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Relatedness and economic complexity as tools for industrial policy: Insights and limitations

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ABSTRACT

The use of relatedness and economic complexity (REC) to advise on industrial policy is expanding. Typically, it leads to the recommendation to (not) support activities that are (un)related to a region's comparative advantages. Yet, the implications of such use remain largely unaddressed. Drawing on developmental state and innovation studies, I identify two reasons for caution when using REC for policy purposes. First, technological and economic catch-up may require diversification toward unrelated activities. Second, REC focuses exclusively on domestic supply, ignoring demand and international competition. In addition, I highlight conceptual and methodological limitations that are likely to affect REC's policy implications. Most notably, REC literature might overestimate the magnitude and significance of relatedness, while overlooking the contribution of policy to past diversification outcomes. This paper shows that while REC metrics can provide valuable insights into patterns of structural change, their use in industrial policy requires the concurrent assessment of other crucial elements, including the environmental footprints of diversification options and the dynamics of international supply and demand.

1. Introduction

In their influential article, Hidalgo et al. (2007) argue that convergence between wealthier and poorer nations remains elusive due to the exponentially increasing returns associated with the accumulation of productive capabilities. Since higher-income countries have amassed a greater number of such capabilities, they are able to produce a much wider variety of products, including highly valued ones that only a few other countries can replicate. They also benefit from a larger range of possibilities to combine their many existing capabilities with new ones they acquire in the future, thereby creating increasingly sophisticated products without losing competitiveness in their established industries. By contrast, less affluent nations have accumulated fewer capabilities and therefore have difficulty leveraging them with new ones, as they often miss many others equally required to compete in additional productions (Hidalgo and Hausmann, 2009). Consequently, lower-income countries often get stuck in a 'quiescence trap,' struggling to break through and catch up with the advantages that early industrializers have already secured (Hausmann and Hidalgo, 2011).

The argument that existing productive capacities condition the development of nations is not new. Structuralists contended long before the seminal REC studies that the sectoral composition of economies has a fundamental impact on economic performance, with initial upgrades yielding a persistent advantage to first industrializers while trapping less developed regions in a vicious circle of low productivity (e.g., Hirschman, 1958; Kaldor, 1970; Myrdal, 1957). Evolutionary institutionalists (e.g., Hodgson, 1998) and innovation scholars (e.g., Dosi et al., 1994) echoed these concerns, emphasizing the self-reinforcing nature of the structural features at the core of the divergence in economic outcomes across the globe. But the seminal REC literature had the merit of throwing quantitative evidence behind that argument at a time when those interpretations had been swept out of the main academic and policy arenas. REC corroborated prior statistical evidence, such as Imbs and Wacziarg's (2003), that development implies diversification, contradicting the dominant neoclassical thesis of specialization according to relative factor endowments, namely the Heckscher–Ohlin model. If lower-income economies are to ever catch up with their higher-income peers, they should not further specialize in their most competitive industries but rather move into more complex productions outside their current range of comparative advantage. And to do so, they need to accumulate many more inputs – that is, capabilities – than those considered in conventional neoclassical production functions. REC's argument also challenged the unrealistic assumption by dominant approaches to explain productivity growth that the cost of entering any new production is independent of current installed capacity (Hausmann and Hidalgo, 2011, p. 314). More generally, by confirming the need to look beyond macroeconomic aggregates to understand development outcomes, the REC literature contributed to debunk the widespread emulation of "one-size-fits-all" macroeconomic

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policies deemed to have caused the success of rich countries. In so doing, it made the case for place-based industrial policy at a time when it was discredited as an alleged source of economic inefficiency.

However, whereas REC's empirical findings underscore the need for profound structural transformation in poorer nations to bridge the gap with economic powerhouses, they also suggest caution regarding ambitious diversification endeavors that stray too far from current productive capacities. Long jumps toward unrelated industries seem to have been rare, which REC interprets as evidence of a "natural law" of diversification rendering attempts at leapfrogging too prone to failure. Balland et al. (2019), Boschma (2023), Crespo et al. (2017), Hidalgo et al. (2018), and others advise against such attempts, warning of the potential waste of public funds into cathedrals in the desert. In their view, development policies should adopt less audacious diversification strategies, targeting productions that leverage already existing capabilities.

This approach has been expanding its influence over policymaking. The Growth Lab at Harvard University has been advising governments of developing regions and countries around the world based on REC (see Goldstein, 2020; Hausmann et al., 2020, 2022, 2021a,b) and publishes countries' 'new product opportunities' and 'recommended strategic approaches' to industrial policy according to REC on the website of the Atlas of Economic Complexity (see Growth Lab, 2024). At the same time, the European Commission's Joint Research Centre (JRC) and the World Bank started promoting an enhanced version of REC metrics – the Economic Fitness and Complexity scores (hereafter EFC) – to determine industrial policy (see Lin et al., 2020; Pugliese and Tacchella, 2020, 2021; Pugliese and Tübke, 2019). Yet, the implications of using REC/EFC theory and metrics to define industrial policies remain largely unaddressed. Furthermore, an overall critical assessment of the several contributions to REC/EFC methodology since their seminal articles is lacking. This paper delves into REC/EFC theoretical and methodological strengths and weaknesses seeking to fill these gaps. In particular, it mobilizes theoretical insights and empirical evidence from developmental state and innovation scholarships to assess REC/EFC's ability to explain structural transformation and guide policymaking. It is organized as follows. Section 2 provides a brief overview of the main postulates, metrics, empirical findings, and conclusions of the REC/EFC literature. Section 3 describes the growing influence of REC/EFC in policy advice and Section 4 details the reasons why this expansion is worrisome. In Section 4.1, the potential consequences of unrelated diversification for catching up are discussed, while in Section 4.2 the role of demand and competition in diversification outcomes is analyzed. Section 4.3 inspects methodological and empirical issues that affect the robustness of REC/EFC's normative conclusions and the metrics they propose for selecting diversification options. In Section 4.4, REC/EFC's assumption about the success of related and unrelated diversification is examined. Finally, Section 5 provides a brief discussion of the main findings and policy implications.

2. A brief overview of REC fundamentals

REC pioneer studies were inspired by research showing that the key to sustained prosperity lies in exporting ever more sophisticated products (see Hausmann et al., 2007). They sought to address the fundamental research question that ensued: What determines the composition of export baskets?

Hausmann and Klinger (2006, 2007) theorize that the composition of exports is driven by countries' capabilities, which determine their ability to produce and compete in international markets. In their definition, capabilities encompass any feature that influences export performance, including access to physical inputs, capital, labor, skills, technology, and infrastructure, as well as institutions to control corruption, enforce contracts, maintain political stability, regulate markets, and so on (Hausmann and Hidalgo, 2011; Hausmann et al., 2014; Hidalgo et al., 2007). To be competitive in a particular industry, a certain combination of capabilities is required. More capabilities mean more potential combinations and therefore competitiveness in a wider variety of products.[1]

REC research posits that because it is easier to enter new productions that require few additional capabilities than to venture into productions requiring multiple capabilities that do not exist in the country, the former should be more successful than the latter. Consequently, the likelihood of becoming competitive in a new production should depend on the number of potential new products requiring capabilities akin to those exploited in existing installed capacity, that is, products that are *related* to those in a country's export portfolio (Hausmann and Klinger, 2006, 2007). In short, the ability of a country to become a competitive exporter of a new product should depend on which products it exports today.

2.1. The original REC framework

To test their hypothesis, REC researchers needed to find out which productions require similar capabilities. Since devising a measure of all relevant capabilities is practically unfeasible, Hausmann and Klinger (2006, 2007) and Hidalgo et al. (2007) employed an outcomes-based solution that avoids any priors regarding the root cause of affinity by assuming that if several countries are concomitantly competitive in two productions, these should require similar capabilities (i.e., be related). In this method, competitiveness is measured with the export index of revealed comparative advantage (hereafter RCA) by product, as in Balassa (1965). Relatedness between two products – *proximity*, in REC terminology – is therefore inferred from the likelihood of a country having an RCA in both (see Appendix for details).[2]

REC's innovative approach relies on the application of techniques from network science. The countries' exports by product form a bipartite country-product network with the nodes of countries linked to the nodes of the products in which they have an RCA. This network is represented by a binary matrix with countries in rows and products in columns and its elements equal to one if the country has an RCA in that product or zero otherwise.

The network of all products in the world connected to each other by their proximities is called the *product space*. In its graphical representation, products that are more related are displayed closer to each other. The authors note that the product space is highly heterogeneous because proximities vary considerably. Some areas are highly populated with a dense network of close connections between products, which is interpreted as a sign that they make use of capabilities that are easily adaptable to many productions, as in the case of light manufactures, electronics, and capital goods (Hausmann and Klinger, 2006, p. 25). Other parts of the product space are sparsely occupied by few, relatively isolated products, such as oil or unprocessed raw materials and agricultural goods, which require few capabilities that are often specific (e.g., natural resources endowments). Richer countries' tend to populate the densest parts of the global product space, whereas poorer nations are often confined to peripheral, low-connectivity areas.

Hausmann and Klinger (2006, 2007) and Hidalgo et al. (2007) found that, in a large sample of countries, those products in which

[1] The use of exports instead of total production is also justified with the fact that exports must pass a stricter market test compared to production for the domestic market, therefore they should be more representative of actual underlying capabilities (Hausmann and Klinger, 2007, p. 10). This choice is reinforced by data availability: long time series for international trade in goods are centrally available for most countries in the world (namely in the UN Comtrade database) and contain a large number of breakdowns that allow for fine-grained analyses.

[2] Probabilistic analyses of co-occurrences, commonly used in other scientific fields such as biological disciplines, had been previously applied by Jaffe (1986) and Teece et al. (1994) to estimate the relatedness of technologies used by firms.

they developed new RCAs in the 1990–1995 period were, on average, more closely related to the products in which they already had an RCA than those in which they did not. Hausmann and Klinger (2006, 2007) also found econometric evidence of correlation between the emergence of new RCAs over 1985–2000 and 1975–2000, respectively, and their relatedness to the products in a country's export basket. The authors interpreted these observations as proof that diversification tends to occur toward products related to countries' comparative advantages, which is one of the main conclusions underpinning the REC literature.

REC studies highlight a second statistical regularity, namely, the tendency for an inverse relationship between the number of products in which a country holds an RCA (*diversity*) and the number of countries that hold RCAs in those products (*ubiquity*). This relationship is interpreted as a sign that the goods produced by only a few countries are likely to require a wide range of capabilities, which tend to exist only in economies that are, for this reason, competitive in a vast variety of products, whereas ubiquitous goods presumably require fewer capabilities that are available in many countries. Hidalgo and Hausmann (2009) attempt to infer the complexity of countries and products from this relationship, formalized in Hausmann et al. (2014) by defining the *Economic Complexity Index* (ECI) of a country as the average complexity of the products it exports with an RCA and the *Product Complexity Index* (PCI) as the average complexity of the countries that have an RCA in that product (see Appendix for methodological details). The authors show that economic complexity is strongly correlated with GDP per capita and that the ratio between the ECI and income per capita is a predictor of future growth. Their interpretation is intuitive: countries with high economic complexity for their level of income may have unutilized productive capabilities, which, once employed, contribute to stronger growth. Conversely, countries with a high level of income compared to their economic complexity may have exhausted the potential to grow based on their existing capabilities.

For REC authors, the combination of these two statistical regularities – on one hand, poorer countries tend to have RCAs in only a few, often low-value and poorly related products, and, on the other hand, new RCAs tend to emerge in products related to countries' pre-existing RCAs – implies that convergence between high- and low-income economies is unlikely. Not only are poorer economies behind in the process of structural upgrading, but also the pace of their progress is slower because they have fewer possibilities of diversification, especially into higher-value productions. To catch up with richer nations, they would have to jump over statistically infrequent distances toward unrelated products located in the densest areas of the product space (Hidalgo et al., 2007).

2.2. The EFC approach

The EFC approach emerged within a community of researchers who argue that ECI/PCI formulae do not reflect what REC authors intended to capture. Tacchella et al. (2012) note that a country's ECI is calculated as the simple average complexity of the products it exports competitively regardless of their number; therefore, unlike original REC authors claimed, it does not reflect diversity. Hypothetically, a country specialized in just one product could have a higher ECI than another exporting 100 (see Pietronero et al., 2019). For the same reason, the PCI formula does not fully capture ubiquity. Moreover, it assigns equal weights to all competitive exporters, whereas the minimum required capabilities to be competitive in a product should be inferred from the least fit among them.

To overcome these shortcomings, EFC authors have proposed another specification for complexity indicators (see the Appendix for details). In this formulation, the complexity of a country – its *Fitness* – is given by the sum (not the average) of the complexity scores of the products it exports competitively. In this way, diversity is clearly captured. The complexity of a product is calculated with a non-linear specification that assigns a higher weight to the complexity of the least fit exporters.

Although the EFC literature has been critical of REC's mathematics, it has not challenged the basic reasoning of its theory, nor its policy implications.

3. The growing influence of REC in policymaking

In recent years, the REC and EFC approaches have been increasingly used in policy advice. Crespo et al. (2017) and Balland et al. (2019) recommend the use of REC theory and metrics to decide on EU Member States' Smart Specialization Strategies. The definition of such strategies is a prerequisite for Member States to access the European Regional Development Fund, which accounts for more than half of EU cohesion funds. In Balland et al.'s (2019) policy framework, the relatedness of potential new activities to current comparative advantages indicates the costs (and risks) of different diversification options, whereas the complexity of those activities indicates the corresponding benefits.[3] The ideal smart specialization approach – the 'high road policy' – would support the development of new activities with above-average expected returns (i.e., more complex than the country's main activities on average) that can be developed at relatively low risk (i.e., more related to the country's current fields of expertise). However, as the authors acknowledge, more peripheral EU regions often lack low-risk-high-benefit options. Still, the authors advise against efforts to diversify to complex unrelated activities, which they deem too likely to fail and accordingly dub 'casino policies.' Taking the example of the Spanish region of Extremadura, the authors claim that successfully achieving long jumps would be nearly impossible; therefore, a more gradualist approach should be followed.[4]

Likewise, the European Commission's Joint Research Centre (JRC) is promoting the standardized use of EFC tools to decide on EU Member States' Smart Specialization Strategies (see Alvarez et al., 2021, pp. 27,58; Diodato et al., 2023; Pugliese and Tacchella, 2020; Pugliese and Tübke, 2019). The JRC's vision integrates pre-existing capacities inferred from technological and economic outcomes into industrial policy decisions by using them as the key element to signal to policymakers which diversification options are likely to be most feasible and could, therefore, be prioritized. Unlike Balland et al. (2019), though, the JRC's approach does not suggest classifying diversification options into normative categories, nor does it explicitly discourage unrelated diversification. Following this approach, in 2021, the JRC published EU country factsheets illustrating how EFC analytics could be used to support decision-makers in identifying the most promising diversification paths, based on quantitative tools such as the probability of a region/country becoming competitive in a new product given its current productive structure (see Pugliese and Tacchella, 2021). At the same time, the JRC worked on strengthening the links with the World Bank Group and the UN to define common best practices for using EFC metrics in policy design (Alvarez et al., 2021, p. 28). The article by Lin et al. (2020) issued by the World Bank's International Finance Corporation recommends the use of EFC indicators to identify African countries' best diversification strategies.

Similarly, the Growth Lab at Harvard University applies REC analytics to advise developing regions on industrial policy. Goldstein (2020) and Hausmann et al. (2020, 2022, 2021a,b) rank diversification

[3] Note that while the authors use REC metrics of complexity, they do not employ REC's formula of proximity to estimate relatedness (see Section 4.3.1). Moreover, they use data on patents instead of exports (for an assessment of the drawbacks of patent data see Section 4.3.3).

[4] Note that the recommendation to promote related activities in the context of Smart Specialization Strategies predates the incorporation of references to original REC or EFC (see, e.g., Boschma and Gianelle, 2014).

options based on three measures: distance (reflecting their relatedness to major exports), PCI, and Complexity Outlook Gain (reflecting their relatedness to further, complex options). The Growth Lab also publishes 'recommended strategic approaches' to industrial policy, 'potential growth opportunities' and 'new product opportunities' based on REC for more than 100 countries on the Atlas of Economic Complexity's website (see Growth Lab, 2024). The Atlas has been promoted in The Harvard Gazette as a tool to aid planners in identifying economic opportunities and growth strategies (Smith, 2019). Also, the Observatory of Economic Complexity (OEC), a spin-off of a former MIT project sharing the same research roots as Harvard's Atlas, publishes on its website 'diversification frontier' graphs displaying diversification alternatives according to REC (see OEC, 2024). The OEC has been involved in the development of online REC data platforms for government agencies in Mexico, Peru, and Brazil (Hidalgo, 2023).

4. Why REC should be used with caution in the design of industrial policies

Despite the growing popularity of REC, its theoretical, empirical and normative foundations have shortcomings that call for caution in its application to industrial policy. EFC has overcome important conceptual issues in the underlying mathematics, but other significant limitations persist.

To begin with, REC/EFC indicators do not (and cannot) contain information concerning all key developmental goals (no indicator can). Therefore, they should be combined with data relating to other major societal challenges beyond the development of productive capabilities. In particular, policymakers should consider the environmental impact of diversification alternatives.[5] Other critical dimensions to ponder include the strategic relevance of potential new activities for economic resilience and external accounts balance.

Another reason for caution stems from the tendency of REC/EFC policy implications to neglect the impact of diversification options on economic convergence across regions and countries, often overlooking ample evidence, particularly from developmental state and innovation literature, that leapfrogging into unrelated productions is likely necessary for catching up. Moreover, the evolution of external demand, competition, and technology, which are crucial for the success of diversification efforts, should also be taken into account.

Finally, a number of methodological and empirical shortcomings call into question the use of REC/EFC to decide on diversification policies.

These issues are discussed in detail in the following sections.

4.1. Catching up may require unrelated diversification

The role of radical structural change in the most impressive catching-up trajectories in history, namely the so-called "Asian miracles", has been well documented in developmental state and innovation scholarships (e.g., Amsden, 1989; Kim and Nelson, 2000; Lee et al., 2012; Wade, 2004). It was not referred to as "unrelated" diversification, nor was an attempt made to quantify the degree of unrelatedness, but reports are unequivocal on the path-defying nature of these countries' structural evolution. The transformation of South Korean productive structures in the second half of the 20th century, for instance, was profound and meteoric:

> Korea's export increased from a mere \$40 million in 1960 to \$125 billion in 1995, with virtually all the increase represented by products that Korea did not know how to produce at the start of the era. In the mid-1960s, Korea began exporting textiles, apparel, toys, wigs, plywood, and other labor-intensive mature products. Ten years later, ships, steel, consumer electronics, and construction services from Korea challenged established suppliers from the industrially advanced countries. By the mid-1980s, computers, semiconductor memory chips, videocassette recorders, electronic switching systems, automobiles, industrial plants, and other technology-intensive products were added to Korea's list of major export items. (Kim and Nelson, 2000, p. 2)

The development of steel industry in South Korea in the 1960s is paradigmatic of how comparative advantage was created nearly from scratch, with the country initially missing most of the required capabilities to become competitive in the field. As Amsden (1989) explains, the Korean steel industry had little installed capacity, composed mostly of technologically obsolete furnaces. South Korea lacked capital, equipment, know-how, and the main raw material (iron ore). The domestic market was too small to support economies of scale, and the largest market in the vicinity, Japan, hosted the world's most efficient producer at the time. Nevertheless, the Korean government managed to successfully summon the capabilities required to become competitive in steelmaking. It gathered financing, organized the transfer of technology and the training of engineers, and subsidized the construction of supporting infrastructure such as roads and harbors. In addition, it supported the enterprise created for production, POSCO, with reductions in the prices of electricity, gas, and water, discounts for rail transport and port dues, exemptions from corporate taxes, and an 80% tariff cut on the import of equipment (Lee and Ki, 2017). POSCO was profitable from the first year of production and eventually became an exporter of technology (Amsden, 1989, pp. 292, 296). The success of this endeavor could hardly have been anticipated by looking at South Korea's initial productive capabilities. In fact, the World Bank had held the view that an integrated steel mill would be economically unfeasible in South Korea (Amsden, 1989, p. 291).

The development trajectory of the Irish economy is also often labeled a miracle. Ireland managed to transform from an agrarian nation with traditional manufactures into a technology-intensive economy in a few decades, based on some of the most dynamic sectors in the world, namely, computer engineering, chemicals, and petrochemicals (Hartmann et al., 2021, p. 9). Arguably, the country would not have achieved the speedy climb up the curve of productive sophistication reported in Hartmann et al. (2021, p. 6) if there had been only incremental diversification into related activities.

Taking these historical cases into account, it is difficult to maintain that development strategies should avoid attempts at longer jumps toward unrelated activities. In fact, in their seminal article, Hidalgo et al. (2007) argue that 'it is precisely these long jumps that generate subsequent structural transformation, convergence and growth' (p. 487). If countries diversified only to activities related to their existing comparative advantages, richer economies would go on developing at a faster pace than poorer nations and the gap between them would continue to compound. Related diversification might be a successful development strategy for richer countries, but it is ineffective for poorer nations seeking to catch up: they simply do not have enough related activities to diversify into, especially the kind that could contribute to the upgrade of their productive capabilities and consequently to higher growth. This perspective has been regaining traction in recent years. For example, Pugliese et al. (2017) note that diversification into more complex productions may be the key to escaping the poverty trap, while abstaining from normative considerations on relatedness. Mealy and Coyle (2022) argue that policy interventions based on relatedness may exacerbate geographic inequalities in

[5] The use of data on "green" exports to compile REC/EFC metrics is being explored – see Caldarola et al. (2024) for a comprehensive review – but the standardized classification of products according to their environmental footprints is proving challenging, for many goods have both environmental beneficial and detrimental applications and information on the impact of their production processes is even more elusive than data on use-oriented effects (Mealy and Teytelboym, 2022, pp. 4–5). Policymakers can, nevertheless, combine REC/EFC metrics with ad hoc data on environmental footprints when assessing diversification options.

productivity and income and that addressing them may require non-incremental policy approaches. In fact, Pinheiro et al. (2022a) confirm that, in Europe, related diversification has disproportionately benefited the already advanced regions, creating a spatial inequality feedback loop. And Hidalgo (2023) acknowledges that following relatedness may lock less developed economies in low-complexity activities.

The approach by Harvard's Growth Lab seems to reflect this concern to some extent, as it allows to slightly increase the weight of the complexity of potential new products, to the detriment of relatedness, in the criteria for ranking diversification options (see 'potential growth opportunities' and 'new product opportunities' in Growth Lab, 2024, as well as Goldstein, 2020; Hausmann et al., 2020, 2022, 2021a,b). Goldstein (2020) acknowledges that '[u]ltimately, increasing the magnitude and variety of exports will require both diversifying into adjacent and distant products'; hence, 'low-hanging fruit' and 'long-jump' strategies are not necessarily mutually exclusive (p. 54).

4.2. Domestic capabilities are a necessary but not sufficient condition for successful diversification

As seen in Section 2.2, REC's concept of capabilities encompasses any characteristic of a territory that contributes to competitiveness in certain productions. In Hidalgo and Hausmann's (2009) analogy, if a product were a Lego model, capabilities would be the Lego pieces required to build it: a country would be able to assemble a certain model only if it had all the required pieces (p. 10570). On the other hand, the more pieces, the more possibilities for different combinations leading to different models.

This wide-ranging definition of capabilities resonates with what Lee and Malerba (2017) term 'initial conditions', 'macro factors', and 'sectoral and national systems factors' (pp. 342–343). Initial conditions comprise 'factor endowments, natural resources, culture, the extent of inequality, historical legacies, legal institutions, industrial structure, and entrepreneurship'. Macro factors are macroeconomic variables such as labor costs and exchange rates, which condition the competitiveness of exports, especially in earlier stages of catching-up. Sectoral systems are defined in Malerba (2002, p. 247) as sets of products and the sets of agents 'carrying out market and non-market interactions for the creation, production and sale of those products'. If favorable, the combination of all these features enables the entry and growth of new firms in an industry. But they are not enough to trigger a process that could eventually lead latecomers to reach or even overtake leaders (Lee and Malerba, 2017, p. 343).

To break the vicious circle of under-accumulation of capabilities – Hausmann and Hidalgo's (2011) 'quiescence trap' – countries must seize what Perez and Soete (1988) term 'windows of opportunity', that is, temporary opportunities stemming from changes in techno-economic paradigms triggered by radical scientific and technological breakthroughs. Typically originated in regions at the technological frontier, such opportunities may be seized by imitators, because leading firms heavily invested in the previous technology may face difficulties and inertia in moving into the new one. They may resist the costs of retraining workers and changing equipment, or simply continue to exploit the previous technology's commercial potential for too long. Innovation literature has extensively documented how the "Asian miracles" seized windows of opportunity in electronics to catalyze their economic upgrading (e.g., Kim and Nelson, 2000). Hence, ongoing and expected developments in technology must be considered when deciding on industrial policy.

But as Lee and Malerba (2017) highlight in their extension of Perez and Soete's (1988) concept to all basic components of sectoral systems, windows of opportunity for imitators may also arise from shifts in demand, especially when catching-up initiates with entry in mature products. Therefore, the design of industrial policies also requires a thorough analysis of prospective demand.

To complete this analytical framework, one further element should be added, namely foreign competition not only by leaders, but also by future latecomers. In short, a country's chances of upgrading its export capacities are conditioned by its current capabilities, the additional capabilities it may (or may not) acquire, the future evolution of external demand, and the evolution of the capabilities of all potential future competitors. The identification of diversification opportunities should take all these elements into account. If only current domestic capabilities are considered, efforts will face increased risks of failure in case demand evolves unfavorably or other countries become more competitive exporters in the meantime. In a highly integrated world economy, industrial strategies cannot be designed as if in autarky (even less so for smaller economies). This is no news to economic thought. However, as noted by Andreoni and Chang (2019), at no other time has the industrial policy debate been so biased toward supply, particularly domestic supply, as in the phase of the 'mainstreaming of industrial policy' within which REC emerged (p. 141).

Certainly, predicting technological progress, demand, and competition cannot be a scientifically accurate exercise. Windows of opportunity are subject to a high degree of contingency. But an industrial strategy that does not consider expected future developments in all these three domains runs a greater risk of failure. This concern seems to have been reflected in the framework recently endorsed by UNIDO to support countries in the prioritization of diversification alternatives. The DIVE (Diversifying Industries and Value Chains for Exports) tool, developed by the authors of Coniglio et al. (2021), takes into account the recent growth in global trade as a gauge of demand dynamic, as well as four indicators of entry barriers and the intensity of competition (see UNIDO, 2023).[6]

4.3. REC empirics have important shortcomings

REC empirics suffer, to different extents, from limitations that affect the ability of their metrics to capture what they are meant to measure and the robustness of their normative implications. Most critically, REC indicators of relatedness often fail to account for the statistical significance of products' proximities; in such cases, spurious connections are mistaken for true relatedness. The next sections dissect this and other methodological limitations in detail.

4.3.1. Relatedness might not be adequately estimated

Statements such as 'studies tend to show that related diversification is the rule, and unrelated diversification the exception' (Boschma, 2017, p. 352), 'it is well known that – on average – related diversification is much more common' (Pinheiro et al., 2022b, p. 1), and 'the principle of relatedness is not only robust and ubiquitous, but also, strong' (Hidalgo et al., 2018, p. 454) reflect the interpretation of REC's empirical results as proof that related diversification is much more frequent. The REC literature justifies this interpretation with the rationale that (un)related diversification is easier (harder) as it requires fewer (more) new capabilities, so it should succeed (fail) more often. This reasoning is the bedrock of REC theory and the basis for the policy advice against the promotion of unrelated diversification.

However, the empirical analyses presented in the REC literature have important weaknesses that may call into question the validity of its major policy implication.

In the most influential REC study, Hidalgo et al. (2007) conclude that related diversification predominates based on the observation that the probability of developing a new RCA increases with relatedness. However, the observed correlation could be driven by the fact that more advanced economies, which have relatively higher relatedness scores for most products, tend to develop more new RCAs than less

[6] https://stat.unido.org/initiatives/dive.

developed countries (Pinheiro et al., 2018, pp. 12–13; Pinheiro et al., 2022b, p. 4).

Several other studies regress the emergence of new RCAs on their relatedness to the country's main exports, measured with *density* (see Appendix for details), to assess the contribution of relatedness to diversification (e.g., Alonso and Martín, 2019; Boschma et al., 2013; Hausmann and Klinger, 2007). However, while the coefficients obtained tend to be statistically significant, they also tend to be rather small and, together with the performance measures of the models, they suggest that density does not explain much of the diversification outcomes.

Pinheiro et al. (2018) estimate that only 7.2% of the new RCAs that emerged in a large sample of countries in the period 1962–2014 were less related to their pre-existing RCAs than the average of their option sets,[7] thus concluding that unrelated diversification is extremely rare. However, Coniglio et al. (2021) perform a similar calculation for the period 1995–2010 and find the same scenario in 39% of the cases (p. 11).[8] Interestingly, the results vary significantly across countries. For example, in Germany, nearly 80% of the new RCAs occurred in products more related to its pre-existing portfolio of RCAs than the average of the option set, whereas in France and the U.S. this occurred in about 40% of the cases (p. 12).

Furthermore, Coniglio et al. (2021) point out that studies such as Hidalgo et al. (2007) and Pinheiro et al. (2018) do not distinguish between spurious relatedness due to random diversification and true relatedness due to similar capability requirements. By contrast, Coniglio et al. (2021) test the hypothesis of random evolution of countries' comparative advantages by comparing the cumulative distributions of the relatedness of actual new RCAs with the cumulative distributions of the relatedness of all products in the countries' option sets. According to their results, the null hypothesis of no path-dependence is rejected for about half of the countries in the sample. While related diversification predominated in lower-income countries, in most high-income (or large) economies productive diversification defied path-dependence.[9]

Saracco et al. (2015, 2017) also emphasize the need to test the statistical significance of estimates of relatedness. For this purpose, the authors propose a null model based on sampling a large set of random co-occurrences in RCAs while preserving certain relevant features of the real data (namely, the average ubiquity of products and diversity of countries). This method is applied in, for example, Pugliese et al. (2019) and de Cunzo et al. (2022). In addition, these studies further normalize co-occurrences in RCAs by dividing them by the diversity of countries, as in Zaccaria et al. (2014). This normalization procedure reduces the weight of co-occurrences in highly diversified economies, as they are more likely to simply be the result of a very large set of capabilities. However, to the best of my knowledge, no studies have estimated the incidence of related versus unrelated diversification in exports using these methods. If, like Coniglio et al. (2021), such studies would find that related diversification is not (much) more common, the normative implications of REC/EFC would be further weakened.

Balland et al. (2019) and Boschma et al. (2023) use a different probabilistic measure of relatedness, which, unlike proximity (see Appendix for details), allows a straightforward divide between relatedness and unrelatedness.[10] Yet, again, to the best of my knowledge, no studies have reported the incidence of related versus unrelated diversification in exports using this measure.

The calculation of symmetric proximities between products, on the other hand, may affect the selection of diversification options based on metrics of relatedness. Although this approach facilitates the graphical display of the product space, it distorts the estimates because relatedness is directional, as noted in Boschma (2017, p. 355). While the production of i may require a few more capabilities than those needed to produce j, the production of j may require many more capabilities than those necessary to produce i, in which case the chances of diversifying from i to j would not be equal to but lower than the chances of diversifying from j to i.

The EFC approach is now using machine learning techniques to estimate relatedness based on many-products correlations (decision trees) instead of two-products correlations. Albora et al. (2023) propose a new metric – the product progression probability (PPP) – which is being applied to formulate policy recommendations (e.g., in Pugliese and Tacchella, 2020). According to the authors, the PPP outperforms methods based on counts of co-occurrences in RCAs, in particular REC's product space, by significantly reducing spurious relatedness. Nevertheless, false positives (i.e., predictions of new comparative advantages that did not materialize in reality) remain more than twice the number of false negatives (i.e., new comparative advantages that actually emerged but the model failed to predict). The fact that the number of products is usually much larger than the number of locations in which to count the co-occurrences may imply that methods for measuring relatedness based on co-location are inherently frail (Tacchella et al., 2023, p. 2). But the rather small number of true positives in any of the methods assessed in Albora et al. (2023) suggests that statistical regularities in diversification are simply too weak; low precision, recall, and F1 scores indicate a large degree of randomness in diversification.[11] The implications for the use of REC/EFC in policymaking are clear: identifying the best diversification paths based on relatedness, even if using the best measurement technique possible, remains an intrinsically inexact exercise.

4.3.2. *Complexity might not be adequately estimated*

As the EFC critique points out, ECI/PCI formulae do not reflect what pioneer REC researchers had intended to capture (see Section 2.2). However, although the alternative specification proposed in the EFC literature is conceptually more adequate, it might overvalue the diversity of countries and the rarity of products, leading to very low complexity scores for many poorer nations and the products they specialized in (see Mariani et al., 2015; Pugliese et al., 2016).

EFC rankings differ substantially from rankings based on ECI/PCI. For example, China ranks 1st in the Fitness scores for 2018 available in the EFC data repository (see CREF, 2024), while ranking 30th in the OEC's ECI for the same year (OEC, 2024).[12] Oil producers tend to rank

[7] A country's option set is the pool of products in which it does not have an RCA. It therefore represents all the potential diversification options for that country.

[8] The results are not perfectly comparable, though. Besides the different timespan, Coniglio et al. (2021) use proximity to the closest RCA instead of density and define the emergence of a new RCA as a change from below 0.25 to above 1 within five years while Pinheiro et al. (2018) consider a change from four consecutive years below 1 to four consecutive years above 1 within two years. Additionally, Coniglio et al. use exports classified according to the Harmonized System from CEPII BACI database, whereas Pinheiro et al. use exports classified according to SITC-4 by Feenstra et al. (2005) for 1962–2000 and from the U.N. Comtrade for the remaining period.

[9] Note, however, some intriguing results. For instance, although close to 80% of the new comparative advantages that emerged in Germany were more related to the country's initial RCAs than the option set on average, the null hypothesis of random diversification was not rejected.

[10] With this measure (known as "lift" in data mining), values close to unity suggest unrelatedness, while values above that threshold indicate relatedness (values below unity signal conflict, which could be interpreted, in this context, as meaning that the capabilities required to produce one product are detrimental to or incompatible with the capabilities required to produce the other).

[11] The PPP method (based on the Random Forest algorithm) registered a precision score of 0.035 compared to 0.023 for the RCA benchmark. The two methods recorded recall scores of 0.073 and 0.103, and F1 scores of 0.0476 and 0.0369, respectively (Albora et al., 2023, p. 6).

[12] These rankings correspond to the indices compiled with data on exports of goods (services not included) classified according to the Harmonized System revised in 1992 (HS92) at six digits.

much lower in Fitness scores than in ECI (since oil is also an important export of a few complex economies, such as the U.S., both oil and its less developed exporters get inflated PCI/ECI).

Fitness scores are, by construction, more stable than ECIs. On the other hand, EFC product scores can change more dramatically than PCIs if a country with much lower economic complexity than the (other) competitive exporters of a product gained a new (lost its previous) comparative advantage in its production (Mariani et al., 2015).[13]

To address some of these shortcomings, several further adaptations have been proposed.[14] The proliferation of reshuffled and complementary metrics of complexity is symptomatic of their intrinsic limitations. In particular, in the projection of a bipartite network of countries and the products they export into one of its partitions, important information is inevitably lost.

Another important shortcoming of REC/EFC complexity indicators stems from the fact that the statistical classification of trade flows by product type, which has been designed mainly for tariff purposes, says little about the complexity of the underlying production processes. Rudimentary handmade shoes, for instance, are bundled together with high-end designer shoes produced with modern equipment. Since products manufactured with markedly different techniques may be classified in the same statistical category, REC/EFC scores necessarily fail to some extent in their intent to infer productive sophistication from exports.[15]

4.3.3. Patent data are not a good proxy of productive capabilities

Patent data are sometimes used instead of trade data as a proxy of productive capabilities (especially in analyses at sub-national level when data on exports with the required breakdowns are not available). But overall, the use of REC/EFC metrics based only on patents to decide on diversification policies is more problematic than the use of such metrics based on exports. Patents differ greatly in their technical and economic significance (Griliches, 1998, p. 292), and they are often granted to submissions with negligible innovation quality, sometimes even 'devoid of any novelty or with insignificant original contributions' (Henry and Stiglitz, 2010, p. 242). Consequently, many patents are not representative of comparative advantages translatable into superior economic performance. More importantly, patents provide a skewed snapshot of productive capabilities, as they tend to be concentrated in a few technological domains and countries. Hence, they do not reflect the productive capabilities of more peripheral regions that tend to show disproportionately low patent activity (if catching up required prior patenting rather than imitation throughout, the history of economic development would have been very different). For this reason, an analysis based on patent data should identify even fewer diversification opportunities for poorer regions (this limitation has been acknowledged in Balland and Boschma, 2019; Diodato et al., 2023).

Nevertheless, the fact that patents are less representative of productive capabilities than exports does not mean that the former do not contain relevant information for making informed decisions on diversification policy. Despite the above-mentioned shortcomings, patent data provide important clues on existing technological capabilities that are relevant for economic performance. They should be used as a complement to data on actual productive capacities, though, not as a substitute.

4.4. The success rates of related and unrelated diversification are not known

Evidence that related diversification is more common than unrelated diversification, though weak, helped cement the reasoning that the former is more successful than the latter. This reasoning instigated the formulation of policy recommendations advising against the promotion of unrelated diversification, assuming it was rarer because making it work is too difficult. Pinheiro et al. (2022b), for instance, conclude that unrelated diversification is, on average, less frequent at lower levels of economic complexity because it is less viable at those stages of development; therefore, public policy in poorer nations should refrain from promoting it. Similarly, the authors suggest that attempts at longer diversification jumps have higher chances of success and therefore should be performed preferentially at intermediate levels of productive sophistication based on their observation that, on average, unrelated diversification has been more common at those stages.[16]

The main problem with this apparently intuitive reasoning is that higher frequency may suggest but does not prove a higher success rate. Certainly, related diversification should be less challenging, but we do not know how often it nevertheless fails. Likewise, unrelated diversification is more difficult, since it calls for significant coordination efforts to summon several capabilities nonexistent in the territory, or capabilities that are especially difficult to get, but we do not know if it might be less common because it fails more or because it is not attempted as much.

Moreover, REC overlooks the extent to which the successes and failures of both related and unrelated diversification are the product of policy. This fundamental fragility is intrinsic to REC's outcomes-based measurement of relatedness, which throws all factors, including those shaped by policy, into a black box of capabilities. But a higher incidence of related diversification, if confirmed, could be largely the result of policies that primarily incentivized diversification into related activities. REC assumes the existing product space is the spontaneous outcome of 'natural' diversification when it is, to a large degree, the product of past industrial policies (Andreoni and Chang, 2019, p. 140).

The use of REC for industrial policy purposes is, therefore, marred by a peculiar incoherence: while the REC literature suggests using relatedness inferred from past diversification outcomes to define future policy, relatedness itself is interpreted as if past policy had no effect on those outcomes.

In sum, normative conclusions about the feasibility or desirability of long leaps in diversification require more robust evidence, not only on the incidence of related versus unrelated diversification, but also on their success rates and the underlying causes of their predominant success or failure. Based on the evidence presented in the REC/EFC

[13] How complexity scores should change in such cases is a valid conceptual question concerning both REC and EFC indicators. For instance, if a low-complexity country became competitive in a complex product, would this be a sign that the product became easier to produce or that the country's capabilities increased?

[14] For instance, to prevent the lowest scores from approaching zero, Lin et al. (2018) suggest halting the EFC algorithm after a certain number of iterations. Servedio et al. (2018) propose a slightly modified EFC specification, which also aims at convergence of the ranking rather than absolute convergence of the scores. Pugliese et al. (2017) propose the 'Complex Index of Relative Development' combining the Fitness indicator with GDP per capita. Other authors opt for complementing ECI/PCI with metrics of relatedness to complex products in the option set, since two countries with similar ECI may have comparative advantage in very different products and therefore face different diversification opportunities and challenges. Hartmann et al. (2021) and Pinheiro et al. (2018, 2022b) use the Pearson correlation between the PCI and the density of the products in the country's option set. Harvard's Growth Lab uses the Complexity Outlook Index (COI) and the Complexity Outlook Gain (COG) introduced in Hausmann et al. (2014). The COI of a country consists of the sum of the densities of all products in its option set weighted by their PCIs and the COG consists of the change in the COI of a country that would arise if it acquired an RCA in a certain product.

[15] The experimental work by Patelli et al. (2024) explores the use of the unit values of exports, instead of total trade values, as a possible way around this limitation. The results are too preliminary, though, to draw conclusions in the context of this analysis.

[16] It should be clarified, though, whether the higher frequency – on average – of unrelated diversification at intermediate stages of economic complexity in 1970–2010 could have been driven by the exceptional catching-up trajectories of a few economies.

literature, it cannot be ruled out that utilizing metrics of relatedness for selecting diversification options may result in discarding potentially promising options. Indeed, there is a strong need for a better understanding of the diversification process in order to find ways to promote it in the future (Diodato et al., 2022, p. 28).

5. Discussion and conclusions

This paper shows why recommendations to decide on diversification policies based on the relatedness (as a measure of feasibility) and complexity (as a measure of the benefits) of potential new economic activities should be taken with a grain of salt.

The REC literature claims that related diversification is more common than unrelated diversification and argues that the reason for this tendency is that diversifying into related activities is easier and, therefore, more likely to succeed. Based on this reasoning, the REC literature concludes that industrial policy should favor related diversification because it is more viable.

This paper identifies three problems with this argument. First, evidence suggests that related diversification may not be much more common than unrelated diversification. Second, even if related diversification is more common, a higher frequency may suggest, but does not prove, a higher success rate. The predominance of related diversification, if confirmed, could be the result of being tried more often, which in turn could be due not only to the fact that it is less challenging, but also to past policies promoting mostly diversification into related activities (as the REC literature recommends that future policies should do). For these reasons, and despite the relevant improvements to the original REC methodology that have been proposed – namely the pruning of statistically insignificant co-occurrences, the use of more appropriate probabilistic measures, and the application of machine learning techniques – the assessment of the feasibility of different diversification options should not rely solely on metrics of relatedness. Advice to policymakers should identify the specific required capabilities that may be lacking and evaluate what it would take to fill those gaps. Finally, even if related diversification is more common and has a higher success rate, unrelated diversification may still be necessary for catching up. The recommendation not to attempt greater leaps in structural upgrading until the productive structure has reached a considerable level of sophistication is of limited use as policy guidance for the large share of nations seeking to escape development traps. Evidence from developmental state and innovation studies (e.g., Amsden, 1989; Kim and Nelson, 2000; Wade, 2004) suggests that promoting unrelated diversification may in fact be required for poorer economies to catch up with their richer peers.

The complexity of potential new productive activities, on the other hand, cannot be fully inferred from exports because their statistical classification by product type only partially reflects productive sophistication. The EFC indicators are methodologically sounder than the original REC indices, but they cannot overcome this inherent limitation; no single indicator can.

In addition to highlighting the limitations of relatedness and complexity as measures of the feasibility and benefits of diversification alternatives, this paper also shows that relatedness and complexity are only two of many fundamental and context-specific characteristics of potential diversification options that policymakers should consider. In particular, industrial policy should take into account the implications of the different diversification alternatives for other key strategic challenges (such as the green transition), as well as the dynamics of international demand and competition and expected technological developments that may affect the success of diversification efforts. In short, relatedness and complexity should not be considered in isolation, but in conjunction with other criteria.

Limited as they may be as tools to support industrial policy decisions, REC/EFC metrics may be particularly useful in historical studies of structural transformation. The study by Hartmann et al. (2021) is a good example of the use of REC in this way. The authors employ REC indicators to identify the countries that successfully upgraded from intermediate to high complexity between 1970 and 2010, and then compare their diversification paths with those of two countries that did not. They draw on earlier evidence from development case studies to explain differences and similarities in these processes of structural transformation, highlighting the link between broad trends in policy intervention and overall upgrading trajectories over time. The full potential of relatedness and complexity metrics could be exploited by taking a further step to investigate the link between specific diversification outcomes (i.e., the emergence of new or the loss of previous comparative advantages), policymaking and underlying political factors. For this purpose, comparisons of specific sectors are probably more adequate than economy-wide analyses. As the literature on sectoral systems of innovation has shown, economic upgrading occurs unevenly across industries, and, for this reason, the study of structural transformation calls for the historical grounding of sector-specific dynamics.

CRediT authorship contribution statement

Cristina Pinheiro: Writing – review & editing, Writing – original draft, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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Appendix. Methodological details of REC metrics

Revealed comparative advantage (RCA), RCA_{cp}, is measured as:

$$RCA_{cp} = \frac{X_{cp} / \sum_{p'} X_{cp'}}{\sum_{c'} X_{c'p} / \sum_{c'} \sum_{p'} X_{c'p'}}, \tag{A.1}$$

where X_{cp} denotes the exports of product p by country c. Country c is deemed competitive (i.e., has an RCA) in product p if RCA_{cp} is (equal to or) greater than one, meaning product p weights (as much or) more in country c's exports than in total world exports.

In seminal REC research (see Hidalgo et al., 2007) and several other studies, *proximity* between products p and p', $\phi_{pp'}$, is defined as the minimum of the pairwise conditional probabilities of having an RCA in one of the two products while having an RCA in the other:

$$\phi_{pp'} = \min\{P(RCA_{cp} > 1 \mid RCA_{cp'} > 1), P(RCA_{cp'} > 1 \mid RCA_{cp} > 1)\}. \tag{A.2}$$

Considering M_{cp} a matrix of binary RCAs with countries in rows and products in columns and its elements equal to one if country c has an RCA in product p or zero otherwise, proximity is in practice calculated as:

$$\phi_{pp'} = \frac{\sum_c M_{cp} M_{cp'}}{\max(u_p, u_{p'})}, \tag{A.3}$$

where u_p and $u_{p'}$ are the ubiquities of products p and p' (i.e., the number of countries having an RCA in those products).[17]

Density, ω_{cp}, is calculated as the sum of the proximities between product p and all the products in which country c has an RCA divided by the sum of the proximities between product p and all the products in the world:

$$\omega_{cp} = \frac{\sum_{p'} M_{cp'} \phi_{pp'}}{\sum_{p'} \phi_{pp'}}. \tag{A.4}$$

Density varies between zero and one, with higher values indicating higher relatedness of a product to a country's major exports.

ECI and *PCI* correspond to the vectors k_c^n and k_p^n defined iteratively as the averages of $k_p^{(n-1)}$ and $k_c^{(n-1)}$, respectively (see Hausmann et al., 2014, p. 24 and Hidalgo, 2021 for details on the method employed to obtain the solutions):

$$k_c^n = \frac{1}{k_c^0} \sum_p M_{cp} k_p^{(n-1)} \tag{A.5}$$

and

$$k_p^n = \frac{1}{k_p^0} \sum_c M_{cp} k_c^{(n-1)}, \tag{A.6}$$

with the initial conditions k_c^0 and k_p^0 corresponding to the vectors of countries' diversities and products' ubiquities, respectively:

$$k_c^0 = \sum_p M_{cp} \tag{A.7}$$

and

$$k_p^0 = \sum_c M_{cp}. \tag{A.8}$$

The *Fitness* of countries, $\tilde{F}_c^{(n)}$, introduced by Tacchella et al. (2012), corresponds to the sum of the complexity scores of the products in which they have an RCA:

$$\tilde{F}_c^{(n)} = \sum_p M_{cp} Q_p^{(n-1)}, \tag{A.9}$$

while the complexity of products, $\tilde{Q}_p^{(n)}$, is a non-linear function of the Fitness scores of the countries that have RCA in those products:

$$\tilde{Q}_p^{(n)} = \frac{1}{\sum_c M_{cp} \frac{1}{F_c^{(n-1)}}}, \tag{A.10}$$

with the initial conditions $F_c^{(0)} = 1$ for all countries and $Q_p^{(0)} = 1$ for all products, and normalization of $\tilde{F}_c^{(n)}$ and $\tilde{Q}_p^{(n)}$ at each iteration step.

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[17] Some studies use other probabilistic measures, such as the association strength measure employed in Balland and Boschma (2019) and Boschma et al. (2023), as mentioned in Section 4.3.1.

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