Economic Complexity Analysis

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Papers in Evolutionary Economic Geography

24.30

Utrecht University Human Geography and Planning

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This Version: September 2024

This article will be a contributed chapter to the SFI edited volume: The Economy as a Complex Evolving System, Part IV

Abstract

Economic complexity analysis (ECA) is a newly emerging research program that aims to understand what determines the set of goods and services that a country can make, and how this set changes over time. At its core, this research program assumes that production of a given good or service requires a combination of fine-grained and highly complementary capabilities. As a consequence, economic growth is driven by a process of diversification that is enabled by the acquisition of capabilities. This chapter traces the intellectual antecedents and origins of ECA and illustrates core tenets in a simple model of production that is analyzed using complex network theory. It then reviews current debates surrounding core concepts in the field – in particular measures of relatedness and complexity of economic activities – and reflects on policy implications. We conclude by sketching a broad research agenda, identifying five key areas: (1) relaxing overly restrictive assumptions of current models, (2) better connecting ECA to debates in the wider field of economics, (3) exploring connections across scales, from countries to cities to firms, (4) addressing questions related to capability coordination, and (5) developing applications to important large-scale societal transitions, such as the green transition and the digitization of work.

1 Introduction

Why are some countries rich and others poor? Why do standards of living differ so much across cities in the same country? What determines whether these standards of living diverge or converge? These questions have inspired generations of economists. In essence, they ask what determines an economy's capacity to generate prosperity. The consensus since at least Abramovitz (1986) is that the ultimate driver of prosperity is progress in "technology", i.e., in the ways in which economies produce output. Initially, economists aimed to estimate a country's technological prowess from how efficiently it converts broad factors of production, such as capital, labor and land, into aggregate output. However, by summing across many types of inputs and outputs, this "agglomerative approach" (Sbardella et al., 2018b; Balland et al., 2022) left much information on economies' production unused. Recently a new research program at the intersection of complexity science and economics has gained traction that aims to shed new light on the issue of economic development. This field uses detailed information on what economic entities produce, leveraging insights from complex network analysis. We will refer to this emerging field of research as Economic Complexity Analysis (ECA).

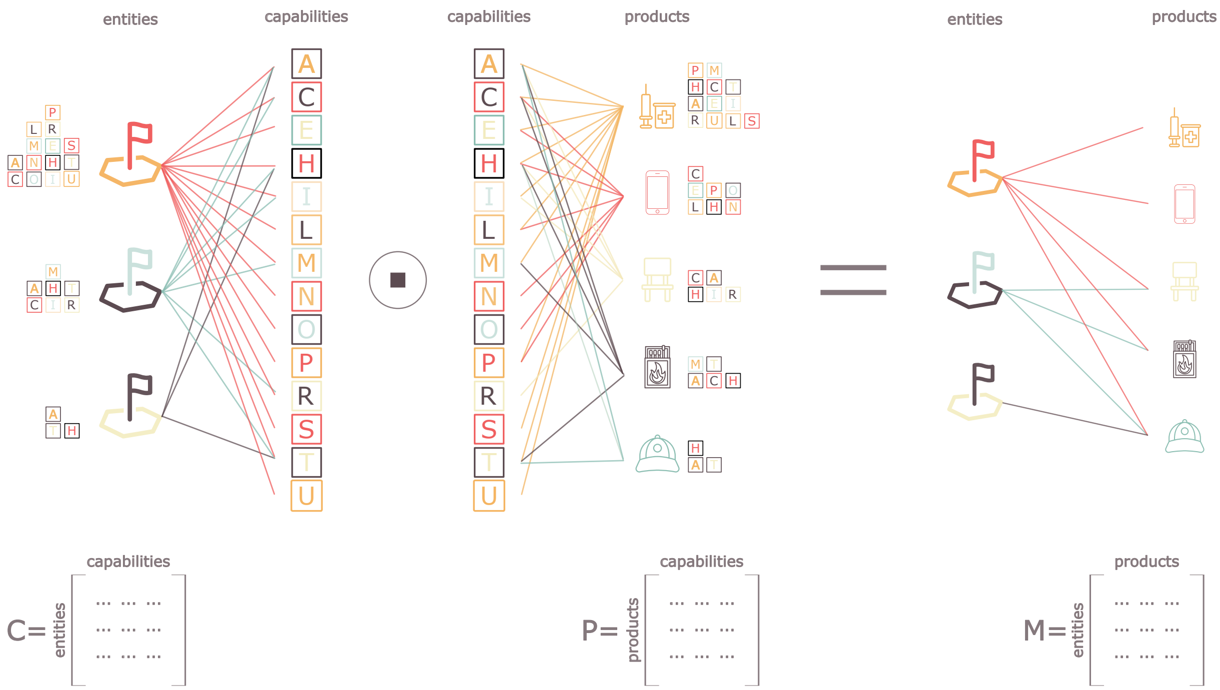
ECA synthesizes insights from diverse intellectual traditions. It draws from the structuralist perspective, which emphasizes the importance of the composition of countries' activity baskets and views economic development as changes in how resources are allocated across sectors (Hirschman, 1958; Prebisch, 1962; Lin, 2011). Echoing evolutionary economics and capability-based theories of the firm (Penrose, 1959; Nelson, 1982; Barney, 1991; Dosi and Nelson, 1994), ECA furthermore underscores the significance of productive capabilities – fine-grained inputs (broadly defined) to production – as the primary catalyst for transformative growth, where these capabilities range from specialized know-how to infrastructure and state capacities. In terms of complexity science, ECA incorporates principles from complexity economics, which emerged at the Santa Fe Institute in the late 1980s and 1990s as reviewed in earlier volumes of this publication. This approach treats economic phenomena as complex systems, in which interconnected and heterogeneous actors evolve, learn, and adapt their strategies in ways that result in macro-level patterns of collective behavior (Arthur, 2013). Exhaustive reviews of the literature on ECA can be found in Balland et al. (2022) and Hidalgo (2023). Our aim here is not to repeat these efforts, but rather to describe the main features of ECA in a way that highlights current challenges, policy implications, and opportunities for future research.

2 Assumptions of ECA

ECA starts from a stylized depiction of the process by which economic entities, be they countries, cities, regions or firms, *make* things, where each product or service requires its own subset of a large but finite range of capabilities. This sets ECA apart from more traditional bodies of economic thought, which emphasize strategic behavior or focus on the puzzle of how to allocate scarce resources.

The capabilities that modern economies mobilize – ranging from specialized know-how to

Figure 1: Model of production in ECA



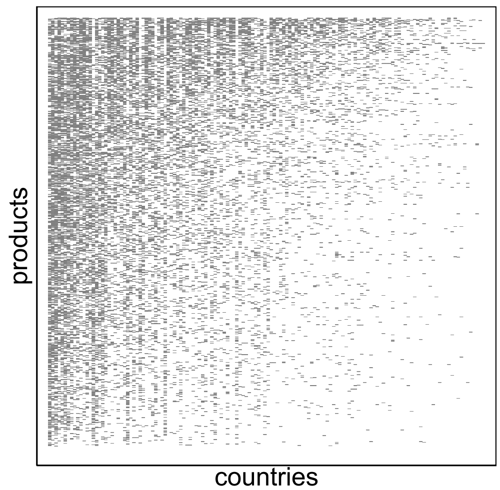
Tripartite network composed of two bipartite networks, described by matrices P and C, that are connected through a generic operator that shows how capability endowments interact with capability requirements in economic production. The tripartite network connects capabilities to productive entities (such as countries, cities or firms) on the left and to products on the right. The operation yields a new network that shows which entities make which products, described by matrix M.

a variety of different public goods – are numerous. Moreover, capabilities are taken to be non-substitutable. Therefore, ECA assumes that, to a first approximation, economies can only produce the products and services for which they have all required capabilities.

Cast in the language of networks, this model of production can be described by a tripartite network that first connects economic entities to the capabilities they possess – shown in the left of Fig. 1 and captured by matrix C – and then connects these capabilities to the products or services that require them – shown in the center of Fig. 1 and captured by matrix P (Hidalgo and Hausmann, 2009; Cristelli et al., 2013). This path also connects, albeit indirectly, countries to the products they can make, viz. the products for which they possess all required capabilities. This bipartite network is shown in Fig. 1 on the right and captured by matrix M. An important challenge in empirical applications is that while the economic activities that entities produce, summarized in matrix M, are readily observable, the underlying capability structure in matrices C and P typically are not. We will get back to this point momentarily.

This tripartite model of production implies a highly nonlinear relationship between the capability endowments of economic entities and their capacity to produce a product, i.e., the structure of the resulting bipartite network that connects entities to the products they make. The reason is that the addition or removal of a single capability (i.e., a

Figure 2: Nested trade matrix



Matrix whose elements reflect the exports by countries (in rows) of products (in columns). The matrix is *nested* as shown by its triangular structure.

link in the tripartite network) may trigger the appearance or disappearance of a link in the bipartite network. That is, such changes do not just result in a proportional increase or decrease in competitiveness, but in a complete gain or loss of the capacity to produce certain products. Moreover, the combinatorial nature of production – captured by the assumption that production combines product-specific sets of capabilities – implies that the added value of an extra capability increases super-linearly with the number of available capabilities (Hausmann and Hidalgo, 2011; Fink and Reeves, 2019; Van Dam and Frenken, 2022, and Chapter 2 of the current volume). The reason is that each combination of capabilities potentially allows to make a product, and the greater the number of pre-existing capabilities, the more additional combinations become feasible when adding a capability. This introduces nonlinearities that lead to poverty traps and path dependence in economic development (Hidalgo et al., 2007; Hausmann and Hidalgo, 2011; Pugliese et al., 2017; Diodato et al., 2022).

An important finding in ECA is that many of the observed M matrices are *nested* (Hausmann and Hidalgo, 2011; Tacchella et al., 2012; Mariani et al., 2019; Schetter, 2020). Nestedness is a concept that originated in ecology where it describes a situation in which specialist species, species that are adaptable and able to draw from a large variety of food sources, interact with generalist species, species with a more limited diet that occupy narrower ecological niches. ECA carries this metaphor over to economic production, by highlighting that, empirically speaking, rare products (specialists) are often only exported by diversified countries (generalists), while diversified countries often export both rare and ubiquitous products. Visually, this results in the triangular shape (see Fig. 2) that adjacency matrices of country-product networks assume when their rows and columns are appropriately sorted. We will get back to this issue later on.

3 Empirical implementation

A basic challenge of the ECA framework is that capabilities are hard to observe. As a consequence, the tripartite network of Fig. 1 is not immediately available to the researcher. What is readily observable is the bipartite network that connects economic entities to the products and services they produce. The core methodological insight of ECA is that, although the bipartite network in the right part of Fig. 1 cannot be easily used to uncover the exact capability endowments of an economic entity or the capability requirements of a product or service, it can be used to learn about the topology and complexity of capability endowments and requirements.

The idea of looking at the composition of output baskets to infer the topology of the capability base that underlies observed production patterns goes back to Hausmann and Klinger (2006). Using international trade data, these authors infer the technological proximity between two exported products (i.e., the degree to which they, presumably, share the same capability requirements) by counting how often two products are exported by the same countries. The idea of inferring the similarity between products in terms of their production requirements from coproduction patterns has a long history in management science, going back to at least the work of Teece et al. (1994). These authors studied co-occurrences of industries in firms to estimate among which industries economies of scope exist. The rationale behind studying co-occurrences of products at the country level is similarly straightforward: if countries make the products for which they have all required capabilities, then (properly rescaled) co-occurrence counts should signal similarities in capability requirements. Subsequently, Hidalgo et al. (2007) cast this work in the language of network analysis, where products are connected if they are often co-exported. The resulting network, or *product space*, helps predict how countries diversify their export baskets: countries are more likely to start producing new products that are closely related to – viz. are often co-exported with – their current exports than unrelated products.

This work has inspired a stream of research papers that apply this insight to predict how cities and regions diversify into new industries (Neffke et al., 2011; Boschma et al., 2013; Essletzbichler, 2017; Zhu et al., 2017), technologies (Napolitano et al., 2018; Barbieri et al., 2022; Zhang and Rigby, 2022), or academic research fields (Guevara et al., 2016; Patelli et al., 2017). These different types of activity can also interact. This is captured in multidimensional measures of relatedness that aim to map how, for instance, competitiveness in an academic research field facilitates innovating in technological areas, which in turn yields comparative advantage in exporting specific products Pugliese et al. (2019a). By now, the prediction of related diversification has been replicated across so many datasets and domains that it has been dubbed the *principle of relatedness* (Hidalgo et al., 2018). Furthermore, the principle of relatedness also operates at levels other than countries or regions. For instance, individual careers (Gathmann and Schönberg, 2010; Yildirim and Coscia, 2014; Mealy et al., 2018; Frank et al., 2024; Neffke et al., 2024, see also Chapter 25 in this volume) and firm diversification trajectories (Bryce and Winter, 2009; Neffke and Henning, 2013; Napolitano et al., 2018) also often follow a path of related diversification.

However, inferring the similarity of economic activities from colocation frequencies presents challenges, in part because the number of activities is much greater than the number of locations. As a consequence, most geographical areas host hundreds of activities that are often only indirectly related to one another. This has led to the development of statistical validations techniques for filtering network links (Saracco et al., 2015, 2017; Cimini et al., 2019), or other types of similarity metrics (Neffke and Henning, 2013; Li and Neffke, 2024), more sophisticated machine learning methodologies (Albora et al., 2023; Tacchella et al., 2023) and approaches that directly build on observable capabilities (Diodato et al., 2022; Aufiero et al., 2024; Schetter et al., 2024).

The insight that the structure of output, i.e., the portfolio of products, services or industries in which an economic entity is active, can be used to estimate the complexity of the entity's underlying capability base goes back to Hausmann et al. (2007). Once again relying on trade data, these authors propose that the productivity of a country is reflected in its export basket: countries that export high-income goods tend to be highly productive, or, "what you export matters." Hidalgo and Hausmann (2009) reformulate this work in terms of the network of the entity-product matrix, M. Starting from this matrix, they propose an iterative algorithm – the "method of reflections", equivalent to reciprocal averaging in correspondence analysis (Hill, 1974; van Dam et al., 2021) – that assesses the complexity of countries using only information on the products they make and vice versa. The resulting metrics, the Economic Complexity Index (ECI) for countries and the Product Complexity Index (PCI) for economic activities, converge to the second eigenvectors of a rescaled version of M, multiplied with its transpose.

The work by Hidalgo and Hausmann (2009) has generated substantial debate (e.g. Tacchella et al., 2012; Servedio et al., 2018; Mealy et al., 2019; Sciarra et al., 2020; van Dam et al., 2021; McNerney et al., 2021). A first challenge, by Tacchella et al. (2012), highlighted that the ECI/PCI pair does not always behave in the way the model of economic production of Fig. 1 would suggest. In particular, a country's ECI is, by construction, equal to the average PCI of the products it makes and a product's PCI is the average ECI of the countries that make it. Consequently, a country's ECI may go up or down if the country adds a new product to its export basket, depending on whether the product is more or less complex than the existing products in this basket. However, a strict interpretation of the capability model of Fig. 1 prohibits this. After all, this model implies that adding extra products should never be associated with a decrease in the number of capabilities in a country. Similarly, the complexity of a product should not change if more complex economies start producing it, but should remain anchored by the least complex economy capable of doing so.

To remedy this, Tacchella et al. (2012) propose an alternative algorithm – the Fitness Complexity (FC) algorithm – that retains the monotonous relation between diversification and complexity and the nonlinearity required to bound a product's complexity to the least complex of its exporters. This leads to a new set of complexity or *Fitness* measures. In terms of predictive validity, like a country's ECI, Fitness is a strong predictor of per capita GDP and GDP growth (Tacchella et al., 2018). Interestingly, Fitness also turns out to be closely connected to the concept, central to ECA, of nestedness. In fact, the FC algorithm ranks rows and columns of nested matrices in a close-to-optimal way to reveal the matrices' nested structure (Mariani et al., 2019, 2024).[1]

Other authors have focused on the interpretation of the ECI. In particular, because the ECI and PCI metrics are eigenvectors of co-occurrence matrices, they also have more mundane interpretations. For instance, Mealy et al. (2019) show that the ECI is equivalent to spectral clustering, dividing countries into two communities, based on the degree to which they produce similar products. Similarly, McNerney et al. (2021) show that variants of the ECI can be derived from the assumption that the principle of relatedness accurately describes short-term dynamics of international exports. In this case, the principle of relatedness sets up a simple dynamical system where the first eigenvector closely resembles Fitness and the second eigenvector resembles the PCI.

Schetter (2022) shows that the ECI/PCI pair ranks countries and products in accordance with structural notions of complexity, provided that matrix M exhibits a *log-supermodular* structure, a general assumption that covers a range of special cases[2] and that finds strong empirical support in international trade data. He embeds notions of complexity in a general equilibrium trade model to derive nonparametric productivity rankings that correlate highly with the ECI and PCI. Whereas Schetter (2022) provides a flexible microfoundation for complexity *rankings*, Yildirim (2021) builds on these insights by adding specific functional form assumptions that provide an approximate mapping to the underlying complexity *levels*.

The upshot of this debate is that the interpretation of the ECI/PCI pair depends on the assumptions one is willing to make about the data generating process behind the country-product matrix, M. Without any further assumptions, these variables simply recover communities of countries that produce similar products and of products that are produced by similar countries. If, instead, we are willing to assume that the principle of relatedness is a good description of short-run diversification dynamics, the PCI is an important axis of long-lived structural transformation, whereas the ECI approximately captures how far a country has moved along this axis.[3] Finally, if we are willing to assume log-supermodularity, the ECI ranks countries in terms of their underlying productive capabilities.

4 Economic complexity analysis and policy

ECA is widely used in policy making at the international, national, and subnational level to devise strategies for economic development, structural change, and innovation. The adoption of ECA in policy frameworks has two main reasons. On the one hand, ECA provides novel perspectives on countries' productive capabilities and how they foster

[1] As a consequence, the FC algorithm may find useful applications well beyond the field of economic complexity, from assessing the importance of species in mutualistic ecosystems (Domínguez-García and Munoz, 2015) to providing approximate solutions to Optimal Transport problems (Mazzilli et al., 2024).

[2] Examples range from *ladders of specialization*, to nested patterns of specialization, to the random capabilities model in Hausmann and Hidalgo (2011).

[3] Interestingly, another important axis of change closely resembles Fitness, showing that in this interpretation, Fitness and PCI are not in opposition but complement each other to describe the long-term patterns of change implied by the principle of relatedness.

economic prosperity. This is most vividly illustrated by complexity metrics that have been shown to correlate strongly with both countries' current GDP per capita but also their future growth performance (Hidalgo and Hausmann, 2009; Hausmann et al., 2011; Tacchella et al., 2012). Moreover, complex countries have been shown to be more inclusive (Hartmann et al., 2017; Sbardella et al., 2017; Hartmann and Pinheiro, 2022; Barza et al., 2024), suggesting that complexity upgrading fosters more broadly shared prosperity.

On the other hand, the tools and methods developed in ECA and the fine-grained view on the economy they afford allow for context-specific, targeted strategies aimed at diversifying and upgrading economies. This starts with an assessment of an economy's current capabilities and its position in product and related spaces. By now, a range of publicly available tools allows to readily assess this at the national and subnational level. Subsequent analysis allows identifying products or services that may serve as stepping stones onto development ladders and identifying strategies for amassing the capabilities to reach these stepping stones. The latter is facilitated by a recently proposed 'genotypic' approach to the product space (Schetter et al., 2024), which takes the level of analysis from observed outcomes as summarized in matrix M to underlying capability structures as summarized in matrices C and P. The value of this approach is that it offers more actionable information on missing capabilities, but future work needs to explore these opportunities more carefully.

ECA has gained considerable traction among policy making institutions, particularly those focused on investments in developing countries. These institutions often grapple with the challenge of prioritizing investments across diverse geographies and sectors. The ECA framework offers a valuable tool in this context, because it allows direct comparisons between highly diverse investment options across economies and sectors at a granular level of single products or technologies. It does so within a unified framework that is easily applicable at both the national and regional level and that provides a common language for evaluating otherwise incommensurable opportunities.

One of the key strengths of ECA in policy applications is its ability to quantify the likelihood that specific sectors or products can be developed based on an economy's existing competitiveness in related sectors. This stems from the principle of relatedness discussed earlier, which posits that a country is more likely to diversify into industries that require similar capabilities as the industries in which it is active already.

However, it is crucial to note that these quantitative predictions should not necessarily be interpreted as policy prescriptions or priorities. A common misunderstanding of ECA is that it suggests "picking winners". However, exclusively building on a country's existing comparative advantage by following related diversification trajectories may risk to merely strengthen already competitive areas or provoke low-complexity lock-ins in regions that have so far failed to catch up with the technological frontier. Proper application of ECA in policy making therefore often requires flanking it with more qualitative analysis. For instance, Li and Neffke (2024) suggest that ECA can be used to detect anomalies in a country's productive structure. That is, ECA can help identify activities that are surprisingly large or small and therewith point to hidden strengths or weaknesses of the economy as part of a broader diagnostic approach (Hausmann et al., 2008). Such anomalies suggest areas of the economy where deep dives would yield valuable information about binding constraints to development.

Another common misconception is that ECA assumes that complexity itself should always be the main goal of economic development policy. However, policy makers may have different priorities. For instance, they may strive to reduce their economy's carbon footprint or want to create jobs for specific segments of the population. In this case, ECA can be used to assess impacts on complexity and productivity of development strategies guided by such priorities. It can also be used to map the associated development trajectories in spaces that reflect the economy's current capabilities and identify which capabilities would still need to be developed.

Therefore, policy makers and institutional investors, such as development banks, often use ECA as part of a broader decision-making process. They may choose to support projects that are closely related to existing activities, which are more likely to generate market-driven development. Alternatively, and perhaps more importantly, they might opt to invest in projects that are less related to the current productive structure, but offer higher potential for long-term diversification and productivity growth. This latter approach aims to fill capability gaps, enabling countries to access more complex and potentially more lucrative production opportunities in the future. For instance, the World Bank, the EU Commission (Pugliese and Tacchella, 2020; Pugliese et al., 2021), and other development institutions frequently prioritize projects that are less likely to be developed by the market alone to catalyze structural transformation that might not occur organically, pushing countries towards higher levels of economic complexity, fostering the acquisition of new capabilities, and facilitating entry into more sophisticated industries.

ECA also provides policymakers with a framework to understand the potential spillover effects of investments. By identifying the capability requirements of different industries and their connections in the product space, policymakers can better anticipate how support for one sector may create positive externalities for others. This system-level view can help in designing holistic development strategies that leverage synergies across different parts of the economy.

Finally, ECA can also be applied to development strategies for regions within countries. By analyzing the economic complexity and relatedness patterns at subnational levels, policymakers can tailor interventions to the capability endowments of different regions (Pugliese and Tacchella, 2020; Pugliese et al., 2021; Sbardella et al., 2022). This can be particularly valuable in addressing regional inequalities and promoting balanced economic growth within a country.

In summary, while ECA offers powerful analytical tools for quantifying development potential, its true value in policy making depends on how these insights are interpreted and applied. When used judiciously and in combination with other diagnostic tools, ECA can help guide policy makers in making strategic investments that not only build on existing strengths, but also pave the way for transformative economic development by systematically expanding a country's productive capabilities.

5 Future directions for ECA

Despite the rapid expansion of the literature on ECA, there are still many questions about the process of economic development it proposes that remain unresolved. In the model of production underlying ECA, economic growth can in principle come from three sources. First, economies may not yet have fully exploited the potential of their existing products. Second, economies may not yet have fully exploited the potential of their existing capabilities. Third, economies may acquire new capabilities, increasing the number and changing the nature of the products they can make. The first assumes that countries may produce a product at different levels of quality – or, alternatively, at different levels of efficiency. The second implies that countries do not make all products they possibly can. The third requires a theory of how capabilities diffuse, or if they are new to the world, how they are invented. A plausible hypothesis is that capabilities diffuse with the movement of people (e.g., migration) and of teams of people (e.g., foreign direct investments, FDI). This hypothesis finds support in a large literature on spillovers from highly skilled migrants (e.g., Hausmann and Nedelkoska, 2018; Diodato et al., 2022; Lissoni and Miguelez, 2024; Bahar et al., 2024) and from FDI (e.g., Blomström and Kokko, 1998; Javorcik, 2004). Compared to these more traditional literatures, ECA emphasizes the *content* of the know-how that foreign migrants and firms possess, as well as the combinatorial possibilities the capabilities they bring with them unlock. Although such implications remain currently understudied, they suggest clear hypotheses that can be tested in future research.

Another fruitful direction scrutinizes the assumption in ECA that *having* capabilities is sufficient for *using* them. This assumption is problematic, because capabilities are likely to be distributed across individuals, firms and locations. Mobilizing large sets of capabilities therefore requires mechanisms to coordinate them across people, teams, firms and locations. In line with this, Hartog et al. (2024) show that the advent of the industrial research lab – which offered new ways to coordinate the work of inventor teams – coincided with the take-off of teamwork, as well as with a strong increase in the capacity of teams to develop radical innovations. Similarly, in Chapter 30 of this volume, Frenken and Neffke argue that institutions and multinational enterprises play key roles in coordinating capabilities in global value chains that are distributed across different locations (see also, Frenken et al., 2023).

Relatedly, ECA can be used to study how entities at different scales interact. For instance, Laudati et al. (2023) show how nestedness breaks down when studying firm level data. The reason is that the limited size of firms forces them to concentrate on specific subsets of products. However, after appropriately partitioning economic activities into communities of closely related industries or products, nestedness is recovered within these communities. That is, within a given community, the population of firms that are active there can be sorted according to the FC algorithm such that nested firm-activity submatrices emerge. Because economies are essentially collections of firms, this finding shows that nestedness at the macro-level of entire economies builds on fine-grained nestedness patterns within firm populations. Building further on this insight may help us gain an understanding of how complexity is distributed and aggregated at different levels of analysis, from individuals, to firms, cities, countries and value chains.

The greater specialization at the firm vis-à-vis regional or national level is related to another issue often ignored in ECA: scarcity of capabilities. In essence, ECA typically assumes that capabilities are public goods. That is, capabilities are nonrivalrous and nonexcludable. As a consequence, once developed, capabilities can be freely used in the production of all products without impeding their use in other products. While this assumption simplifies the analysis, it is not obvious that it is always a reasonable approximation of reality. For example, one often cited capability, specialized know-how, resides in the human capital of workers. Workers, however, can typically only be employed by one firm at a time. Scarcity of capabilities may have profound consequences for ECA. For instance, ECA proposes that a country's prospects of starting to make a new product are better, the denser the web of related products it is already making. With scarce capabilities, this is no longer necessarily the case, and scarcity may thus help explain why the relationship between density and entry is not always monotonous (Schetter et al., 2024). Analyzing more carefully the public-goods character of capabilities (or lack thereof) and its implications for ECA would be a fruitful avenue for future research.

At a more fundamental level, ECA differs from large parts of related literature in economics in two important respects: first, by emphasizing the granularity of capabilities that are needed as inputs for modern production and, second, by considering international specialization and structural change at the *extensive* margin, that is by analyzing at a highly disaggregated level the set of products that countries make and how this set evolves. Recently, a series of advances helped these literatures move closer together. This includes macroeconomic analyses of disaggregated economies, but with a focus on changes at the intensive margin of production (Baqaee and Farhi, 2019, 2024); economic theories with a ladder of development at the extensive product margin (Lucas, 1993; Foellmi and Zweimüller, 2008; Sutton and Trefler, 2016; Schetter, 2020; Atkin et al., 2021; Diodato et al., 2022); work that explains how a nested pattern of specialization can arise even if countries specialize according to their comparative advantage (Schetter, 2020; Bruno et al., 2023) and macroeconomic implications of a 'nested' pattern of specialization (Atkin et al., 2021; Gersbach et al., 2023); studies analyzing the macroeconomic implications of a greater division of labor in larger cities (Tian, 2021); and papers that analyze related diversification of firms or countries (Napolitano et al., 2018; Pugliese et al., 2019b), using information about input-output relations (Boehm et al., 2022) or occupational structures (Diodato et al., 2022; Aufiero et al., 2024). Yet, there are many open questions at the intersection of economics and ECA that future research should address, concerning, for instance, the aforementioned topics of global value chains and of identifying fundamental drivers of economic growth.

Finally, ECA has proven to be highly effective in shedding light on important recent economic transformations, because it provides a comprehensive toolbox for analyzing the connections between the growth and spatial concentration of economic activities as well as the flows of knowledge, people and resources among them. A particularly important area in this space applies elements of ECA to study the green transition. This research merges insights from sustainability studies and evolutionary economic geography with ECA to analyze the shift towards more sustainable and equitable socio-economic systems.[4] For instance, connecting green products to the capability bases of cities and countries allows

[4]For a comprehensive review, see Caldarola et al. (2024).

evaluating the degree to which existing productive structures support new green specialization paths. Initial research suggests that green products and technologies (Barbieri et al., 2020a; Mealy and Teytelboym, 2022) are comparatively complex and often intertwined with nongreen counterparts in product (Hamwey et al., 2013; Fankhauser et al., 2013; Fraccascia et al., 2018) and technology (Barbieri et al., 2022) spaces. In fact, nongreen and green innovation capabilities often complement one another (Montresor and Quatraro, 2020; Perruchas et al., 2020; Barbieri et al., 2022), such that the relatedness to pre-existing nongreen knowledge bases often plays a key role in fostering new green technological advancements (Montresor and Quatraro, 2020; Barbieri et al., 2022). Countries therefore typically adopt a dual strategy: diversifying into green technologies that align with their existing nongreen capabilities, while specializing in mature green technologies where they have already accumulated expertise (Barbieri et al., 2020b; Perruchas et al., 2020). This however may lead to significant gaps in green innovation capacity at subnational levels (Grashof and Basilico, 2023; Napolitano et al., 2018; Sbardella et al., 2018a).

Currently, this literature is still in its infancy and there are many ways to move this agenda forward. First, exploring the interplay between productive, technological, and scientific capabilities can help understand transformation at the frontier of knowledge where much of these transitions are taking place (e.g., de Cunzo et al., 2022). Second, ensuring a just transition will require studying “left-behind regions” (Rodríguez-Pose et al., 2024) and the structural change and labor reallocation processes they face, as well as the distributional effects of the associated creation and destruction of jobs (see, e.g. Mealy et al., 2018; Vona et al., 2019; Rughi et al., 2023, and Chapter 25 in this volume). Third, the reliance of green and digital technologies and products on critical minerals (Diemer et al., 2022; de Cunzo et al., 2023; International Energy Agency, 2023) has led to concerns about supply chain disruptions (European Commission, 2023; Kowalski and Legendre, 2023) for which ECA’s product and technology spaces may help identify bottlenecks, but also workarounds.

The seamless connection between finegrained and coarsened views on economic production that ECA provides, combined with the framework’s focus on economic transformation, makes it an excellent starting point to study such transitions and their socio-economic effects. Further developing the framework, both in terms of its theoretical foundations and its methodological toolbox, will therefore not only guide academic debates, but also inform economic policy on how to plot a course in periods that are characterized by large societal challenges, as well as substantial technological and structural change.

Acknowledgements

F.N. receives financial support from the Austrian Research Promotion Agency (FFG), project #873927 (ESSENCSE). A.S. and AT acknowledge the financial support under the National Recovery and Resilience Plan (NRRP), Mission 4, Component 2, Investment 1.1, Call for tender No. 1409 published on 14.9.2022 by the Italian Ministry of University and Research (MUR), funded by the European Union – Next Generation EU – Project Title ”Triple T – Tackling a just Twin Transition: a complexity approach to the geography of capabilities, labour markets and inequalities" – CUP F53D23010800001 - Grant Assignment Decree No. 1378 adopted on 01.09.2023 by the Italian Ministry of Ministry of University and Research (MUR).

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