflects changes in PCI scores, weighted by the average export shares. Since the PCI depends on the number and diversity of countries exporting a product, this effect is positive when the products exported become more complex over time, and negative when they become less complex. Finally, there is the net extensive effect that includes the entry and exit margins. The entry effect is positive when new products are more complex than the country' average basket and negative otherwise. While the exit effect will be positive (negative) when relatively simpler (more complex) products disappear.

Because parent groupings are defined as a weighted average of the complexity of its subcomponents, the decomposition can be extended hierarchically. At the HS2 level, the change in WEC can be expressed as:

$$\Delta WEC_c = \sum_k^n \Delta s_k \times (\overline{WC_k} - \overline{WEC_c}) + \sum_k^n \Delta WC_k \times \overline{s_k} + \sum_{k\in\mathcal{N}_k}^{\mathcal{N}_k} s_{k,t} \times \left(WC_{k,t} - \overline{WEC_c}\right) - \sum_{k\in\mathcal{D}_k}^{\mathcal{D}_k} s_{k,t-1} \times \left(WC_{k,t-1} - \overline{WEC_c}\right) \quad (5)$$

Then, the change in the weighted complexity at the HS2 level (ΔWC_k), which is the within effect, can be further decomposed as previously at the HS4 level:

$$\Delta WC_k = \sum_{j\in k}^{m_k} \Delta s_j \times \left(\overline{WC_j} - \overline{WC_k}\right) + \sum_{j\in k}^{m_k} \Delta WC_j \times \overline{s_j} + \sum_{j\in\mathcal{N}_j j\in k}^{\mathcal{N}_j} s_{j,t} \times \left(WC_{j,t} - \overline{WC_k}\right) - \sum_{j\in\mathcal{D}_j j\in k}^{\mathcal{D}_j} s_{j,t-1} \times \left(WC_{j,t-1} - \overline{WC_k}\right) \quad (6)$$

Similarly, changes in weighted complexity within HS4 level (ΔWC_j) can again be decompose at the product-level:

$$\Delta WC_j = \sum_{i\in j\in k}^{l} \Delta s_i \times \left(\overline{WC_i} - \overline{WC_j}\right) + \sum_{i\in j\in k}^{l} \Delta WC_i \times \overline{s_i} + \sum_{i\in j\in k\in\mathcal{N}_i}^{\mathcal{N}_i} s_{i,t} \times \left(WC_{i,t} - \overline{WC_j}\right) - \sum_{i\in j\in k\in\mathcal{D}_k}^{\mathcal{D}_i} s_{j,t-1} \times \left(WC_{j,t-1} - \overline{WC_j}\right) \quad (7)$$

Replacing equation (6) and (7) in the equation (5), we obtain the full decomposition of changes in WEC across HS4, HS4, and HS6 levels:

$$\Delta WEC_c = \underbrace{\sum_k^n \Delta s_k \times \left(\overline{WC_k} - \overline{WEC_c}\right) + \sum_{k\in\mathcal{N}_k}^{\mathcal{N}_k} s_{k,t} \times \left(WC_{k,t} - \overline{WEC_c}\right) - \sum_{k\in\mathcal{D}_k}^{\mathcal{D}_k} s_{k,t-1} \times \left(WC_{k,t-1} - \overline{WEC_c}\right)}_{Between\ HS2} +$$
$$\underbrace{\sum_k^n \overline{s_k}\left[\sum_{j\in k}^{m} \Delta s_j \times \left(\overline{WC_j} - \overline{WC_k}\right) + \sum_{j\in k\in\mathcal{N}_j}^{\mathcal{N}_j} s_{j,t} \times \left(WC_{j,t} - \overline{WC_k}\right) - \sum_{j\in k\in\mathcal{D}_k}^{\mathcal{D}_j} s_{j,t-1} \times \left(WC_{j,t-1} - \overline{WC_k}\right)\right]}_{Within\ HS2} +$$
$$\underbrace{\sum_k^n \overline{s_k}\left[\sum_{j\in k}^{m} \overline{s_j}\left[\begin{array}{c}\sum_{i\in j\in k}^{l} \Delta s_i \times \left(\overline{WC_i} - \overline{WC_j}\right) + \sum_{i\in j\in k}^{l} \Delta WC_i \times \overline{s_i} + \\ \sum_{i\in j\in k\in\mathcal{N}_i}^{\mathcal{N}_i} s_{i,t} \times \left(WC_{i,t} - \overline{WC_j}\right) - \sum_{i\in j\in k\in\mathcal{D}_k}^{\mathcal{D}_i} s_{j,t-1} \times \left(WC_{j,t-1} - \overline{WC_j}\right)\end{array}\right]\right]}_{Within\ HS4} \quad (8)$$

At each level, the complexity indices at the HS2, HS4 and HS6 are centred respectively at the country ($\overline{WEC_c}$), HS2 ($\overline{WC_k}$) and HS4 ($\overline{WC_j}$) levels to represent the relative deviations from the complexity of the parent category. Then, for each level, reallocation captures shift between continuously exported elements within the same level, entries and exits measure the impact of new and dropped products, industries and sectors, while the PCI changes over time can be reduced to the product level (HS6).

This last effect reflects how difficult products become to be exported competitively. For instance, if a product that was previously complex becomes easier to produce because its required capabilities spread across a larger number of countries, then the relative rarity decreases and its PCI falls. Conversely, a product may become more difficult to export competitively if competitive pressures intensify from countries with more, rarer or with a more innovative combinations of capabilities (developed countries), improving productivity and the desirability of their varieties, thus, driving out countries with less capabilities.

Such a relativistic definition of complexity is consistent with the idea that the technological frontier is constantly shifting and may even be accelerating (Moore's law). A striking example is the textile industrialisation of the United Kingdoms, which was a significant technological advantage associated to rare capabilities. Today, however, textile production has relocated from developed countries to developing ones in search of cheaper labour, and the industry is no longer associated with highly desirable capabilities.

Therefore, this hierarchical decomposition makes it possible to identify whether changes in export complexity are driven primarily by structural changes across sectors (HS2), reallocations within industries (HS4), or specialisations at the product level (HS6).

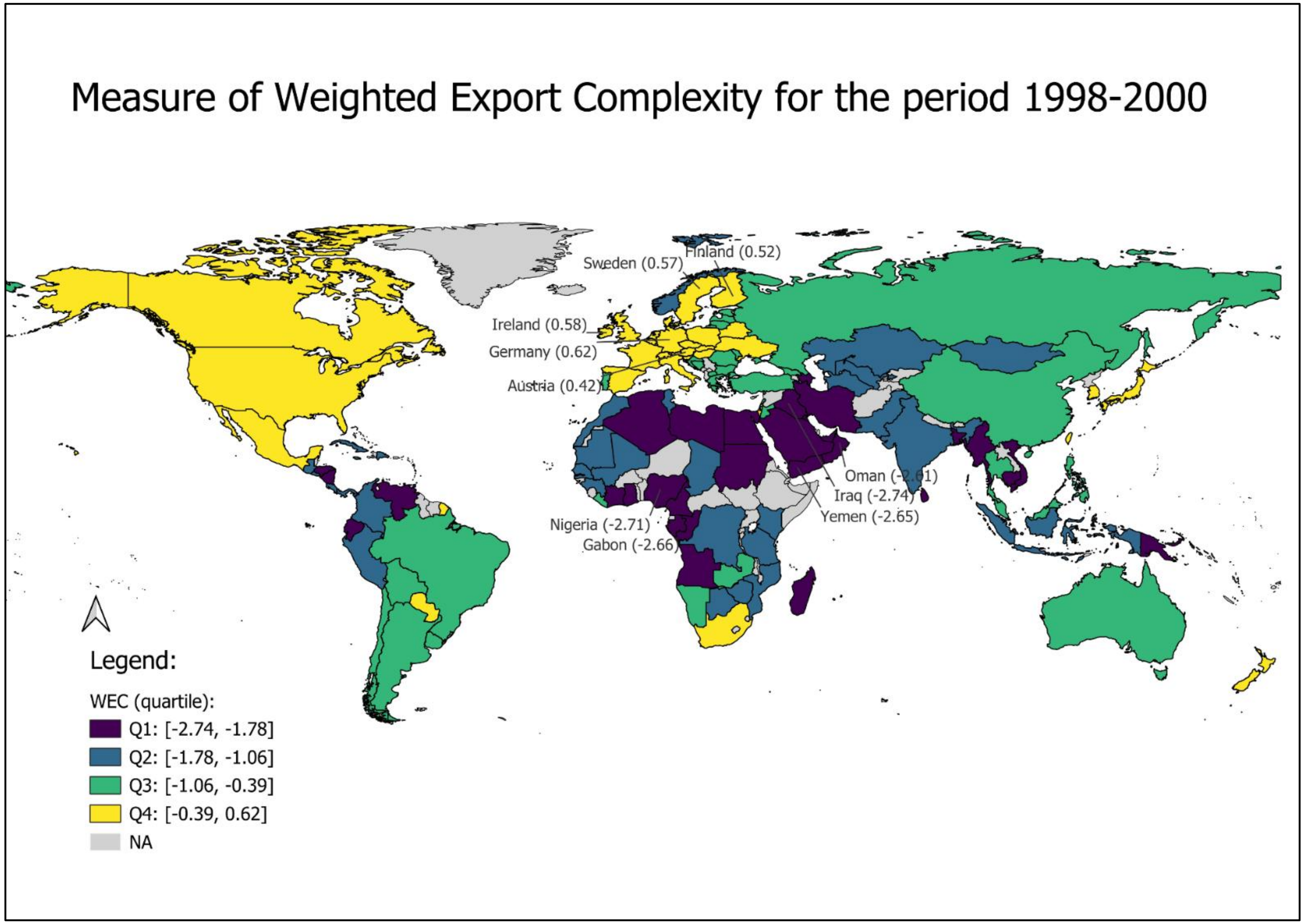
Finally, note that the classification of a product entry can be assigned at different levels depending on the pre-existence of the parent category. If a new product is the first within a HS4 industry inside an already existing HS2 sector, it is recorded as an entry at the HS4 level. Likewise, if the sector were not pre-existent, the entry is counted at the HS2 level. This ensures that the centring terms are always a two-period average.

4.2. Results description

Map 1 presents the WEC scores of selected countries (except for Serbia) during the base period 1998-2000. The legend divides equally countries into four groups. High WEC countries are mostly situated in Europe and North America. Three countries in East Asia also rank in the top quartile (Q4): Japan, Korea and Taiwan, while in Oceania, Africa and South America, only one country in each region appears in the top group, namely New Zealand, South Africa and Paraguay. Several emerging economies such as China, Brazil, and Turkey display relatively lower level of WEC falling into the third quartile. By contrast, countries whose exports are dominated by natural resources such as petroleum, gas and ores exhibit the lowest WEC values, reflecting both the low complexity of these goods and their large shares in total exports.

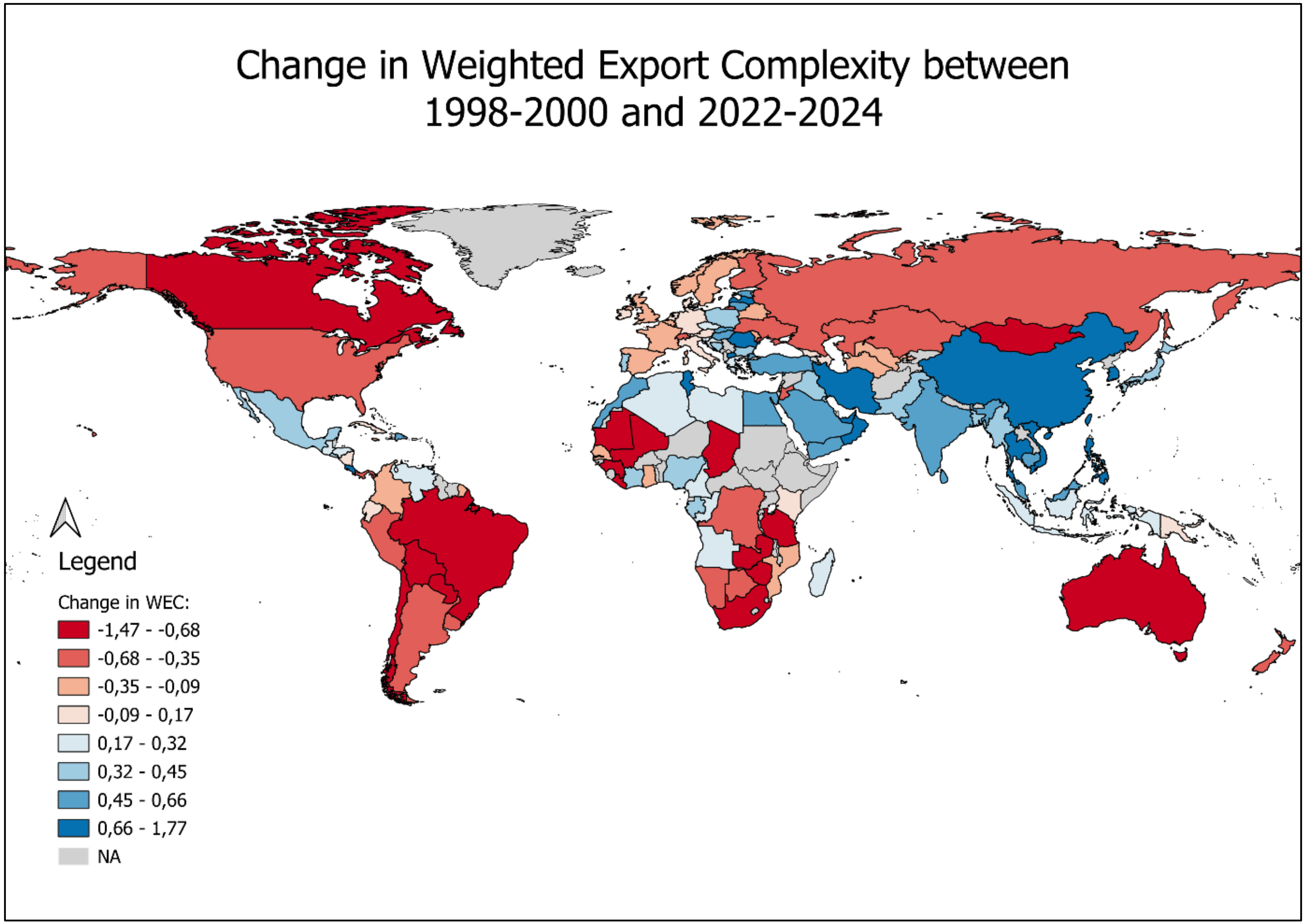
Then, map 2 illustrates the change in WEC between the base period and 2022-2024. South-East Asian countries stand out as those that complexified their exports the most, with Vietnam, China, Taiwan, and Thailand, all increasing their industrial capacities over time. Easten Europe also saw positive changes in their WEC through industrialisation and integration to the European Union during the period under study. We can further see that the largest reductions in weighted export complexity are observed in resource-rich countries like Canada, the United States of America, several South American and African countries, Australia, and Mongolia. This pattern suggests that over the period examined, these economies disproportionately expanded their exports of simple products, likely natural resources.

Map 1: Measure of Weighted Export Complexity for the period 1998-2000



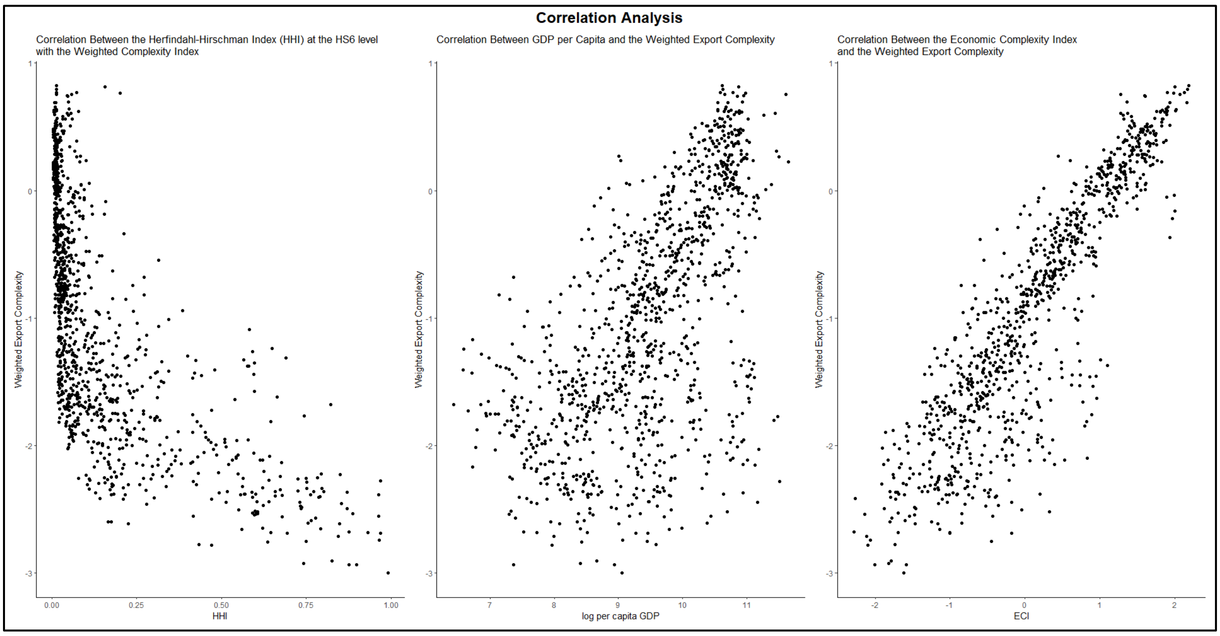
Note: Non-NA observations correspond to the results for selected countries presented in the Annex A.2 at the exception of Serbia, for which data are missing. The legend split countries into quartile and displays cut-off ranges. The top five (in Europe) and bottom five countries (in Africa and in the Middle East) are highlighted.

Map 2: Change in Weighted Export Complexity between 1998-2000 and 2022-2024



Note: countries with non-NA observations correspond to selected countries at the exception of Serbia and Sudan for which data are missing. The legend splits observations into octiles. Top ten and bottom ten changes are presented in table 2

Graph 1: Correlation Analysis: WEC, HHI, per capita GDP, ECI



Note: From left to right, the graphs present the correlation between WEC and the Herfindahl-Hirschman Index (HHI), the logarithm of per capita GDP, and the Economic Complexity Index (ECI). Each point represents the observation of a given country for a given period.

A correlation analysis between the WEC and the concentration, measured by the Herfindahl-Hirschman Index (HHI)[2], shows that higher (lower) concentration is correlated to a lower (higher) WEC. The former case, where a small number of products account for a large share of exports, usually corresponds to natural resource exporters, while the latter case, where countries are highly diversified, tends to represent industrialized economies. This explains the overall negative relationship between concentration and export complexity.

Then, the relationship between the logarithm of per capita GDP and WEC exhibits a positive correlation of 0.61, which increases to 0.79 when countries with a high natural resource rent[3] are excluded. It suggests that exporting more complex products is associated with higher incomes particularly in economies less reliant on mineral fuels, oil and their distillation.

Finally, these two results are consistent with previous findings on the ECI. This stems from the strong correlation between the ECI and WEC, which stands at 0.89 and reaches 0.94 when excluding countries with significant oil rent.

[2] $HHI = \sum_i^n s_i^2$

[3] Countries with over 50% of their exports in *Mineral fuels, mineral oils and products of their distillation* (HS2: 27)

Table 2 reports the WEC for the period 2022-2023 together with the change in export complexity (ΔWEC) between the base period (1998-2000) and the last period (2022-2023) for the ten countries with the largest increases and decreases in complexity. To facilitate interpretation and clarity, the decomposition results from the within-HS2 and within-HS4 levels are aggregated (including the reallocation, entry and exit effects), into a single within effect, while the HS2 level will be referred to as the between effect. This aggregation is motivated by confusing and hard to interpret results in preliminary analyses due to the number of levels.

Among the ten countries that experience the largest increases in export complexity, several are East and South-East Asian countries that industrialised over the past two decades, namely, Vietnam, China, Taiwan, Thailand, South Korea and the Philippines. Two European countries, Romania and North Macedonia, also appear, both of which shifted significantly towards the chemical and machinery sectors. Costa Rica is the only country in the top group from the Americas, driven by the relative expansion in exports of optical, photographic and film equipment (medical instruments), a sector with a PCI score of 0.99 ranking as the third most complex. Finally, Iran is a special case since its increase in export complexity reflects the plummeting of its exports in natural resources due to international sanctions. In 1998, exports in mineral fuels and related products represented 77% of Iran's exports, by 2023, this share had fallen to about 9.5%. This is not the result of diversifications, the total export value remained nearly unchanged from USD 12.5 billion in 1998 to USD 13.2 billion in 2023 after peaking at USD 125 billion in 2011.

By contrast, the ten countries with the largest decreases in export complexity are predominantly resource-rich economies specialising in crude oil, natural gases, ores such as gold, zinc, and iron, or agricultural and food commodities including cotton, soybeans, and fish. Decline of WEC in these cases may be attributed to higher demand for carbon-intensive energy (partly from re-directed demand following international sanctions against Iran and Russia), higher international prices, or the discovery and subsequent exploitation of new resource deposits.

The remainder of Table 2 represents the decomposition of ΔWEC. Three main components are highlighted: the between-sector effect, the within-sector effect, and the change in product complexity (ΔPCI). Together, these sum to the overall change in WEC, though, minor discrepancies might arise due to rounding. Both the between and within levels are further decomposed into three effects: (i) continuity, representing reallocations of export shares among continuously exported sectors or products, (ii) new, capturing contribution of sectors or products entries, and (iii) drop, measuring the effect of sectors or products exits. By adding the continuity and new effects and subtracting the drop effect, we obtain the net contribution of each level to changes in export complexity. A positive value for the drop effect indicates that, on balance, a country exited relatively simpler sectors or products.

Taking Taiwan as an example, the between effect is relatively small, suggesting that the broad sectoral structure of exports remained stable between the first and last periods, and its contribution is primarily driven by the continuity effect. Concerning the within effect, it is substantially higher at 0.271 and explained largely by the drop effect, indicating that Taiwan ceased exporting relatively simple products within existing industries. Finally, the largest contribution in Taiwan's increase in export complexity stems from changes in PCI of its exported products, meaning that they became relatively more complex to export competitively over time. Altogether, the main source of export complexification comes from rising PCI values, followed by within-sector upgrading through the discontinuation of simple exports, the introduction of more sophisticated products, and the increased export shares of high-complexity goods.

Table 2: Countries with the most important changes in WEC over the sample period

Top and Bottom Changes in Export Complexity

1998-2000 vs 2022-2024

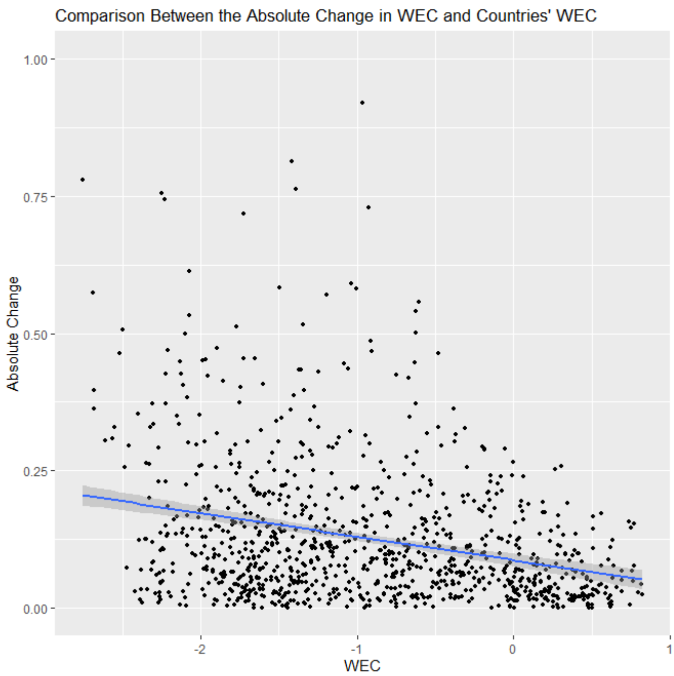
Country	**WEC**	**Δ**	**Between**	Continuity	New	Drop	**Within**	Continuity	New	Drop	**Δ PCI**
Viet Nam	-0.187	1.766	1.215	1.212	0.004	0.001	0.405	0.125	0.216	-0.063	0.146
China.	0.3	1.256	0.441	0.439	0.001	-0.001	0.42	0.205	0.177	-0.037	0.3949
Iran	-1.374	1.094	0.758	0.717	0.043	0.002	0.224	0.254	-0.002	0.028	0.1113
Taiwan	0.767	0.943	0.026	0.023	-0.002	-0.005	0.271	0.094	0.023	-0.154	0.6457
Romania	0.096	0.909	0.639	0.63	0.008	-0.002	0.172	0.06	0.084	-0.028	0.097
Costa Rica	-0.314	0.86	0.484	0.482	0.003	0.001	0.102	0.008	0.043	-0.051	0.2741
Thailand	-0.001	0.845	0.139	0.145	-0.009	-0.002	0.301	0.172	0.061	-0.069	0.4045
South Korea	0.564	0.832	0.127	0.126	0.001	-0.001	0.335	0.104	0.092	-0.138	0.3706
Philippines	0.059	0.803	-0.134	-0.126	-0.01	-0.002	0.212	-0.031	0.075	-0.168	0.7252

Top and Bottom Changes in Export Complexity 1998-2000 vs 2022-2024											
Country	**WEC**	**Δ**	**Between**	Continuity	New	Drop	**Within**	Continuity	New	Drop	**Δ PCI**
North Macedonia	-0.015	0.8	0.761	0.762	0	0.001	0.077	0.04	0.009	-0.028	-0.0376
Zimbabwe	-1.998	-0.864	-0.078	-0.023	0	0.056	-0.127	0	-0.015	0.113	-0.6586
Paraguay	-1.227	-0.888	0.095	0.093	0.003	0	-0.089	-0.054	-0.008	0.027	-0.8947
Bolivia	-1.761	-0.952	-0.191	-0.204	0	-0.014	-0.052	-0.028	-0.027	-0.003	-0.7098
Brazil	-1.473	-1.056	-0.456	-0.459	0.001	-0.002	-0.124	-0.052	-0.055	0.017	-0.4768
Canada	-0.826	-1.057	-0.676	-0.676	0	0	-0.133	-0.136	-0.006	-0.008	-0.2478
Zambia	-2.138	-1.193	-0.041	-0.052	0.022	0.012	-0.285	-0.148	-0.092	0.045	-0.8667
Mali	-2.68	-1.21	0.224	0.24	0.005	0.022	-0.438	0.004	-0.006	0.435	-0.9956
Mauritania	-2.308	-1.245	-0.314	0.02	-0.334	0	0.036	0.06	-0.044	-0.02	-0.9672
Australia	-1.971	-1.308	-0.359	-0.328	0	0.032	-0.062	-0.089	-0.002	-0.029	-0.8859
Liberia	-2.248	-1.397	-0.393	-0.361	-0.024	0.007	-0.6	-0.214	-0.372	0.014	-0.4045
Guinea	-2.778	-1.475	-0.242	0.039	0.002	0.283	-0.098	-0.061	-0.002	0.035	-1.1343

Following the subset results presented in table 2 and in graph 2, it appears that most developed countries experienced only small changes in their WEC. A straightforward explanation may rely on the fact that developed economies tend to be more stable. First, simple products often have elastic demand. Second, fluctuation in natural resource prices can significantly affect the weighted export complexity, even when data are averaged over three years. Third, less complex countries are typically less diversified, which makes them more dependent on a narrower basket of products. By contrast, complex products are likely to face less elastic demand, while complex economies are industrialised and diversified.

Graph 2 illustrate this relationship by plotting the absolute change in export complexity between each time period against the WEC. Confirming the initial intuition, the size of changes tends to be larger for less complex economies and smaller for complex ones.

Graph 2 : Absolute change in WEC vs WEC



Note: each point represents the change in WEC for a country between two successive periods. A regression line with confidence intervals is added to highlight the relationship.

4.3. Within-Between analysis: relative contribution of decomposition terms

A natural question arises from these results: which level and which effect explain the observed changes in WEC, and does this depend on a country's WEC? Different development patterns may imply that the source of variation differs between least developed, developing, and developed countries.

To address this, I estimate ordinary least squares (OLS) regressions of changes in WEC on all decomposition terms, including unit and time fixed effects. This specification removes time-invariant country characteristics and period-specific shocks common to all countries. Since the objective is to assess how much each effect account for variations in changes of WEC, the main statistic of interest is the R^2, and in particular the within-R^2 net of temporal shocks. This measures how much of the variation in WEC within a country is explained by each source, while abstracting common time shocks such as financial crises or pandemics. The regression is expressed as follows:

$$\Delta WEC_{c,t} = \delta_c + \gamma_t + \beta decomposition\_term_{c,t} + \varepsilon_{c,t} \tag{9}$$

where δ_c is the unit fixed effect, γ_t the time fixed effect, and $\varepsilon_{c,t}$ is the error term. The coefficient β represents by how much the dependent variable (ΔWEC) changes following a one-point increase in decomposition term. Since the independent variables are constructed directly from a decomposition of the dependent variable, in theory, each coefficient should equal one, or minus one for the drop effects. Indeed, including all decomposition terms simultaneously yield estimates of one and explains 100% of the variations in the dependent variable.

Nevertheless, running separate regressions for each decomposition term, the R^2 remain informative as it indicates how much of the variation in ΔWEC can be attributed to each effect. Because covariance across terms is likely, estimates may differ from one and lead to a R^2 that do not sum to one. To address this issue, and to improve comparability, R^2 values are normalised by expressing them as percentages of their respective totals: the R^2 values from the between, within and ΔPCI components are normalised together, while continuity, entries and exits effects are normalized within the level they belong.

Results are reported in Table 3. They show that the between-sector changes explain more variation that within-sector changes, accounting 34.48% and 24.63% respectively. The largest contribution, however, comes from changes in PCI, which explains 40.89% of the variation. Then effects at the between and within levels are dominated by the continuity effects explaining 47.28% for the between-sector level and 38.91% for the within-sector level. The smaller share of continuity within sector is offset by relatively larger contribution from entries and exits, showing that product turnover occurs more frequently within industries than between them.

Table 3 : Normalised percentage of variation explained by each decomposition term

Regression Results		
Origine	Estimate	Normalized R^2
Between-sector	1.111 ***	34.48%
• Continuity	1.158 ***	47.28%
• Entries	1.576 ***	26.45%
• Exits	-1.784 **	26.28%
Within-sector	1.33 ***	24.63%
• Continuity	1.57 ***	38.91%
• Entries	1.882 ***	31.00%
• Exits	-1.631 **	30.09%

Regression Results		
Origine	Estimate	Normalized R^2
Δ PCI	1.03 ***	40.89%

Similarly, to test whether these shares are influenced by the level of development, I cluster countries into quartiles computed periodically on the basis of current WEC, so that the variation explained are measured within groups of similarly complex economies. For each quartile, the regressions are then re-estimated for all decomposition terms.

Results are presented in table 4. Considering the contributions of the levels (within-between) and the PCI effect, three patterns emerge: (i) the share of variation explained by between-sector changes increases with WEC until the fourth quartile where the contribution declines, (ii) the within-sector contribution is high for the first quartile, falls for the second one, and then rise again with the WEC, and (iii) the contribution of PCI changes is the largest for the first quartile, decreases until the third quartile, and then increases sharply in the fourth quartile. At the exception of the least complex economies, where the PCI effect explains the largest share of the variation, the between sector component is the main explanatory variable.

These findings suggest a non-linear relationship between the decomposition terms and the share of variation they explain across quartiles. Intuitively, this indicates that (i) countries rely more on between-sector changes during the development process until reaching a certain level of complexity, (ii) the least developed countries depend relatively more on within-sector changes, a pattern than weaken for developing ones but strengthens again among complex economies, and (iii) both the least and most complex economies are relatively more sensible to changes in the PCI of the products they export.

Turning to the decomposition of the between-sector level, the main driver of change in export complexity is the reallocation of shares between continuously present sectors, which rises with WEC up to a certain point, before declining. Inversely, the relative importance of exits and entries falls with WEC but increases again among the most complex economies. Generally, the explanatory power of entries and exits is smaller than that of reallocations among existing sectors, reflecting the greater stability of economic structures at the sectoral level. By comparison, at the within-sector level, entries and exits play a relatively more prominent role, but the general trends observed at the between-sector level also hold here.

Table 4 : Share of variation explained by each decomposition term by quartile of countries based on current WEC

Regression Results by WEC Quartile								
	Q1		Q2		Q3		Q4	
Origine	**Estimate**	**Norm. R^2**	**Estimate**	**Norm. R^2**	**Estimate**	**Norm. R^2**	**Estimate**	**Norm. R^2**
Between-sector	0.95 ***	32.53%	1.067 ***	39.31%	1.17 ***	47.44%	1.161 ***	37.00%
• Continuity	1.018 ***	35.20%	1.067 ***	45.44%	1.228 ***	53.69%	1.159 ***	41.82%
• Entries	2.52 *	32.31%	1.415	27.53%	2.372 ***	25.32%	9.834 *	29.21%
• Exits	-2.5 ***	32.49%	-0.069	27.02%	1.849	21.00%	-4.431	28.98%
Within-sector	1.053 ***	31.64%	0.976 ***	27.02%	2.024 ***	28.26%	1.249 ***	28.75%
• Continuity	1.396 ***	34.90%	1.259 ***	37.68%	2.227 ***	43.21%	1.083 **	34.08%
• Entries	1.218 *	32.56%	0.261	30.69%	3.117 **	28.65%	3.278 ***	34.34%
• Exits	-1.343	32.55%	-1.884 *	31.63%	-2.48	28.14%	-0.86	31.59%
Δ PCI	0.988 ***	35.83%	0.916 ***	33.67%	1.115 ***	24.30%	0.998 ***	34.25%

To conclude, this section has examined the extent to which changes in WEC between periods are explained by different components of the decomposition, and how this relationship varies with countries' level of export complexity. The results indicate that the changes in PCI over time account for a substantial share of variation in ΔWEC, with the least and most complex economies relatively more sensible to it. Between-sector changes explain relatively more variation than within-sector changes overall. Moreover, both levels are primarily driven by reallocation among continuously existing sectors and products, while the relative importance of entries and exits decline as WEC increases. However, this trend reverses for the most complex economies, where entries and exits gain importance, especially within sectors. Finally, the least complex economies appear to be impacted disproportionately more by within-sector changes and on entries and exits compared to other groups.

4.4. **Long-term contribution of decomposition terms**

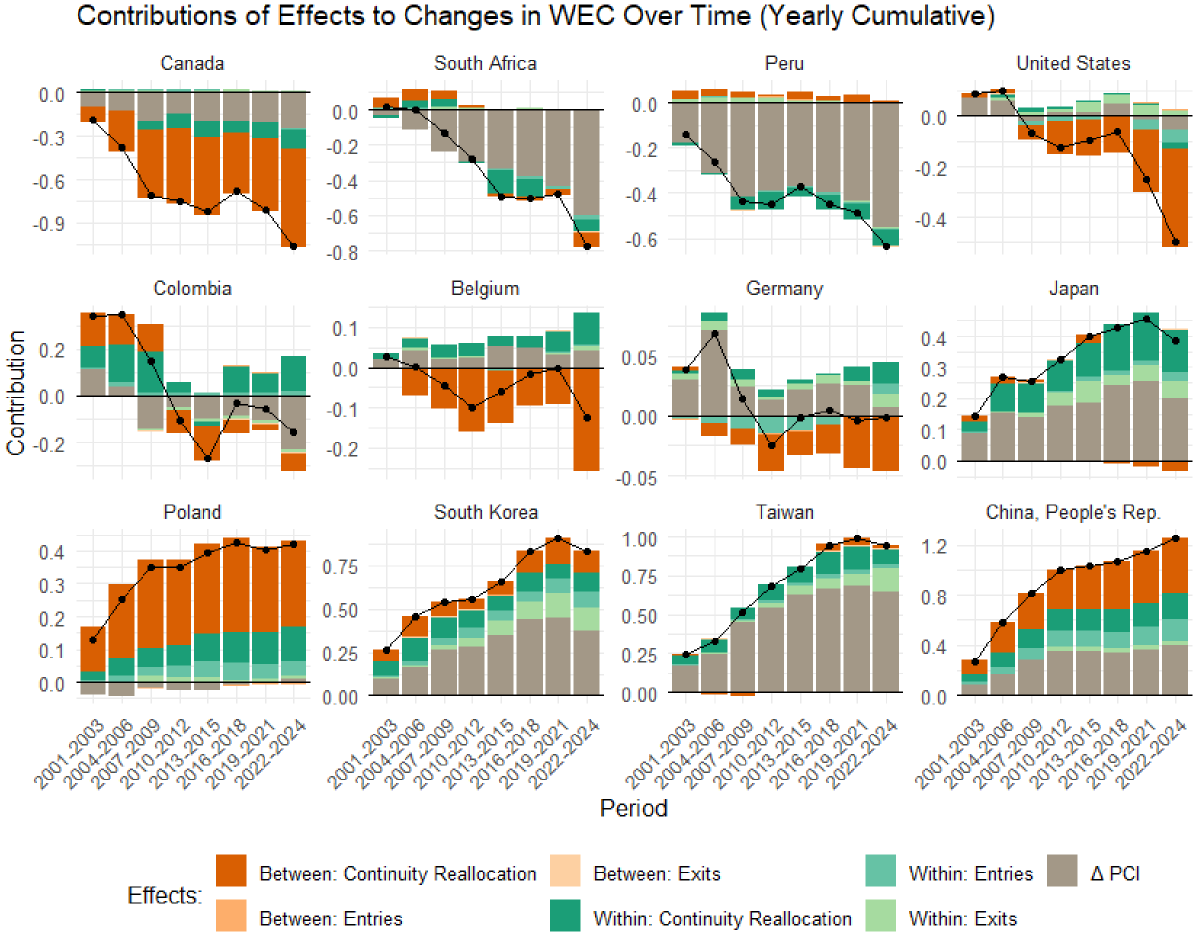
The above analysis already provides a broad direction of the relative importance of the decomposition terms in explaining dynamic changes in WEC. Since we have observed that these effects vary across countries with different levels of WEC, the inquiry can naturally be extended by asking whether their direction and average magnitude are also depentent on a country's level of complexity. Furthermore, it is worthwhile to investigate whether the trends strengthen or weaken over time. These two considerations motivate a long-term analysis of the contribution of each decomposition component.

The evolution across time of the within-between redistribution, of their determinants, and of the PCI changes is computed by setting an initial period (1998-2000) and applying the decomposition to each period (2001-2003 through 2022-2024) always comparing the considered period with the base.

Graph 3 presents a subset of results for selected countries that experienced either a strong negative change in WEC, a near-zero change, or a significant increase. ΔWEC between a period and the base period is represented by a black line. Orangish elements represent between-sector effects, greenish ones within-sector effects, and light brown the PCI effect. Countries are ordered according to their overall changes in WEC between the initial and the last period. The y-axis is not normalized across countries, which causes both the scale and x-axis to differ, making direct cross-country comparison slightly more difficult. However, this choice allows changes in countries with relatively smaller variation, such as Belgium and Germany, to be seen more clearly, especially when extreme cases are included.

Several exemples highlight that the PCI effect can substantially drive both increases and decreases of WEC, as seen for South Africa, Peru, Japan, South Korea and Taiwan. The graphs also show that between-sector reallocation (continuity), rather thanentry or exit, has been a keay determinant of the decline in WEC for Canada and the United States of America, and, conversely, of the increase for Poland and China. Japan's experience is different, its WEC increased through specialisation within sectors rather than through changes in sectoral shares. Finally, having a look at Belgium, the decomposition reveals that the country expanded exports in relatively less complex sectors, yet still experienced within-sector upgrading and vaforable PCI changes.

Graph 3: Contribution Effects to Changes in WEC Over Time (Yearly Cumulative)



Note: Representation of cumulative contribution by the decomposition terms over time for a subset of countries. Countries are ranked according to the cumulative change over the period under study. The black line connecting periods represents this cumulative change evolution. Readers should be careful about the y-axis scale as it is country dependent.

To examine whether general trends differ by countries' level of export complexity, the decomposition terms are next plotted against time by quartile of countries. Results are presented in Graph 4. The orange line shows the average between-sector reallocation effect for countries in each quartile across periods, while the green line represents the within-sector specialisation effect.

In the least complex group (Q1), the between-sector reallocation line is positive and rise until 2016-2018, when it becomes significantly positive, before declining. On the contrary, the within-sector specialisation line exhibits a downward trend. Looking at the period 2016-2018, the graph indicates that countries with a low WEC increased their complexity by reallocating towards more complex sectors, but reduced it through specialisation in simple products within sectors.

In the second quartile (Q2), the between-sector effect is positive but begins to decline slightly from 2010-2012 onwards, while the within-sector effect is not significantly different from zero and remains flat over time. For the third quartile (Q3), the between-sector effect is strongly positive, while the within-sector effect is also positive, though modest in size. Finally, in the fourth quartile (Q4), the main driver of WEC changes is the within-sector specialisation towards more complex goods. For this group, the between-sector effect plays a more limited role, only turning positive from 2013-2015.

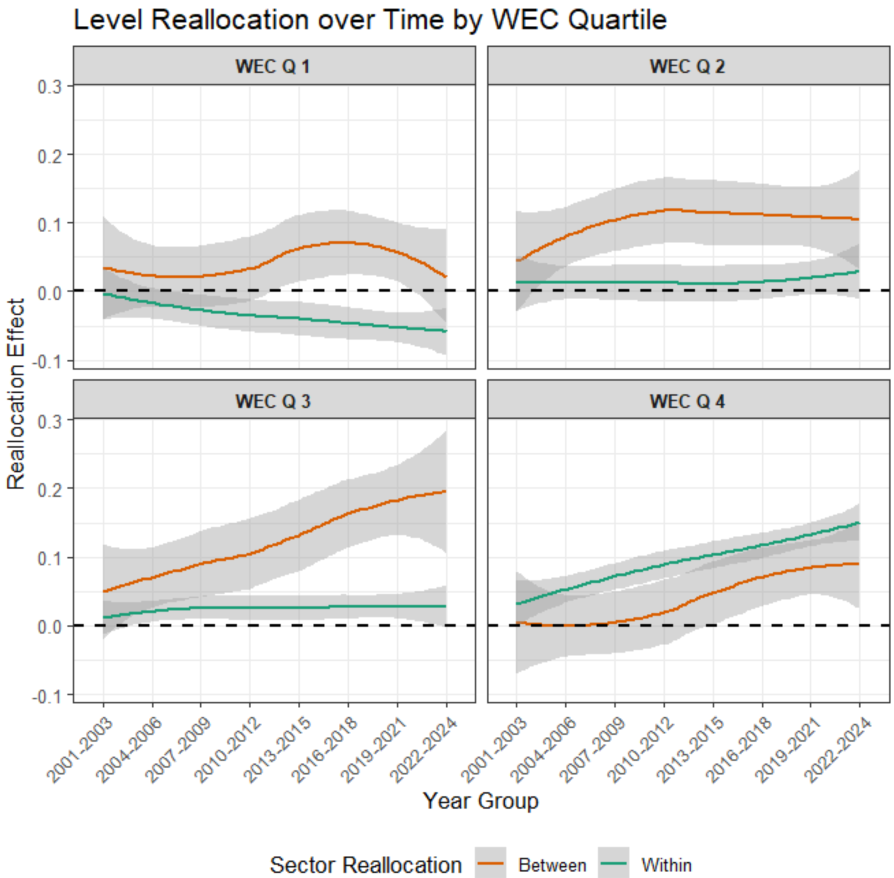
Overall, these time profiles highlight how the contributions of within- and between-sector changes vary with countries' levels of complexity. First, the between-sector effect increases in importance as WEC rises up to the third quartile but plays little role for the most complex economies. Second, the within-sector effect appears to follow a linear relationship with WEC: in the least developed countries it is negative, but its contribution increases steadily with complexity, becoming strongly positive among advanced economies.

These patterns suggest, first, that economies with initially low WEC complexify their exports and develop by shifting towards more complex sectors. Second, less developed countries that do not undergo such structural transformations tend to expand production in simpler products within sectors, either to diversify revenue sources or through the discovery and exploitation of natural resources. Finally, the positive role of within-sector upgrading grows as countries accumulate capabilities and, in advanced economies, may be driven by a positive feedback loop in which new capabilities facilitate the creation of further and potentially rarer capabilities or more innovative combinations among them.

To test the robustness of these results, quartiles are also defined using alternative groupings based on either the first or the last period. The first approach answers the question: *"Given initial conditions, how did countries' WEC evolve, and through which channels?"* The second asks: *"Which processes led countries to end up in their final group?"* Results are provided in the Annex A4. The baseline results (Graph 3) are equivalent to those obtained using the last-period definition of quartiles. However, when quartiles are defined by the first period, notable differences emerge. In particular, the between-sector effect is the strongest for countries initially in Q1, before declining with complexity. This suggests that the least complex economies underwent substantial structural shifts at the beginning of the period, consistent with the idea that such shifts are necessary for development, while these effects become less important as complexity increases.

Finally, the odd shape of the Q1 curve in Graph 4 can, thus, be explained by countries moving across groups over time. As some of the least complex economies developed in more complex sectors, they moved into higher quartiles, ensuring that Q1 represents only the very simplest economies. This dynamic also explains why the between-sector effect is large in Q3 and remains positive, though smaller, in Q4. In this sense, the quartile definition used in Graph 4 can be seen as filtering out countries that gained capabilities from the Q1 group, thereby isolating the characteristics of each state of development based on current economic realities.

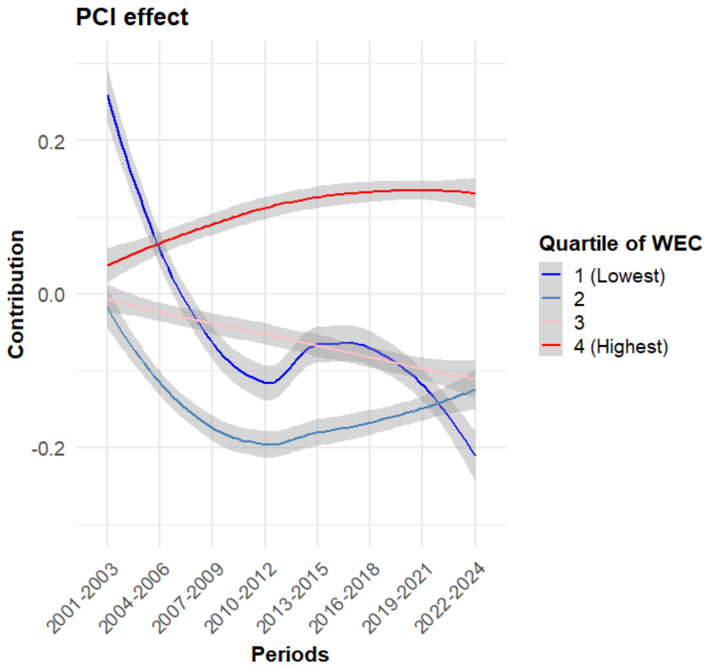
Graph 4 : Within-Between reallocation effect on WEC changes in the long-run



Note: The graphs show the evolution of the mean contribution with confidence intervals form the within-sector and between-sector effect. The sample of countries is divided in quartiles at each period based on their corresponding WEC. A positive (negative) value is interpreted as a positive (negative) contribution to the change in export complexity.

It has already been noted that changes in the PCI over time, stemming from the calculation method, may constitute an important determinant of WEC dynamic, as illustrated in the case of Taiwan. Graph 5 demonstrates how this effect varies across countries depending on the complexity of their export basket. The evidence suggests that only the most complex economies derive positive gains from this effect, whereas other countries experience, on average, a downgrading in the complexity of the products they export.

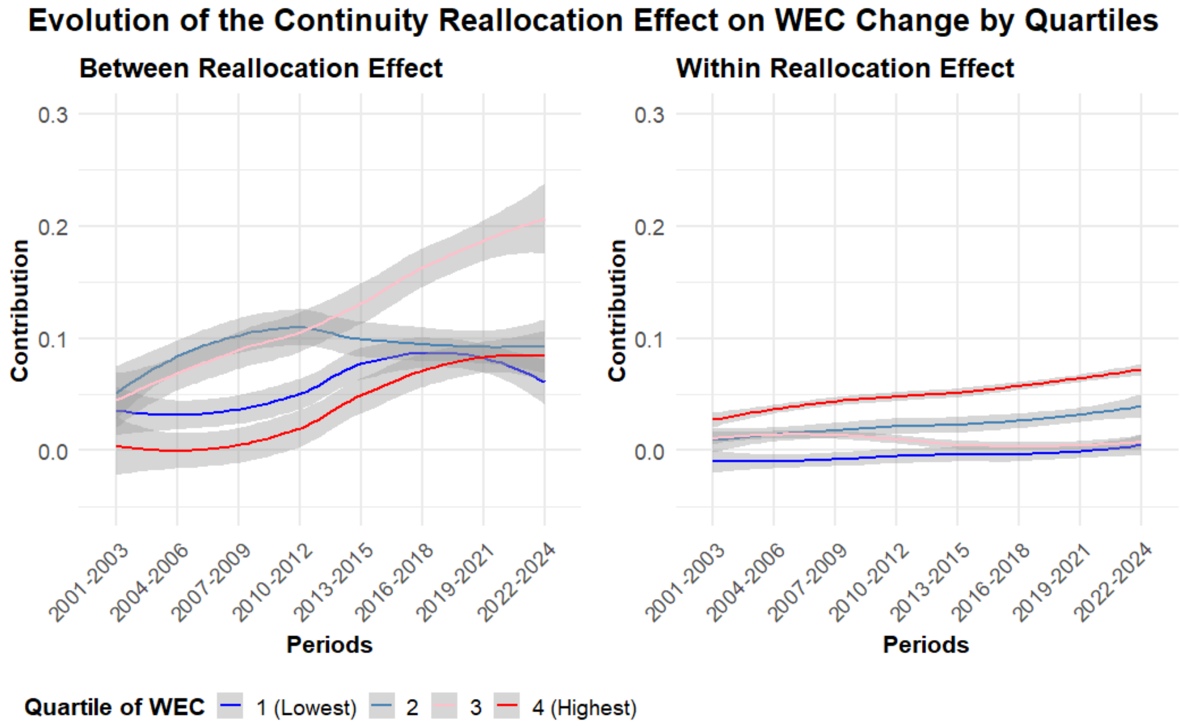
Graph 5: Contribution of the change in PCI over time per quartile



Similarly, the following section plots the contribution of decomposition terms (continuity, entries, and exits) over time and compares differences across quartiles. Moreover, for each effect, both the between- and within-level contributions are presented.

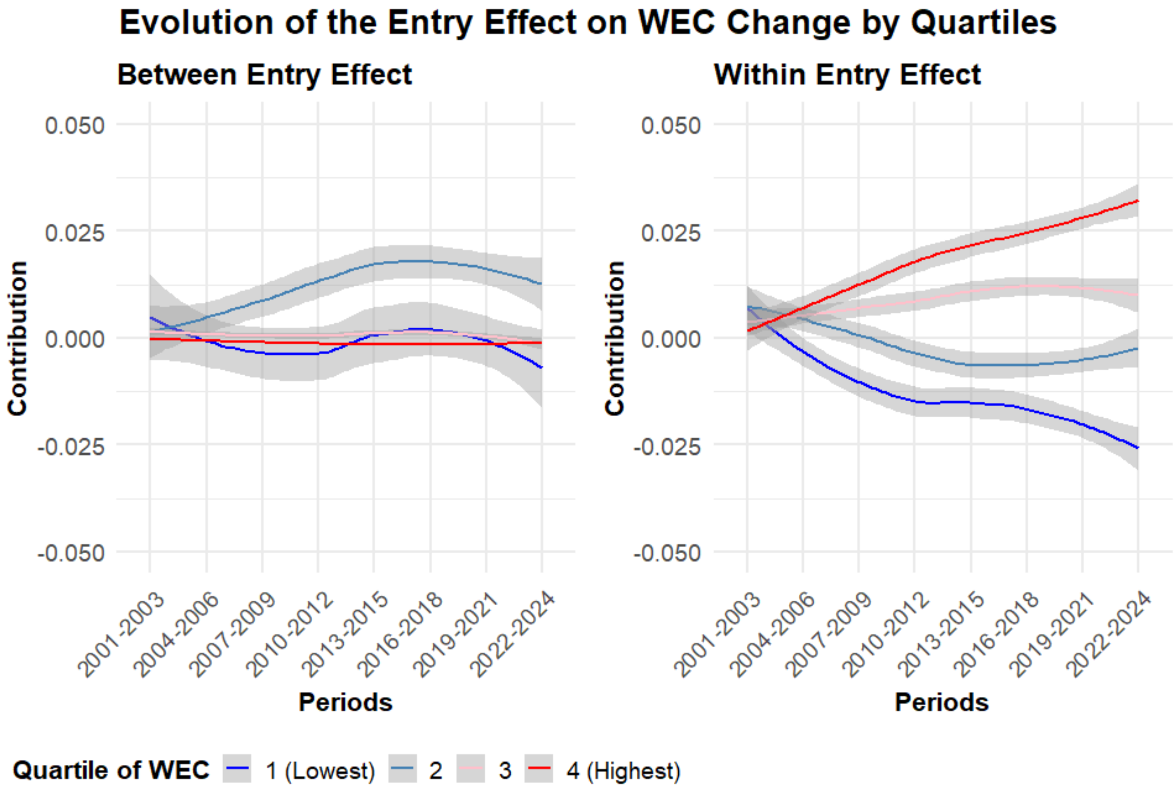
Graph 6 reports the results for the reallocation effect between continuously existing sectors and products. In the long run, the sign of the reallocation effect at both levels tends to be positive, although the contribution at the between level is, on average greater than the within level. This pattern is particularly evident for Q3, whereas for Q4 the two contributions remain broadly similar at the end of the period. The role of the within-sector specialisation may even be relatively greater when the hump in the between-level contribution is attributed to countries that entered the top quartile after a development phase characterised a shift towards complex sectors.

Graph 6: Long-term Within-Between Impact of Continuity Reallocation per quartile



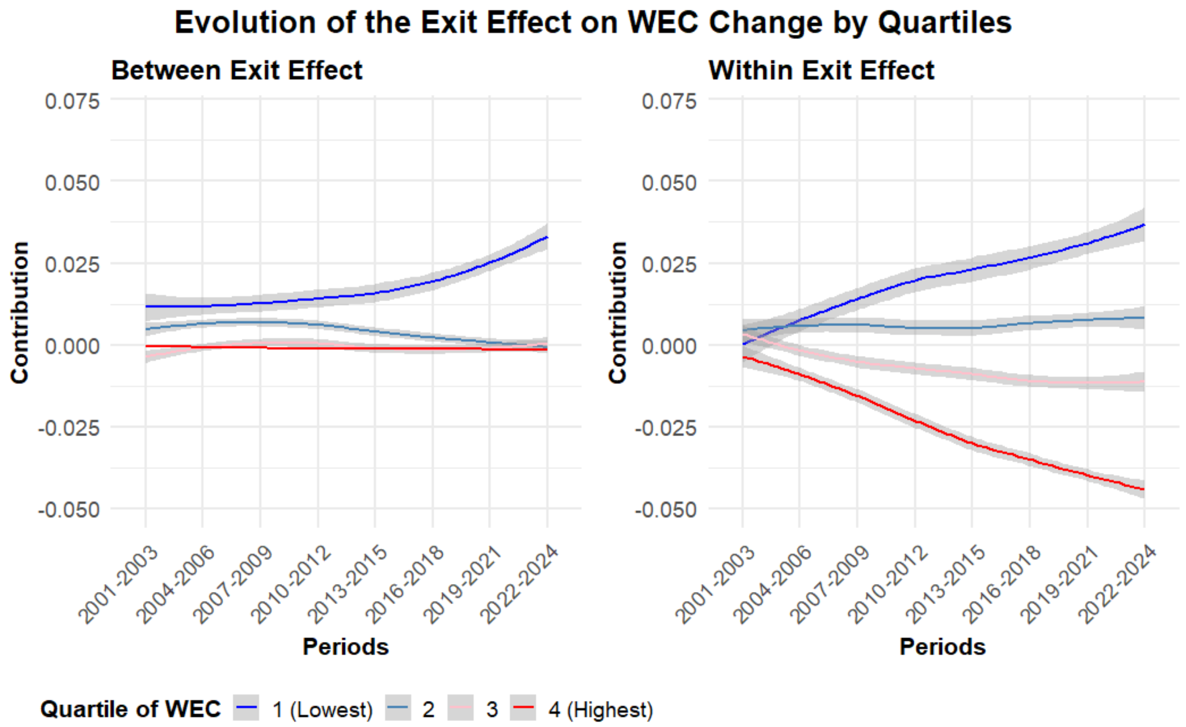
With respect to the entry effect (graph 7), opposite signs emerge depending on whether complex or less complex economies are considered. As countries rarely establish entirely new sectors, the entry effect is largely driven by the within-sector level, with the exception of Q2, where entries into new sectors make appositive contribution to WEC. The within-sector entry effect reveals clear divergent tendencies: complex economies tend to enter relatively more sophisticated products, while the least complex economies expand in simpler goods.

Graph 7: Long-term Within-Between Impact of the entry effect per quartile



Finally, the exit effect showcases broadly similar results to those of the entry effect. In this case, however, note that a positive contribution reflects exits from complex sectors or products, while a negative contribution indicates the exit from simpler ones. The first graph depicts clearly divergent patterns: less complex economies withdraw from complex productions, whereas, with rising WEC, countries start abandoning simpler products. As with entry effect, most of the variation arises at the within-sector level, apart from countries in Q1 who exited complex sectors.

Graph 8: Long-term Within-Between Impact of the exit effect per quartile



This part has shed light on the signs and magnitudes of the decomposition terms conditional on countries' WEC, thereby illustrating differences on how countries see their WEC change over time. First, countries in Q1 tend to specialise in simpler products within sectors and are likely to remain trapped in this group unless they undergo structural transformations by reallocating activities across sectors. The robustness check, which fixes groups based on the initial period, confirms this observation. It further suggests that the strong between-sector contribution observed for Q3 in the baseline case reflects countries that underwent sectoral shifts toward more complex economic activities and subsequently moved into Q3. Once countries reach high-complexity sectors, however, further gains are increasingly driven by within-sector specialisation, while the relative importance of between-sector effects diminishes.

In addition to section 4.2.2, this analysis highlights that the impact of the product reclassification is not random and disproportionately benefits complex economies, while the three lower quartiles suffer from product downgrading over time. These results likely point to a shifting knowledge frontier driven by the top quartile and operating to the detriment of less complex countries. As knowledge diffuses, more economies begin producing goods that was once regarded as complex, thereby lowering the PCI both directly through reduce ubiquity, and indirectly through the lower WEC of the producing countries.

As a last point, the contribution of continuity reallocations, entries, and exits at the within- and between-sector levels were examined. At the between-sector level, entries and exits contribute, on average, close to zero, standing out that sectoral shifts occur predominantly within continuously existing sectors, as highlighted in Graph 6. Two exceptions emerge: countries in Q2, which increase their WEC through entry into complex sectors, and countries in Q1, which are negatively affected by exits from complex sectors. At the within-sector level, however, divergent trends are observed. Complex economies tend to enter (exit) complex (simple) products, while less complex economies follow the opposite trajectory by entering (exiting) simple (complex) products.

Then, the reallocation of continuously exported products contributes positively to WEC changes in Q4 and Q2 but remains close to zero in other quartiles. The size and direction of these contributions depend on the group of countries considered: (i) countries in Q1 are negatively affected by both entries and exits, while continuity reallocations have, on average, no effect, (ii) countries in Q2 face similar negative impacts from entries and exits, though they benefit from positive continuity reallocations, which are insufficient to offset the losses, (iii) in Q3, the within-sector contribution is driven by entries and exits, which are positive, while continuity reallocations remain negligible, (iv) in Q4, within-sector specialisation is determined positively by all three components, reallocations, exits, and entries, in descending order of importance.

4.5. Persistent entries: opportunity costs vs capabilities requirements

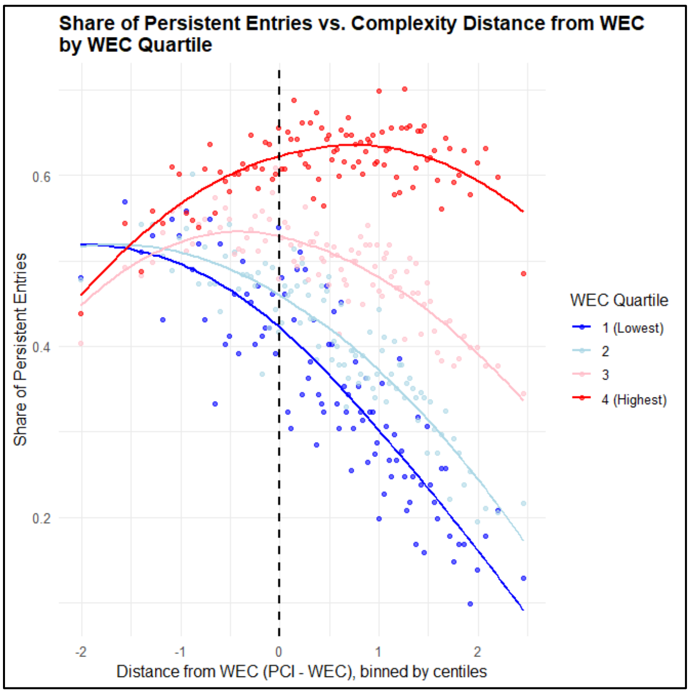
The complexity of product entries can reasonably be expected to depend on the locally available capacities, as proxied by WEC. Countries with a higher WEC possess broader and more advanced capacities, enabling them to enter the production of complex goods and to sustain such entries over time. By contrast, countries with lower WEC are more likely to face difficulties in maintaining entry into complex products, as they lack the requisite capacities.

What matters mist for structural transformation and the long-term complexification of exports is the persistence of entries. The share of persistent entries in total entries is likely to vary according to the gap between a country's WEC and the PCI of the products entered. Differences in persistence, conditional on the relative complexity of entries, may therefore explain the variation in both the size and direction of the entry effects at the within and between levels on WEC changes.

For the purpose of this analysis, an entry is defined as persistent if it is exported for three consecutive periods (including the initial entry period) and is considered as a non-persistent entry otherwise. For each country quartile, the PCI of both persistent and non-persistent entries is centred on the WEC of the country in which the entry occurs. The differences are then grouped into centiles, for which the shares of persistent and non-persistent products are computed.

Graph 9 plots the resulting shares by their relative distance from the WEC for each group of countries. Q4 and Q3, represented in blue and light blue, are characterised by a negative slope, indicating that the highest share of persistent entries arises from products simpler than the country's WEC. Conversely, the more complex the entry relative to the WEC, the lower the likelihood that it will persist over time. In contrast, Q1 and Q2, shown in red and pink, display a bell-shaped curve: persistence is least likely at both extremes of relative complexity. However, the two groups differ in the relative position of their maxima. The second quartile reaches its highest persistence share at a complexity level slightly below its WEC, whereas the most complex economies reach their maximum above their WEC. Moreover, the curve for the top quartile lies consistently above the others, indicating a greater overall tendency towards persistent entries.

Graph 9 : Share of persistent entries by current quartile of WEC normalized by the WEC of countries



Note: Distance between the entryies' PCI and the WEC are binned into centiles for each quartile of countries.

4.6. Discussion

This section addressed the question of what drives changes in export complexity: whether they stem primarily from shifts in the relative importance of sectors or from specialisation within them. To examine this, I adapted the GR approach to construct a dynamic hierarchical decomposition, in which each level (within and between) is further broken down into continuity reallocations, entries, and exits. Moreover, changes in WEC attributable to shifts in PCI values over time are explicitly accounted for.

A first analysis of the resulting contributions per decomposition term is conducted by regressing changes in WEC successively on each individual component within quartiles of countries. The explanatory power of each regression, measured by the R^2 statistic, was then normalised to facilitate comparison. Intuitively, a component that explains relatively more of the variation can be regarded as a more important determinant of how countries experience changes in WEC over time. The main findings highlight the relative importance of the PCI effect compared to both the within- and between-sector effects. Among the latter, continuity reallocations emerge as the dominant driver, although entry and exit contributions are relatively stronger within sectors than between them. In addition, these relative contributions differ across quartiles, suggesting that the determinants of WEC changes vary with the level of economic complexity.

Nonetheless, while this approach provides an interesting perspective by attributing variation explanatory power to different sources, it is limited as it does not capture the actual size or direction of these effects. Moreover, it is possible that the signs of the variations observed within quartiles are random and the result of specific industrial strategies and policies, rather than broader economic patterns. Extending the analysis by plotting the average contribution of effects across quartiles therefore makes it possible to assess not only the signs and magnitudes for each group, but also variations and changes in trends within them.

Robustness checks, for example, suggest that positive between-sector contributions may be driven by countries initiating their development process yet remaining in the bottom quartile for one or more periods. In Q3, the first analysis points to a relatively strong influence of within-sector continuity reallocations. Nonetheless, in the long run, this effect is near zero. Yet, this can be explained as, until the period 2013-2015, the contribution of continuity reallocations is at least twice as large in magnitude as that of both the entry and exit effects.

Taken together, the two approaches provide meaningful economic insights. First, countries initially endowed with fewer capabilities complexify their exports by shifting from low- to high- complexity sectors, which are generally already present in the economy. Second, as economies become more complex, within-sector specialisation assumes an increasingly positive role, whereas for less complex economies it contributed negatively to changes in WEC. The direction and magnitude of contributions from continuity reallocations, entries and exits differ across quartile: entries and exits enable relatively more complex (simpler) economies to increase (decrease) their WEC, while reallocations among continuously exported products raise WEC in Q4 and Q2 but are negligible for other quartiles. Finally, the PCI effect, understood as the upgrading or downgrading of product complexity, positively affects only the complex economies. Intuitively, this reflects changes in the number and rarity of capabilities required to export a product competitively.

After looking at these results, one may question whether the structure of the HS classification could bias the findings. As Cadot et al. (2011) emphasise, the nomenclature was not initially designed for meaningful economic analysis but rather for tariff-collection purposes. In the context of this work, one might suspect that less complex sectors are less granular than most complex ones. This would mechanically create greater scope for within-sector reallocations, entries, and exits in complex economies than in simpler ones.

To examine this possibility, the annex (A5) plots the number of HS4 subclasses per HS2 category against the average product complexity (at the HS6 level) of the parent group (HS2), and similarly the number of HS6 products per HS4. In both cases, the results show an upward correlation between the degree of granularity and the complexity of the parent group. However, this possible nomenclature bias is expected to play only a minor role, since even the least complex economies in the first quartile display a significant negative within-sector contribution.

Lastly, a third approach is employed to examine the persistence of entries, as this is expected to influence their long-run effect. The results show that all countries experience declining persistence when attempting to enter the production of more complex goods. Nonetheless, sufficiently complex economies also face an opposite constraint: lower persistence when attempting to enter overly simple goods. The former observation is consistent with the literature emphasising the crucial role of knowledge creation and absorptive capacity in shaping long-term specialization trajectories. Accordingly, a strategy that seeks to stimulate entry into some highly complex activities may be inefficient, or even doomed to failure, if the country lacks requisite capabilities to produce and remain competitive in these products. From another perspective, entries into very simple products may also be unsustainable due to opportunity costs and competitive pressures from low-wages economies. Consequently, policies aimed at promoting the domestic entry and the production of simple goods are equally likely to prove ineffective.

5. Foreign Direct Investments and WEC

In this section, the analysis turns to how countries acquire capabilities through inward foreign direct investments (FDI). First, the complexity of FDI received for a set of 21 OECD countries over the period 1998-2023 is computed. The weighted FDI complexity is then compared with the WEC for each country and period. Following this descriptive part, a shift-share instrumental variable strategy is introduced to test for causality between growth in FDI stocks and growth in WEC. Finally, results are presented and discussed.

5.1. Descriptive statistics

Using data from the OECD on inward FDI stocks per country and per industry over time, the PCI data at the HS6 level from the OEC, and trade data from BACI, the WEC and the FDI complexity received by countries can be compared. To link the PCI at the HS6 level and FDI stock per industry denominated with ISIC rev.4 codes, I use the function *concord_hs_isic* from the *concordance* package on R. This function splits HS6 observations into one or more ISIC4 codes with weights. Then, trade data and PCI data at the HS6 level can easily be meaned with weights into, first ISIC4 codes, and then into the classification used for FDI stock data.

Table 5 : Economic sectors classification and description

CLASSIFICATION : FDI DATA	CORRESPONDING ISIC2 CODES	NAME CATEGORY
A	01, 02, 03	Agriculture, forestry and fishing
B	05, 06, 07, 08, 09	Mining and quarrying
C10T12	10, 11, 12	Manufacture of food products, beverages and tobacco products
C13_14	13, 14	Manufacture of textiles and wearing apparel
C15_23_27_31T33	15, 23, 27, 31, 32, 33	Other manufacturing
C16T18	16, 17, 18	Manufacture of wood and of products of wood and cork
C19	19	Manufacture of coke and refined petroleum products
C20	20	Manufacture of chemicals and chemical products
C21	21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
C22	22	Manufacture of rubber and plastics products
C24_25	24, 25	Manufacture of basic metals and fabricated metal products, except machinery and equipment
C26	26	Manufacture of computer, electronic and optical products
C28	28	Manufacture of machinery and equipment n.e.c.
C29	29	Manufacture of motor vehicles, trailers and semi-trailers
C30	30	Manufacture of other transport equipment

Results of the PCI aggregation into sectors are presented in the following Table 6. The less complex sectors are: (A) Agriculture, forestry and fishing, (B) Mining and quarrying, (C10T12) Manufacture of food products, beverages and tobacco products, and (C13_14) Manufacture of textiles and wearing apparel. On the other hand, the most complex sectors include: (C21) Manufacture of basic pharmaceutical products and pharmaceutical preparations, (C26) Manufacture of computer, electronic and optical products, and (C28) Manufacture of machinery and equipment n.e.c.

Some sectors over time saw important changes in complexity over time. Primary sectors (A&B) decreased in complexity as well as sectors related to agricultural products (C10T12) and to the production of vehicles (C29). Conversely, the manufacturing of computer, electronic and optical products (C26), the manufacturing of textiles and wearing apparel, and other manufacturing (C15_25_27_31T33) increased in complexity.

Table 6 : Complexity score by sectors over time

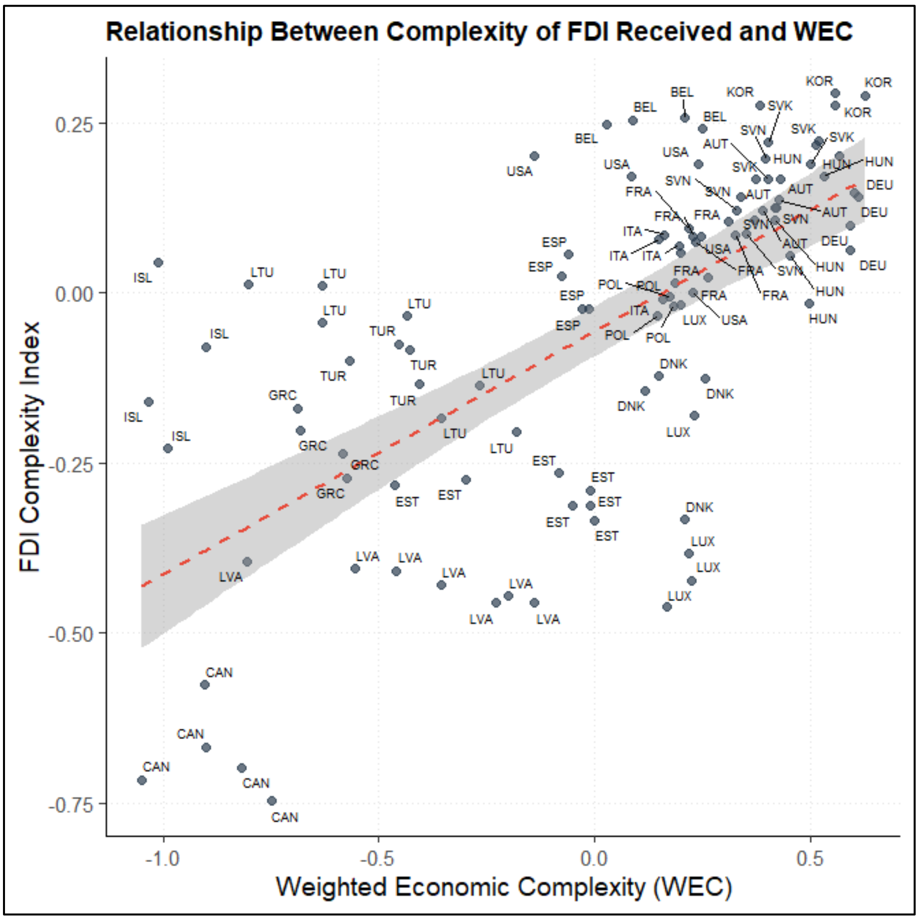
FDI Complexity Index Across Time by Sector									
Sectors	1998-2000	2001-2003	2004-2006	2007-2009	2010-2012	2013-2015	2016-2018	2019-2021	2022-2024
A	−0.935	−1.064	−1.192	−1.189	−1.166	−1.214	−1.229	−1.204	−1.203
B	−1.059	−1.136	−1.219	−1.457	−1.472	−1.603	−1.620	−1.685	−1.780
C10T12	−0.432	−0.581	−0.630	−0.750	−0.770	−0.728	−0.753	−0.836	−0.775
C13_14	−1.255	−1.295	−1.226	−1.153	−1.145	−1.151	−1.100	−1.039	−1.011
C15_23_27_31T33	−0.223	−0.199	−0.155	−0.106	−0.069	−0.038	−0.031	−0.009	0.009
C16T18	0.051	−0.052	−0.132	−0.121	−0.151	−0.157	−0.174	−0.184	−0.198
C19	0.112	0.192	0.275	0.294	0.300	0.315	0.309	0.301	0.282
C20	0.386	0.418	0.437	0.419	0.407	0.421	0.429	0.405	0.393
C21	0.501	0.627	0.610	0.547	0.485	0.490	0.518	0.519	0.594
C22	−0.171	−0.160	−0.196	−0.125	−0.066	−0.077	−0.055	0.001	−0.034
C24_25	0.207	0.214	0.230	0.267	0.296	0.303	0.319	0.320	0.286
C26	0.183	0.317	0.367	0.467	0.552	0.574	0.574	0.567	0.607
C28	0.590	0.626	0.607	0.607	0.593	0.607	0.615	0.618	0.629
C29	0.648	0.560	0.572	0.432	0.367	0.384	0.456	0.457	0.427
C30	0.046	0.051	0.035	0.041	0.176	0.136	0.167	0.164	0.199

Note: The table shows the evolution sectors complexity computed from products complexity at the HS6 level which are related to them. Whiter boxes are for more complex values and darker red are for less complex ones.

With sectors complexity data, the complexity of FDI can be computed with the share of FDI in each sector multiplied by the complexity index of the sector. Because FDI data may not be available for all sectors (see Annexe A8), the WEC is computed only considering sectors for which FDI data are observed, so that the complexity of FDI is comparable to the complexity of exports. For example, Austria has no observation for sectors C19, C29,and C30, so Austria WEC is computed leaving apart exports observations associated to the missing sectors.

Graph 10 plots the results and highlights that countries with a high (modified) WEC also tend to hold FDI stocks that are relatively more concentrated in complex sectors. This positive correlation suggests that FDI generally follows the economic structure of the host country.

Graph 10 : Relationship between weighted FDI complexity and WEC



Note: The graph represents the relationship between weighted FDI complexity and weighted export complexity. Each point represents a country for a given period of three years. The red dotted line with confidence intervals highlights the correlation.

5.2. Research design

The results described above raise the question to know how a country can increase its WEC. It is common in the literature to consider first the capacities available locally (ECI) and suggest, based on these capabilities, where a country should start producing. This first approach has been criticised because it hardly explains successful economic development such as for the Four Asian Tigers (South Korea, Taiwan, Hong Kong, and Singapore), Tiger Cub Economies (Indonesia, Malaysia, Thailand, the Philippines, and Vietnam), and other "economic miracles", which saw rapid development of the production of products unrelated to the existing exports and derived presence of capacities (Pinheiro, 2025). Many factors are usually invoked to explain those rapid economic growth periods. One hypothesis concerns the importation of foreign knowledge and knowhow through FDIs (Mahembe and Odhiambo (2014)).

The direction of the relationship between FDI and countries' complexity score is ambiguous. In the literature, it is argued that countries with a high ECI usually attract more FDI as investing countries aim at learning by investing allowing them to import some capacities (Sadeghi, Shahrestani, Kiani and Torabi, 2020). The reverse direction consists in explaining ECI growth through increased FDI stocks (Javorcik, Turco and Maggioni, 2018; Khan, Khan and Khan, 2020; Antonietti and Franco, 2021).

To test the causal relationship between the received FDI and the export complexity of a country, I test whether an increase in FDI stock in a country causes an increase in export complexity (WEC) by bringing in and developing local non-tradable capabilities. Estimating a causal relationship between those two variables can be quite tricky given first endogeneity issues, namely, reverse causality, simultaneity, and omitted variables bias (Breuer, 2021).

First, reverse causality can happen as a country experiencing a technological shock driving the exportation of more complex goods might attract a higher level of FDI. This direction has already been studied and observed such as for the internet revolution in the USA. Firms aiming to benefit from technological spillovers will invest in the region where the technological shock happened. Furthermore, a more dynamic country producing and exporting more complex goods can be synonymous of economic success which would also attract foreign FDI.

Then, simultaneity problems can also arise, in periods of higher economic growth (peak of a business cycle) exports in more complex goods and higher inward FDI flow can coincide.

Finally, omitted variable bias emerges when a variable not included in the model is correlated with the dependent variable and one or more explanatory variables. The left-out variables will result in biased estimates of the dependent variable. Part of the problem may be solved by adding control variables and including unit and time fixed effects for unobserved variables that are country-invariant such as cultural traits, geography, or the language; or time-invariant like a global crisis or a worldwide tech wave. Nonetheless, it does not account for unobserved factors that vary over time within country such as the improvement in R&D efficiency, or country's institutional reforms over time.

To account for those classic estimation problems, I will use an instrumental variable model to estimate the impact of FDI on export complexity. Specifically, I will use a shift-share instrument to isolate variations in inward FDI so that it can be considered as more likely exogenous than the raw variation. The canonical paper of Bartik (1991) has sparked many discussions about the methodology and inspired many researchers to apply it. The

Bartik instrument has the advantage of using a continuous treatment variation which helps for the identification by exploiting heterogeneity in the exposure to a treatment, i.e., it isolates the treatment variation via the differential impact of common shocks on units with distinct pre-determined exposure (Breuer, 2021).

There exist two ways to respect the exclusion restriction to ensure an unbiased estimate of the instrument coefficient. For the expectation of the product between the instrument and the error term to be conditionally independent, the identifying assumption can rely on either the share exogeneity assumption (Goldsmith-Pinkham, Sorkin, and Swift, 2018 revised 2019) or on the shock exogeneity assumption (Borusyak, Hull, and Jaravel, 2020).

In this setting, the restriction condition is assumed to be on the shocks. By building the instruments based on measured global shocks of FDI, which are the results of global industry and policy trends rather than local ones, these shocks are more likely to be as-good-as-randomly distributed with respect to the error term conditioned on controls. On the other hand, the share exogeneity appears as unlikely exogenous, with FDI impacting the size of the sector possibly resulting in even more FDI. Furthermore, a country with an important industry might benefit from cluster-specific complementary infrastructure and localized shared inputs allowing it to be more profitable, to increase competition, and thus to increase the incentive and pressure to innovate. Consequently, the share will be correlated to the dependent variable through the treatment, and through the error term via unobserved variables such as the changes in the innovation environment.

First, the basic OLS model with unit and time fixed effects (FE) and control variables, regressing growth in export complexity on growth in FDI stocks as a treatment, we can first set the following basic model:

$$CI_{ct} = \delta_c + \gamma_t + \beta x_{ct-1} + \gamma' w_{ct-1} + \varepsilon_{ct} \tag{10}$$

Where, CI_{ct} is the growth of export complexity of a country c at time t, δ_c and γ_t are respectively the unit FE and the time FE, x_{ct-1} is the treatment (growth in FDI stock) lagged by one period to reduce the risks of simultaneity issues, w_{ct-1} is a vector of control variables expressed in growth terms which includes: the lagged value of the growth of export complexity, capital formation, education as a proxy for human capital, information and telecommunication technologies, income level, and the institutional quality. The lagged value of CI is included to account for persistence of economic sophistication as in Lapatinas (2019). Last, ε_{ct} is the error term. To account for endogeneity problems as stated above, I will run a first stage regression to instrument for x_{ct}. The instrument used is a shift-share instrument which is a sum-product of two components: a pre-determined exposure (share) and a common trend (shift or shock). It aims to drive part of the treatment variation and to only affect the outcome through its impact on the treatment. Focusing on a subpart of the differential exposure variation that is more likely to be exogenous, i.e. that the instrumental variable impacts the dependent variable and is orthogonal to the error term, reduces endogeneity problems. The shift-share instrument can be represented as follows:

$$z_{ct} = \sum_k w_{c,k,t-1} \times g_{k,t} \tag{11}$$

Where $w_{c,k,t-1}$ is the predetermined (lagged) share of FDI stock in sector k and $g_{k,t}$ is the world common FDI stock change in industry *k* at time *t*. In this setting, shocks are not exactly observed, they are estimated by considering $g_{k,t}$ as a noisy estimate of some latent true shocks $g^*_{k,t}$. Estimating shocks from sample data observations, by computing a weighted average of FDI stock changes over time, creates a mechanical bias between the instrument and the error term. The estimated shock includes unit specific observations which depend on unobserved variables explaining the dependent variable. This, in itself, violates the exogeneity restriction of the instrumental variable. To remove this source of bias, we can use a Leave-One-Out shock estimation method:

$$z_{ct}^{LOO} = \sum_k w_{c,k,t-1} \times g_{k,t,-c} \tag{12}$$

Here, the varying world level trend is calculated separately for each country by computing the global growth in FDI stocks in an industry at time t, always excluding the observations of the country for which the instrument is intended. Now, compared to the full treatment variation, the inner product of a predetermined share varying across units and a common world trend, in addition to using lagged treatment, lagged control variables and FE, is less likely to be influenced by reverse causality, simultaneity and omitted variables.

Then, the first stage regression can be written as:

$$\widehat{x_{ct}} = \delta_c + \gamma_t + \hat{\beta} z_{ct}^{LOO} + \alpha' w_{ct} + \eta_{ct} \tag{13}$$

Where $\widehat{x_{ct}}$ is the instrumented treatment effect, w_{ct} is a vector of controls (as defined for Equation 8), α is the corresponding vector of estimates, and η_{ct} is the error term. Finally, the second stage regression can be written as:

$$CI_{ct} = \delta_c + \gamma_t + \beta \widehat{x_{ct}} + \gamma' w_{ct} + \varepsilon_{ct} \tag{14}$$

For each country, a fixed number of industries is kept, with complete data between 2013-2015 and 2022-2024. In other words, the number of industries may vary across countries, but remains constant over time. Furthermore, to match the data availability in FDI per industry, only products linked to these industries are kept, and the dependent variable is computed as a weighted sum. This improves the causal identification. The next part presents and discusses the results.

5.3. Results and discussions

The first model with instrumental variable is presented in table 7 with successive addition of control variables. The number of observations is severely reduced after computing variables as growth and using lagged variables. The sample consists of 20 OECD countries (N=20) for two periods (T=2). The non-significance of the variable of interest regardless of the controls used is problematic. After demeaning to account for country and time specific unobservable, the fully specified model exhibits two significant results among the controls: the lag export complexity growth, and the lagged ICT index growth. Furthermore, the income and capital variables are only weakly significant at the 10% confidence interval.

Results appear odd. The coefficient estimates for the CI indicate that a one-point increase in the growth of export complexity is associated with almost a one-point decline in export complexity growth in the following period. This might be interpreted as convergence, however, with only two periods, the meaningfulness of this result is substantially reduced. Then, the sign of the ICT control variable is not the one expected, Lapatinas (2019) shows that the internet has a positive effect on the sophistication of exports.

Table 7: Fixed effect OLS regression: results table

Fixed effect OLS regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable	CI	CI	CI	CI	CI	CI	CI
$FDI_{(t-1)}$	0.717	-0.545	-0.289	-0.544	-0.709	-1.037	-0.941
	(1.495)	(0.808)	(0.842)	(0.872)	(0.792)	(1.199)	(1.007)
$CI_{(t-1)}$		-0.798***	-0.940***	-0.974***	-0.986***	-1.014***	-1.059***
		(0.138)	(0.110)	(0.105)	(0.103)	(0.123)	(0.118)
$ICT_{(t-1)}$			-6.943*	-7.755*	-7.128*	-7.233*	-7.573**
			(3.064)	(3.211)	(3.097)	(2.774)	(2.484)
$Income_{(t-1)}$				1.024 ·	0.876 ·	0.818	0.846 ·
				(0.503)	(0.438)	(0.486)	(0.471)
$Institutions_{(t-1)}$					4.262	4.088	1.485

Fixed effect OLS regression							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
					(3.209)	(3.137)	(2.848)
$Capital_{(t-1)}$						-2.074	-2.765
						(3.619)	(3.286)
$Education_{(t-1)}$							10.003
							(6.588)
Observations	40	40	40	40	40	40	40
R^2	0.545	0.818	0.889	0.898	0.906	0.908	0.920
Adj. R^2	0.014	0.582	0.730	0.736	0.737	0.725	0.739
FE: country & period	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE by country	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: significance levels: *** = 0.001 significance level, ** = 0.01 significance level, * = 0.05 significance level, . = 0.10 significance level

Despite the non-conclusive initial results, I continue with the IV regression analysis. Table 8 presents the first-stage results. Model 1 shows that the instrument is significant and close to one, which is the expected sign. Moreover, the F-statistic, which is an indicator of the strength of the IV by assessing how strongly the instrument is associated with the endogenous variable, is higher than 10 suggesting a strong instrument according to the "rule of thumb". Even if using the threshold of 10 is not perfect, we may, for now, interpret this result as supporting the relevance condition of the instrumental variable.

Nonetheless, the instrument significance is not robust to the addition of control variables. The instrument may be correlated to omitted variables, that when included, give the true predictive power out of the spurious correlation. With the full model, the instrument is no-longer significant, and the F-statistic is very low, suggesting a weak instrument.

Table 8: First-stage of the fixed effect SSIV regression: results table

Fixed effect SSIV regression: first stage results							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable	$FDI_{(t-1)}$	$FDI_{(t-1)}$	$FDI_{(t-1)}$	$FDI_{(t-1)}$	$FDI_{(t-1)}$	$FDI_{(t-1)}$	$FDI_{(t-1)}$
$SSIV_{(t-1)}$	0.992**	0.972**	0.968*	1.044	0.929	0.532	0.511
	(0.277)	(0.281)	(0.387)	(0.843)	(0.845)	(0.853)	(0.838)
$CI_{(t-1)}$		-0.044***	-0.044*	-0.043**	-0.044**	-0.056***	-0.053***
		(0.008)	(0.016)	(0.013)	(0.013)	(0.013)	(0.013)
$ICT_{(t-1)}$			0.027	0.051	0.123	0.013	0.030
			(0.754)	(0.711)	(0.850)	(0.888)	(0.850)
Income per $capita_{(t-1)}$				-0.053	-0.035	-0.022	-0.017

Fixed effect SSIV regression: first stage results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				(0.365)	(0.333)	(0.272)	(0.279)
$\text{Institutions}_{(t-1)}$					0.514	0.324	0.457
					(1.913)	(1.561)	(1.613)
$\text{Capital}_{(t-1)}$						-1.692*	-1.656 ·
						(0.788)	(0.798)
$\text{Education}_{(t-1)}$							-0.477
							(1.809)
Observations	40	40	40	40	40	40	40
R^2	0.690	0.715	0.715	0.715	0.718	0.790	0.790
Adj. R^2	0.328	0.346	0.306	0.260	0.215	0.369	0.319
FE: country & period	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F (excluded instrument)	12.8	12.0	6.2	1.5	1.2	0.4	0.4

Note: significance levels: *** = 0.001 significance level, ** = 0.01 significance level, * = 0.05 significance level, . = 0.10 significance level

The second-stage results are presented in Table 9. As expected by the initial basic model, and the weak instrument, no significant results are found for the treatment.

Table 9: Second-stage of the fixed effect SSIV regression: results table

Fixed effect SSIV: Stage two

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable	CI	CI	CI	CI	CI	CI	CI
$\text{FDI}_{(t-1)}$	-0.123	-0.486	0.814	-0.865	-2.092	-3.960	-3.255
	(1.082)	(1.075)	(1.766)	(2.209)	(2.993)	(4.962)	(5.031)
$\text{CI}_{(t-1)}$		-0.795***	-0.897***	-0.989***	-1.053***	-1.187***	-1.188***
		(0.128)	(0.107)	(0.136)	(0.178)	(0.295)	(0.262)
$\text{ICT}_{(t-1)}$			-7.285 ·	-7.750*	-6.887**	-7.138**	-7.446***
			(3.938)	(3.022)	(2.367)	(2.132)	(1.894)
Income per $\text{capita}_{(t-1)}$				1.132	1.270	1.263	1.192
				(1.001)	(1.144)	(1.340)	(1.294)
$\text{Institutions}_{(t-1)}$					5.745	5.875	3.288
					(6.166)	(7.747)	(8.018)
$\text{Capital}_{(t-1)}$						-7.391	-6.843
						(8.510)	(8.023)
$\text{Education}_{(t-1)}$							8.478
							(10.133)

Fixed effect SSIV: Stage two

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Observations	40	40	40	40	40	40	40
FE: country & period	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F (excluded instrument)	12.8	12.0	6.2	1.5	1.2	0.4	0.4

Note: significance levels: *** = 0.001 significance level, ** = 0.01 significance level, * = 0.05 significance level, . = 0.10 significance level

Several reasons can be invoked to explain the lack of significant results. The first limitation is the sample size, which ends up being very small reducing the variance to be estimated. Access to more detailed FDI data over a longer time span and for a broader set of countries would likely improve the analysis.

The nature of the countries itself may weaken the instrument. OECD countries are generally active in similar industries and export comparable products which leads to highly similar shares across countries. Excessively similar exposure shares reduce the sources of identifying variation, thereby weakening the instrument. Including mor diverse countries or using finer subclassifications of economic activities targeted by FDI could help strengthen the instrument's relevance (Borusyak, Hull and Jaravel, 2020).

Then, the dynamic structure of the model introduces endogenous correlation between the persistence term and the error term. The use of unit fixed effects, by demeaning the variation with the unit's time mean, mechanically creates correlation: the error term at period t now contains the error term of t-1, which is also included in the persistence variable. With only a few time periods, the bias does not diminish. Alternative estimation methods, such as the Generalised Method of Moments (GMM), as employed by Sadeghi, Shahrestani, Kiani and Torabi (2020), may help address this problem. Extending the time span of the sample would also mitigate this bias.

Finally, beyond methodological considerations, there are economic reasons why FDI shocks may not be strongly correlated with growth in export complexity. Developed countries may rely less on imitation or foreign technology assimilation to enhance their export sophistication. Instead, as Agénor and Alpaslan (2018) argue, investment in advanced infrastructure to foster innovation—rather than imitation—may be more effective once countries have reached a certain knowledge threshold, as it promotes knowledge networks and sustains growth in labour productivity and innovation.

6. Conclusion

This paper first examined the contribution of between-sector structural shifts and within-sector specialisation in explaining changes in export complexity across 124 countries from 1998 to 2023. The analysis reveals that sectoral reallocations play a crucial role in driving export complexification over time, while within-sector specialisation as well as product reclassifications exhibit divergent trends: negatively affecting simple economies but reinforcing more advanced ones. Furthermore, while all countries face capabilities constraints that limit the persistence of entries, complex economies also encounter opportunity costs that reduce the durability for simple products entries.

These findings align with the literature and highlight three central insights: (i) the development trap faced by less complex economies, (ii) the importance of structural transformations towards advanced industries, and (iii) the re-concentration of exports in complex products, driven by opportunity costs. More broadly, the distribution of exports shares between simple and complex products, in other words, the structure of economic activities, was shown to follow distinct long-term trajectories, underscoring that not all production carries the same implications for future growth.

Motivated by the observed positive correlation between income and share of complex exports, and the negative relationship between income and simple exports, this paper contributes by proposing a decomposition method inspired by Griliches and Regev (1995).This approach makes it possible to trace the origins of changes in weighted export complexity.

Some limitations must be acknowledged. First the PCI does not account for international demand, competition pressures, or the social and environmental costs of production, all of which are crucial for designing industrial policies that both, maximise welfare, and minimise the risk of policy failure. Second, the analysis does not incorporate the diversity of export baskets, a factor that plays an essential role for economic stability. Third, complementarities between simple and complex products are overlooked, even though inputs may play a crucial role in the ability of a country to produce complex products.

Future research might explore the conditions (if any) under which producing complementary simple and complex products domestically may be welfare-enhancing compared to full specialisation in complex activities. In addition, the decomposition framework could be extended sector-level contributions, providing more precise insights into their relative importance across countries and in the structural transformation process, while also enabling the evaluation of targeted policy impacts on specific sectors.

While the second inquiry on the relationship between FDI and export complexity yield inconclusive results, the empirical strategy may still prove useful in other settings, particularly with higher quality and more granular data.

Finally, the policy implications of this study can be interpreted as a cautionary tale for governments considering re-industrialisation strategies or even re-opening mines to reduce foreign dependence. Since not all forms of production generate the same long-term benefits for innovation and growth, short-term gains from reducing reliance on imports may be offset by future losses in income and innovation capacity.

7. Annexes

A.1. Methods to compute the complexity indices

To compute the Economic Complexity Index (ECI) and the Product Complexity Index (PCI), an adjacency matrix M_{cp} of binary Revealed Comparative Advantage (RCA) is first constructed. The rows of the matrix correspond to countries and columns to products where its elements equal to one if a country c has an RCA (≥ 1), computed as in Balassa (1965), in a product p and zero otherwise. This matrix maps connections between a country and the products it exports and between a product and the countries that export it, but does not directly map connections between countries or products among themselves. The bipartite network has two distinct types of nodes (countries and products) that are treated symmetrically. The same characteristic, the number of connections a node has with its neighbours (degree), is calculated for both types, creating a symmetric structure and leading to symmetric variables: the Economic Complexity Index (ECI) for countries and the Product Complexity Index (PCI) for products.

The initial method used to determine these variables is named the “method of reflection”. Initially, the number of connections for each node is calculated, which determines the diversity of countries (how many products a country exports), and the ubiquity of products (how many countries export a specific product). This node properties are only based on the direct neighbours of each node. However, neighbours’ properties also matter to grasp the complexity of a product or of a country. For example, to distinguish between two countries having the same diversity, the ubiquity of the products the countries are linked too may be indicative. The country exporting on average products that are exported by fewer countries will be considered more complex, as it reveals the presence of rarer capabilities. Similarly, products exported by more diverse countries will be considered as more complex. To get a precise measure of complexity, Hidalgo and Hausmann suggest iteratively calculating nodes' properties as follows:

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

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

With N≥1 is the iteration number, and the initial condition is defined as:

$$k_{c,0} = \sum_{p} M_{cp}$$

$$k_{p,0} = \sum_{c} M_{cp}$$

Then, the first iteration gives $k_{c,1}$ which corresponds to the average ubiquity of products exported by a country, and $k_{p,1}$ which corresponds to the average diversity of countries exporting the product. By repeating the iteration successively, the resulting variable takes into account nodes further away, updating the complexity value of products and countries' nodes back and forth propagating properties across the network eventually reflecting the structure of the whole network and provide insight into the interconnections between the two types of nodes generating a symmetric set of variables (Hidalgo and Hausmann, 2007).

It was later shown in the first edition of *The Atlas of Economic Complexity: Mapping Paths to Prosperity* (2011, reedited 2013) that these variables coincide with the mean-centring and variance scaling of the second largest eigenvalues of either the normalized matrix $\widetilde{M}_{cc\prime}$ for ECI or $\widetilde{M}_{pp\prime}$ for PCI, which are computed as follows:

$$\widetilde{M}_{cc'} = \frac{1}{k_c^{(0)}} \sum_{p} \frac{M_{cp} M_{c\prime p}}{k_p^{(0)}}$$

$$\widetilde{M}_{pp\prime} = \frac{1}{k_p^{(0)}} \sum_{c} \frac{M_{cp} M_{cp\prime}}{k_c^{(0)}}$$

These matrices are basically measure how similar two countries or products are. The first matrix consists of the sum of products commonly exported by two countries weighted by the goods' rarity and normalized by the diversity, thus producing a CC matrix. Similarly, the second matrix is built as the sum of common countries exporting the product weighted by their diversity and normalized by the product's rarity, thus producing a PP matrix.

This process ends up in matrices where rows add up to one (row-stochastic matrix) so that the highest eigenvalue is one and trivial. Standardising the second largest eigenvector then gives respectively the ECI and PCI, where the ECI can also be viewed as the average of the PCI of goods exported competitively by a country, and the PCI as the average ECI that export competitively the good considered (Hausmann et al., 2013; Balland et al., 2022).

A.2. Countries selected for the WEC analysis

Selected Countries			
Algeria	Egypt	Libyan Arab Jamahiriya	Saudi Arabia
Angola	El Salvador	Lithuania	Senegal
Argentina	Estonia	Madagascar	Serbia (2004–2023)
Australia	Finland	Malaysia	Singapore
Austria	France	Mali	Slovakia
Azerbaijan	Gabon	Mauritania	Slovenia
Bangladesh	Georgia	Mauritius	South Africa
Belarus	Germany	Mexico	South Korea
Belgium	Ghana	Moldova, Rep. of	Spain
Bolivia	Greece	Mongolia	Sri Lanka
Bosnia and Herzegovina	Guatemala	Morocco	Sudan (1998–2012)
Botswana	Guinea	Mozambique	Sweden
Brazil	Honduras	Myanmar	Switzerland
Bulgaria	Hong Kong	Namibia	Taiwan
Cambodia	Hungary	Netherlands	Tanzania
Cameroon	India	New Zealand	Thailand
Canada	Indonesia	Nicaragua	Trinidad and Tobago
Chad	Iran	Nigeria	Tunisia
Chile	Iraq	North Macedonia	Turkey
China, People's Rep.	Ireland	Norway	Turkmenistan
Colombia	Israel	Oman	Ukraine
Congo	Italy	Pakistan	United Arab Emirates

Selected Countries			
Congo, Dem. Rep.	Jamaica	Panama	United Kingdom
Costa Rica	Japan	Papua New Guinea	United States
Cote d'Ivoire	Jordan	Paraguay	Uruguay
Croatia	Kazakhstan	Peru	Uzbekistan
Cuba	Kenya	Philippines	Venezuela
Czech Republic	Kuwait	Poland	Viet Nam
Denmark	Latvia	Portugal	Yemen
Dominican Republic	Lebanon	Romania	Zambia

Note: All countries have observations for trade data on the whole sample period except for Serbia and Sudan. For the trade data for Taiwan, I use the category “Other Asia” in the CEPII data base, and “Chinese Taipei” in the ECI database.

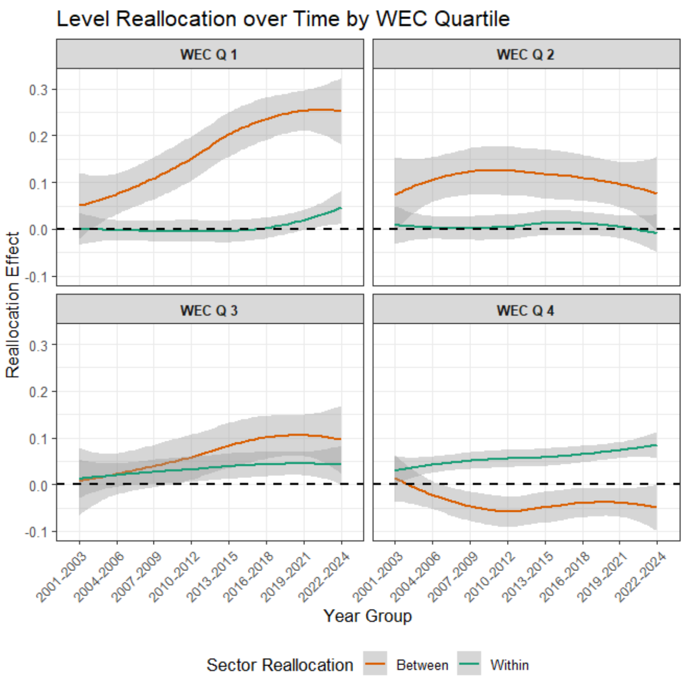
A.3. Descriptive statistics

Variable	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
PCI	-4.6045	-0.6749	0.1493	0.0000	0.7743	2.9800
WEC	-2.7520	-1.6357	-0.9964	-0.9391	-0.2472	0.8226

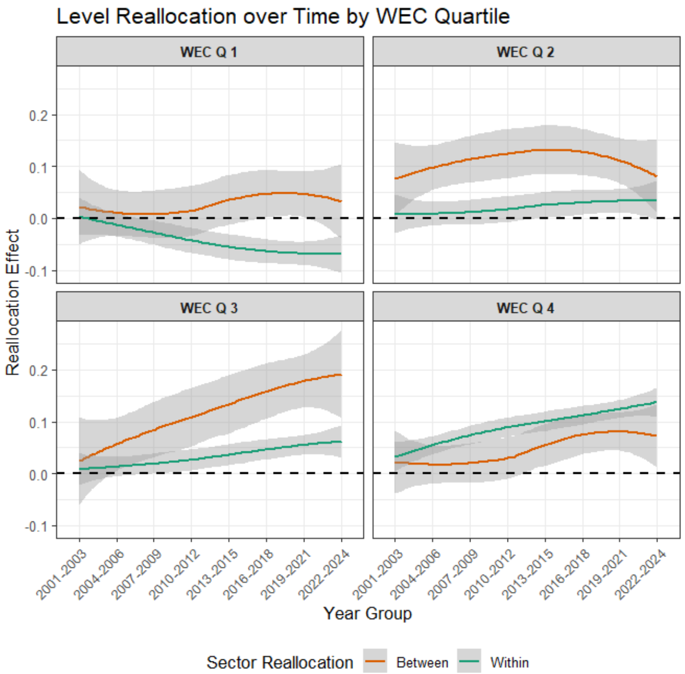
Note: the WEC do not have a mean of zero but is negative and that more than 75 percent of the sample countries have a negative WEC. This observation can be explained by the fact that the simplest economies can export only simple products, while the most complex economies export both simple products and the most complex ones, leading the WEC of complex economies to be skewed toward negative values.

A.4. Robustness check: fixed WEC quartiles on first and last period

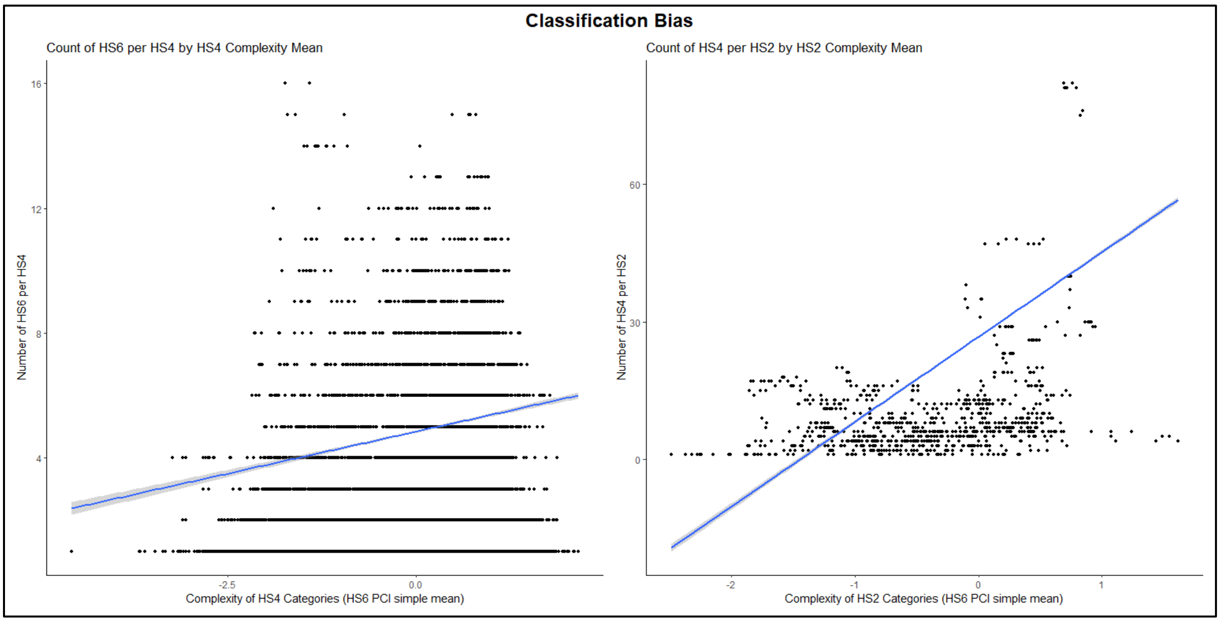
A.4.1. WEC Quartile base on first period WEC (1998-2000)



A.4.2. WEC Quartile based on last period WEC (2022-2024)

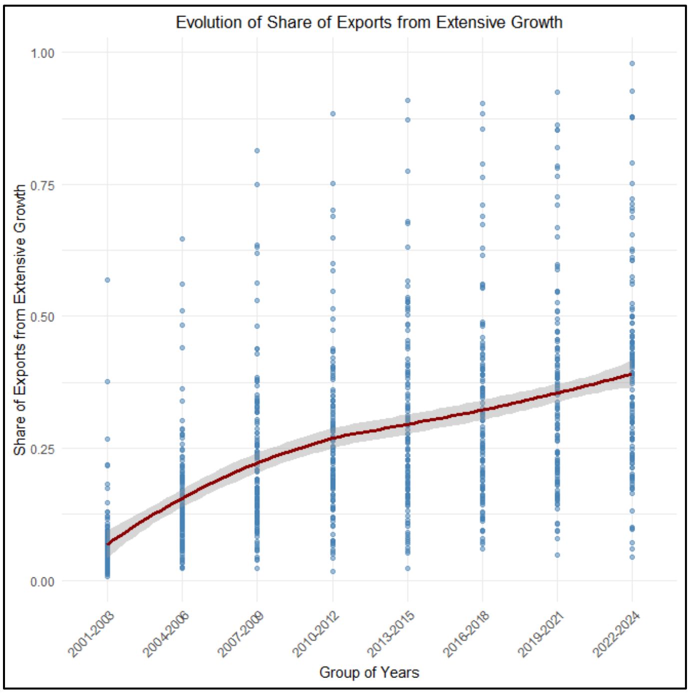


A.5. Granularity Biased towards Complex sectors



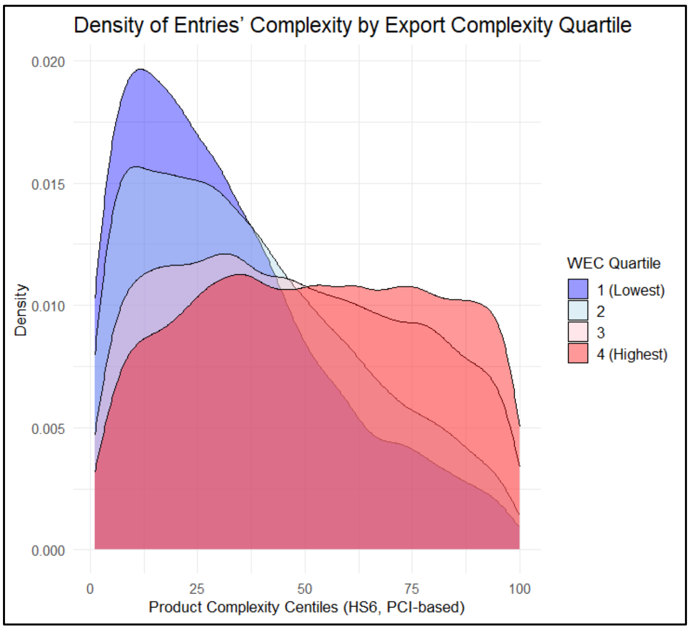
Note: Number of HS6 per HS4 and number of HS4 per HS2 plotted against, respectively, HS4's simple average complexity and HS2's simple average complexity. A regression line with confidence of interval is added

A.6. Evolution of the share of exports accounted by new goods over time



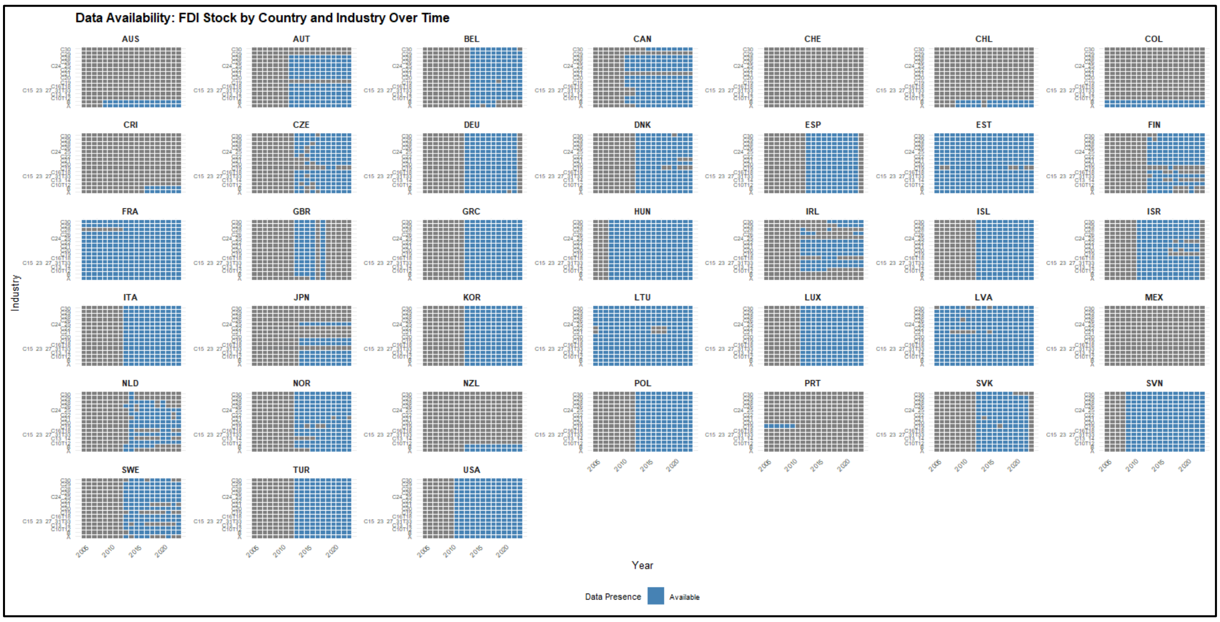
Note: share of exports accounted by cumulative entries over time.

A.7. Density of entries given centiles of complexity by quartile of current WEC



Note: density of entries in each product complexity centiles given country quartiles based on their WEC. Countries in a the bottom quartile (1) have the distribution of its entries concentrated on the left meaning that most entries are in less complex goods, while countries in the top quartile (4) enter in more complex goods' production.

A.8. Data availability: FDI stock by country over time and by industry



Note: blue boxes indicate the data availability, while a grey one indicates its absence. Industries on the x-axis are those described in table 5.

A.9. Selected countries for Section 5

Selected OECD countries for Section 5			
France	United States	Estonia	Austria
Italy	Denmark	Iceland	Canada
Turkey	Hungary	Latvia	
Germany	Lithuania	Slovenia	
Greece	Poland	Slovakia	
South Korea	Luxembourg	Belgium	

8. Bibliography:

Agénor, P., & Alpaslan, B. (2018). Infrastructure and Industrial Development with Endogenous Skill Acquisition. *Bulletin of Economic Research, 70(4)*, 313-334. https://onlinelibrary.wiley.com/doi/full/10.1111/boer.12166

Aghion, P., & Howitt, P. (1992). A model of growth through creative destruction. *Econometrica, 60*(2), 323–351. https://doi.org/10.2307/2951599

Almfraji, M. A., & Almsafir, M. K. (2013). Foreign direct investment and economic growth literature review. *International Scholarly Research Notices*. https://doi.org/10.1155/2013/389710

Antonietti, R., & Franco, C. (2021). From FDI to economic complexity: A panel Granger causality analysis. *Structural Change and Economic Dynamics, 56*, 225–239. https://doi.org/10.1016/j.strueco.2020.11.001

Arnold, J. M., & Javorcik, B. S. (2009). Gifted kids or pushy parents? Foreign direct investment and plant productivity in Indonesia. *Journal of International Economics, 79*(1), 42–53. https://doi.org/10.1016/j.jinteco.2009.05.004

Baiashvili, T., & Gattini, L. (2020). Impact of FDI on economic growth: The role of country income levels and institutional strength *(EIB Working Paper No. 2020/02)*. European Investment Bank. https://www.econstor.eu/bitstream/10419/214165/1/1690460822.pdf

Balassa, B. (1965). Trade liberalisation and "revealed" comparative advantage. *The Manchester School, 33*(2), 99–123. https://doi.org/10.1111/j.1467-9957.1965.tb00050.x

Balland, P.-A., Broekel, T., Diodato, D., Giuliani, E., Hausmann, R., O'Clery, N., & Rigby, D. (2022). Reprint of The new paradigm of economic complexity. *Research Policy, 51*(8), 104568. https://doi.org/10.1016/j.respol.2022.104568

Bartik, T. J. (1991). Who Benefits from State and Local Economic Development Policies?. *Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.* https://doi.org/10.17848/9780585223940

Bénétrix, A., Pallan, H. M., & Panizza, U. (2023). The elusive link between FDI and economic growth. *Policy Research Working Paper Series, 10422*. The World Bank.

Bernard, A. B., Redding, S. J., & Schott, P. K. (2006). Multiproduct firms and trade liberalization. *The Quarterly Journal of Economics, 126*(3), 1271–1318. https://www.princeton.edu/~reddings/papers/mpt_077.pdf

Borusyak, K., Hull, P., & Jaravel, X. (2018, revised 2020). Quasi-experimental Shift-share Research Designs. *National Bureau of Economic Research. Working Paper 24997*. https://www.nber.org/system/files/working_papers/w24997/w24997.pdf

Brambilla, I. (2009). Multinationals, technology, and the introduction of varieties of goods. *Journal of International Economics, 79*(1), 89–101. https://doi.org/10.1016/j.jinteco.2009.06.004

Breuer, M. (2021). How Does Financial-Reporting Regulation Affect Industry-Wide Resource Allocation?. *Journal of Accounting Research, 59*, 59-110. https://doi.org/10.1111/1475-679X.12345

Cadot, O., Carrère, C., & Strauss-Kahn, V. (2011). Export diversification: What's behind the hump? *The Review of Economics and Statistics, 93*(2), 590–605. https://doi.org/10.1162/REST_a_00078

CEPII, (2025). BACI: HS96 (version *202501*) [dataset]. https://www.cepii.fr/CEPII/en/bdd_modele/bdd_modele_item.asp?id=37

CEPII, (2025). CHELEM – GDP [dataset]. https://www.cepii.fr/CEPII/en/bdd_modele/bdd_modele_item.asp?id=17

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly, 35*(1), 128–152. https://doi.org/10.2307/2393553

Dornbusch, R., Fischer, S., & Samuelson, P. A. (1977). Comparative advantage, trade, and payments in a Ricardian model with a continuum of goods. *American Economic Review, 67*(5), 823–839. http://www.jstor.org/stable/1828066

European Parliament. (2025, June 11). *Report on European technological sovereignty and digital infrastructure* (A-10-2025-0107; 2025/2007(INI)). https://www.europarl.europa.eu/doceo/document/A-10-2025-0107_EN.html

Eurostat, (n.d.). statistics Explained : Glossary: Foreign direct investment (FDI). https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Foreign_direct_investment_(FDI)

Evenett, S. J., & Venables, A. J. (2002). Export growth by developing countries: Market entry and bilateral trade flows. *Research Platform Alexandria.* https://www.alexandria.unisg.ch/publications/22177

Felipe, J., Kumar, U., Abdon, A., & Bacate, M. (2012). Product complexity and economic development. *Structural Change and Economic Dynamics, 23*(1), 36–68. https://doi.org/10.1016/j.strueco.2011.11.003

Fleming, L., & Sorenson, O. (2001). Technology as a complex adaptive system: Evidence from patent data. *Research Policy, 30*(7), 1019–1039. https://doi.org/10.1016/S0048-7333(00)00135-9

Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2018, revised 2019). Bartik Instruments: What, when, and how. *National Bureau of Economic Research, Working Paper 24408.* https://www.nber.org/system/files/working_papers/w24408/w24408.pdf

Griliches, Z., & Regev, H. (1995). Firm productivity in Israeli industry 1979-1988. *Journal of Econometrics, 65(1),* 175-203. https://www.sciencedirect.com/science/article/abs/pii/030440769401601U

Grossman, G. M., & Helpman, E. (1991). *Innovation and growth in the global economy.* The MIT Press.

Hartmann, D., Guevara, M. R., Jara-Figueroa, C., Aristarán, M., & Hidalgo, C. (2017). Linking economic complexity, institutions, and income inequality. *World Development, 93*, 75–93. https://doi.org/10.1016/j.worlddev.2016.12.020

Hausmann, R., Hidalgo, C. A., Bustos, S., Coscia, M., Simoes, A., & Yıldırım, M. A. (2013). *The atlas of economic complexity: Mapping paths to prosperity.* MIT Press. http://www.jstor.org/stable/j.ctt9qf8jp

Hausmann, R., Hwang, J., & Rodrik, D. (2007). What you export matters. *Journal of Economic Growth, 12*(1), 1–25. https://doi.org/10.1007/s10887-006-9009-4

Hidalgo, C. A., Hausmann, R., & Dasgupta, P. S. (2009). The building blocks of economic complexity. *Proceedings of the National Academy of Sciences, 106*(26), 10570–10575. http://www.jstor.org/stable/40483593

Hummels, D., & Klenow, P. J. (2005). The variety and quality of a nation's exports. *American Economic Review, 95*(3), 704–723. http://klenow.com/Hummels&Klenow.pdf

Imbs, J., & Wacziarg, R. (2003). Stages of diversification. *American Economic Review, 93*(1), 63–86. https://www.aeaweb.org/articles?id=10.1257/000282803321455160

Javorcik, B. S., Lo Turco, A., & Maggioni, D. (2018). New and improved: Does FDI boost production complexity in host countries? *Economic Journal, 128*(614), 2507–2537. https://doi.org/10.1111/ecoj.12530

Khan, H., Khan, U., & Khan, M. A. (2020). Causal nexus between economic complexity and FDI: Empirical evidence from time series analysis. *The Chinese Economy, 53*(5), 374–394. https://doi.org/10.1080/10971475.2020.1730554

Krugman, P. R. (1979). Increasing returns, monopolistic competition, and international trade. *Journal of International Economics, 9(4)*, 469-479. https://www.sciencedirect.com/science/article/abs/pii/0022199679900175

Krugman, P. R. (1987). The narrow moving band, the Dutch disease, and the competitive consequences of Mrs. Thatcher: Notes on Trade in the Presence of Dynamic Scale Economies. *Journal of Development Economics, 27,* 41-55. https://paulogala.com.br/wp-content/uploads/2016/12/krugman1987.pdf

Lapatinas, A. (2019). The effect of the internet on economic sophistication: An empirical analysis. *Economics Letters, 174*, 35-38. https://www.sciencedirect.com/science/article/pii/S0165176518304269

Liao, S., Kim, I. S., Miyano, S., & Zhang, H. (2020). *concordance: Product concordance* (Version 2.0.0) [R package]. CRAN. https://CRAN.R-project.org/package=concordance

Lucas, R. E. (1993). Making a miracle. *Econometrica, 61*(2), 251–272. https://doi.org/10.2307/2951551

Lucas, R. E., Jr. (1988). On the mechanics of economic development. *Journal of Monetary Economics, 22*(1), 3–42.

https://extranet.parisschoolofeconomics.eu/docs/darcillon-thibault/lucasmechanicseconomicgrowth.pdf

Mahembe, E., & Odhiambo, N. M. (2014). Foreign direct investment and economic growth: A theoretical framework. *Journal of Governance and Regulation, 3*(2), 63–70. https://doi.org/10.22495/jgr_v3_i2_p6

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica, 71*(6), 1695–1725. http://www.jstor.org/stable/1555536

Melitz, M. J., & Polanec, S. 2015. Dynamic Olley-Pakes productivity decomposition with entry and exit. *The RAND journal of Economics, 46(2)*, 362-375. https://onlinelibrary.wiley.com/doi/abs/10.1111/1756-2171.12088

Observatory of Economic Complexity, (2025). ECI HS6 REV. 1996 (1998-2023). [dataset]. https://oec.world/en/resources/bulk-download/international?category=ECI&topic=Complexity

Observatory of Economic Complexity, (2025). PCI HS6 REV. 1996 (1998-2023). [dataset]. https://oec.world/en/resources/bulk-download/international?category=PCI&topic=Complexity

OECD, (2025). Inward FDI stocks by industry. [dataset] https://www.oecd.org/en/data/indicators/inward-fdi-stocks-by-industry.html

OECD. (2025). *Population with tertiary education.* [dataset]. https://www.oecd.org/en/data/indicators/population-with-tertiary-education.html

Pinheiro, C. (2025). Relatedness and economic complexity as tools for industrial policy: Insights and limitations. *Structural Change and Economic Dynamics, 72*, 1-10. https://www.sciencedirect.com/science/article/pii/S0954349X24001486

Pritchett, L. (1997). Divergence, big time. *Journal of Economic Perspectives, 11*(3), 3–17. http://www.jstor.org/stable/2138181

R Core Team. (2025). *R: A language and environment for statistical computing.* R Foundation for Statistical Computing. https://www.R-project.org

Redding, S. (1999). Dynamic comparative advantage and the welfare effects of trade. *Oxford Economic Papers, 51*(1), 15–39. https://www.jstor.org/stable/3488590

Romer, P. (1992). Two Strategies for Economic Development: Using Ideas and Producing Ideas. *The World Bank Economic Review, 6(1),* 63-91. https://documents1.worldbank.org/curated/en/353181468739245145/pdf/multi0page.pdf

Romer, P. M. (1986). Increasing returns and long-run growth. *Journal of Political Economy, 94*(5), 1002–1037. https://doi.org/10.1086/261420

Sadeghi, P., Shahrestani, H., Kiani, K. H., & Torabi, T. (2020). Economic complexity, human capital, and FDI attraction: A cross-country analysis. *International Economics, 164*, 168–182. https://doi.org/10.1016/j.inteco.2020.08.005

Schetter, U. (2019). A structural ranking of economic complexity *(CID Research Fellow & Graduate Student Working Paper No. 119).* https://doi.org/10.2139/ssrn.3485842

Schetter, U. (2024). Quality differentiation, comparative advantage, and international specialization across products. *European Economic Review, 170.*

Schott, P. K. (2004). Across-product versus within-product specialization in international trade. *The Quarterly Journal of Economics, 119*(2), 647–678. https://doi.org/10.1162/0033553041382201

van Dam, A., & Frenken, K. (2022). Variety, complexity, and economic development. *Research Policy, 51*(8), 103949. https://doi.org/10.1016/j.respol.2020.103949

Vernon, R. (1966). International investment and international trade in the product cycle. *The Quarterly Journal of Economics, 80*(2), 190–207. https://doi.org/10.2307/1880689

Weitzman, M. L. (1998). Recombinant growth. *The Quarterly Journal of Economics, 113*(2), 331–360. https://doi.org/10.1162/003355398555595

World Bank Group, (2025). *Gross capital formation (% of GDP).* [dataset]. https://data.worldbank.org/indicator/NE.GDI.TOTL.ZS

World Bank Group, (2025). *ICT indicators database: Percentage of individuals using the internet (ITU).* [dataset]. https://data360.worldbank.org/en/dataset/ITU_DH

World Bank Group, (2025). *Worldwide governance indicators.* [dataset] https://www.worldbank.org/en/publication/worldwide-governance-indicators/interactive-data-access

Note on the use of artificial intelligence:

Both ChatGPT from OpenAI and Le Chat from Mistral AI were used for the following tasks: wording improvements and grammar corrections, make research (in a similar way as for google), debug code, create loops and functions based on hand-made code, and bibliography formatting.