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Complexity: Hausmann–Hidalgo Economic Complexity

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Abstract

Economic complexity is an active field with a growing number of methodologies and applications. Among the different paradigms, the Hausmann-Hidalgo economic complexity framework offers a way to quantify the sophistication and productive knowledge embedded in an economy. In this work, we provide an overview of its foundational concepts, empirical applications, policy uses, and directions for future research. We aim to equip readers with a basic understanding of this framework in simple words and to help them navigate the vast literature. We argue that the Hausmann-Hidalgo economic complexity serves as a flexible framework for understanding the dynamics of knowledge diversification across multiple economic domains and provides a starting point for the design of place-based policies.

JEL Codes: O33 (Technological Change: Choices and Consequences; Diffusion Processes); F14 (Empirical Studies of Trade); O38 (Technological Change; Government Policy)

Keywords: Economic Complexity; Product Space; Comparative Advantage; Productive Knowledge; Innovation Policy

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1. Introduction

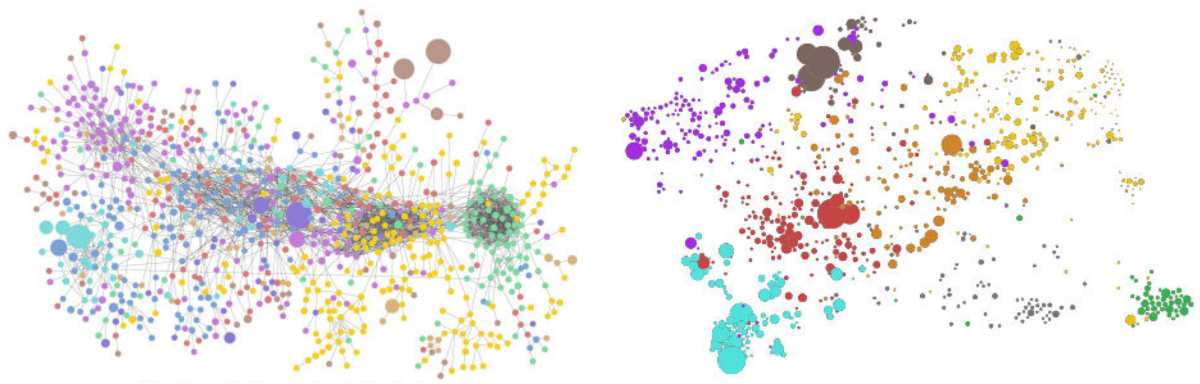
The Hausmann-Hidalgo economic complexity provides a quantitative approach to measuring the productive knowledge embedded within the economies of countries, regions, and cities. It starts from a basic premise: economies vary not just in their total output, but in the diversity and sophistication of the goods they produce. By looking at an economy's comparative advantages (e.g., its competitive exports), researchers can infer the underlying, non-tradable capabilities present in the economy. Over the past two decades, this framework has gained quite some traction in development economics, innovation studies, and industrial policy.

2. Foundational Concepts

There are two complementary approaches in the Hausmann-Hidalgo economic complexity framework. The first one, often called the principle of relatedness, covers the methods used to infer the similarity between economic activities and to explore the dynamics of knowledge diversification. The second one, known as the economic complexity index, focuses on the computation of one-dimensional metrics that account for the complexity of economies and products.

2.1. The Product Space and Relatedness

The foundation of Hausmann-Hidalgo economic complexity traces back to earlier works investigating countries' income differences based on the composition of their export baskets (Hausmann et al., 2007) and the process in which countries move from *poor-country goods* to *rich-country goods* (Hausmann & Klinger, 2006). These ideas were later formalized by Hidalgo et al. (2007), who defined the *product space* as a network mapping the similarity between traded goods (see Figure 1 for an example). Products are considered "proximate" if countries frequently co-export them, implying that they require similar capabilities (e.g., similar institutions or a similarly skilled labor force) to produce them. This resembles economies of scope at, for instance, the plant level, where firms produce different but related products drawing upon the same skills or machinery. Mapping these relationships at the country level uncovers a highly uneven network: complex goods like machinery and chemicals sit in a dense core, whereas raw materials sit in a sparse periphery. This topology explains why economies heavily reliant on peripheral products struggle to diversify; transitioning to new industries requires capabilities they do not yet have, and one cannot easily leapfrog to more advanced areas of the product space. Relatedness thus allows one to measure how big a leap any particular diversification move represents for a given economy.



(a) Network representation (b) UMAP projection

Figure 1: Visualizations of the product space

Source: The Growth Lab at Harvard University (2020, 2026). *Notes:* The product space maps the proximity between different economic activities (dots). Panel (a) shows a traditional network representation, in which links (lines) denote the most significant proximity relationships among products. Panel (b) shows a UMAP projection (McInnes et al., 2018), in which nodes are positioned according to their pairwise proximity and explicit links are therefore not required.

Product space analyses are often used to illustrate that structural transformation is strongly path-dependent. Countries tend to diversify into goods related to goods they are currently specialized in (Hidalgo et al., 2007, 2018). Regional economies have similarly been found to do so (Neffke et al., 2011; Li & Neffke, 2024; Chen et al., 2026). This dynamic concept of relatedness has been referred to as the "principle of relatedness" (Hidalgo et al., 2018). It challenges the often implicit notion that economies can leapfrog into high-value industries with just the right policy tweaks.

2.2. The Economic Complexity Index

Hidalgo & Hausmann (2009) subsequently introduced the *Economic Complexity Index* (ECI) and the *Product Complexity Index* (PCI). These indices are derived from a bipartite network linking countries to the products they export with a revealed comparative advantage (RCA). RCA indicates that a country exports a given product more intensively than would be expected given its overall export profile. An iterative algorithm, the Method of Reflections, is then applied to simultaneously capture two key properties: the diversity of a country's exports (the number of products in which a country holds an RCA larger than one) and the ubiquity of those products (the number of countries exporting them with an RCA larger than one). The underlying intuition is that advanced economies produce a wide variety of goods (high diversity), many of which are rarely produced elsewhere (low ubiquity).

In the first iteration, the complexity of a country is simply its diversity, and the complexity of a product is the inverse of its ubiquity. In each subsequent iteration, the measure is updated by averaging the product-complexity scores of its exports, and each product measure is updated by averaging the country-complexity scores of its exporters. This recursive process accounts for products that appear complex merely because they are exported by many low-diversity countries (e.g., oil), and upgrades countries whose export baskets contain goods that more sophisticated economies produce.

The resulting country scores constitute the ECI, and the related product scores constitute the PCI. A high ECI signals that a country possesses a broad and sophisticated set of productive capabilities (e.g., the tacit knowledge, institutions, and organizational know-how that are difficult to transfer) that enable the production of complex, non-ubiquitous goods. The ECI is thus a measure of the productive knowledge embedded in an economy. A more formal and comprehensive explanation of the Hausmann-Hidalgo economic complexity framework and its applications can be found in Balland et al. (2022) and Hidalgo (2021).

Economic Complexity Index **(ECI)**					
Top 5 Countries			**Bottom 5 Countries**		
Rank	Country	ECI	Rank	Country	ECI
1	Japan	1.69	142	Nigeria	−2.26
2	Switzerland	1.58	143	Republic of the Congo	−2.49
3	Taiwan	1.57	144	Equatorial Guinea	−2.70
4	South Korea	1.56	145	Dem. Rep. Congo	−3.13
5	Singapore	1.45	146	Chad	−3.52

Product Complexity Index **(PCI)**					
Top 5 Products			**Bottom 5 Products**		
Rank	Product	PCI	Rank	Product	PCI
1	Photographic plates and film	2.21	1225	Uranium or thorium ores	−3.52
2	Semiconductor & electronics machinery	1.96	1226	Petroleum oils, crude	−3.61
3	Cermets	1.88	1227	Cocoa residues	−3.69
4	Nickel plates	1.85	1228	Tin ore	−4.48
5	Phosphoric esters	1.79	1229	Cocoa beans	−4.84

Table 1: Top and Bottom ECI and PCI Rankings in 2024

Source: The Growth Lab at Harvard University (2026). *Notes:* The *Economic Complexity Index* (ECI) measures the sophistication of economies (e.g., countries), while the *Product Complexity Index* (PCI) measures the sophistication of activities (e.g., products). Product names are shortened versions of the four-digit HS2012 product descriptions.

Hausmann et al. (2014) expanded on this in *The Atlas of Economic Complexity*, showing that the ECI robustly predicts future economic growth. In fact, their work demonstrated that the ECI often outperforms traditional predictors of growth, such as educational attainment or institutional quality. The framework's predictive power is most visible in the gap between a country's complexity and its income: in the early 2000s, China, Vietnam, and Poland, for instance, exhibited ECI levels well above what their per capita income would have predicted, and each subsequently experienced sustained, capability-driven growth. Conversely, several resource-rich economies have seen their incomes decline toward the level implied by the modest complexity of their productive structures. Countries that consistently rank at the top of the ECI are economies such as Japan, Switzerland, Taiwan, South Korea, and Singapore (see Table 1). Their export baskets are more heavily dominated by sophisticated goods, which are produced in a few places and require a combination of tacit knowledge, supplier networks, skilled labor, and other inputs that are harder to imitate (e.g., advanced machinery, precision instruments, chemicals, and electronics). By contrast, economies whose exports are concentrated in raw materials or less sophisticated agricultural products, such as Chad, Dem. Rep. Congo, and Nigeria, tend to score lower on the ECI.

3. Going beyond Export Data

The Hausmann-Hidalgo economic complexity framework is not limited to export data (Hidalgo, 2021; WIPO, 2024). Although international trade data reflects the capabilities embedded in physical goods, a substantial portion of modern productive knowledge resides in other activities. With the increasing availability of new information sources, researchers have broadened the complexity framework to study these other domains.

The flexibility of the Hausmann-Hidalgo framework has contributed to this surge in applications. For instance, Guevara et al. (2016) and Miao et al. (2022) adapted these metrics to analyze science using scientific publications, while Kogler et al. (2013) and Balland et al. (2019) mapped technologies using patent data. In the domain of human capital, Neffke & Henning (2013) compute relatedness metrics to map skill spaces using inter-industry labor mobility data, and Fritz & Manduca (2021) applied complexity metrics to labor using regional occupational employment data. Furthermore, the framework has been extended by Juhász et al. (2026) to open-source software using GitHub data, and by Stojkoski et al. (2016) to services using international service export data. In general, there is considerable potential to extend the applications of the Hausmann–Hidalgo framework beyond its original design. Researchers, however, should be aware that adjustments to the initial metrics may be necessary, as some of the default assumptions embedded in the framework's original methodological design may not be appropriate in other contexts (Li & Neffke, 2024; Chacua et al., 2026).

Scholars have also adapted the Hausmann-Hidalgo metrics to understand cross-domain linkages. Instead of treating dimensions in isolation, this approach integrates them to create a more comprehensive map of an economy's capabilities. For example, Balland & Boschma (2022) and Catalán et al. (2022) have developed cross-domain complexity metrics to investigate how scientific activity affects technological diversification. Stojkoski et al. (2023) combine individual complexity metrics for trade, patents, and scientific publications in a single regression to explain variations in inclusive green growth. Hausmann et al. (2024a) compute complexity metrics from trade, patents, and scientific publications to understand the multiple dimensions of the innovation process and predict patenting from trade and scientific publications. Moscatelli et al. (2024) and WIPO (2026) combine data from trade, patents, and scientific publications in a single knowledge space to compute single measures of multidimensional complexity. Overall, these multidimensional approaches illustrate how the Hausmann–Hidalgo framework is not limited to a single type of economic output, but can also be used to study the interplay of multiple economic domains.

Beyond broadening the data domains, alternative one-dimensional metrics have also been proposed to summarize capabilities in a single score. Tacchella et al. (2012) introduced the *Fitness-Complexity* algorithm, a nonlinear iterative procedure in which a product's complexity is bounded by the fitness of the least competitive countries that export it (rather than an average across all its exporters). Their measures aim to reflect the nested structure of the country-product matrix, penalizing countries that rely solely on ubiquitous products and preventing simple goods exported by advanced economies from inflating product complexity. More recently, Bustos & Yıldırım (2022) derived measures of a location's *production ability* and a product's sophistication from an explicit capabilities-based model of production. Here, output depends on the capabilities a product requires and those a place possesses. Estimated on both international trade and U.S. employment data, these measures correlate strongly with income and subsequent economic growth at the country and city levels. Hence, different metrics can be more or less appropriate depending on the structure of the data and the question at hand.

4. Economic Complexity in Policy Practice

Given the applied nature of the Hausmann-Hidalgo economic complexity framework, it has been widely adopted in policy discussions (Hidalgo, 2023). Its metrics have been featured in influential policy documents around the world (Draghi, 2024; World Bank, 2024; WIPO, 2024, 2026) and have supported multiple policy interventions globally (Hausmann et al., 2022, 2023, 2021). There are also multiple software libraries that facilitate the computation of Hausmann-Hidalgo complexity metrics,[1] as well as a growing number of online platforms and interactive tools that facilitate their visualization and understanding by a broader public.[2]

The Hausmann-Hidalgo economic complexity framework often serves as a guide for the design of place-based policies. In Namibia, relatedness analysis pointed toward green

[1]To mention a few, `ecomplexity` and `economic-complexity` for Python, as well as `EconGeo` and `economiccomplexity` for R.

[2]For example, the Growth Lab's Atlas of Economic Complexity (`https://atlas.hks.harvard.edu/`) and Greenplexity (`https://growthlab.app/greenplexity/`); and WIPO's Innovation Complexity Navigator (`https://www.wipo.int/innovation-complexity-navigator/`).

hydrogen, agro-processing, and mining-services exports as feasible diversification bets that build on existing capabilities in logistics, mining, and renewable-energy endowments (Hausmann et al., 2022). In South Africa, complexity diagnostics underpinned a strategy emphasizing capital goods and green-industrial value chains adjacent to the country's metallurgical and engineering base (Hausmann et al., 2023). Western Australia used the framework to identify diversification options beyond iron ore in related advanced-manufacturing and services activities (Hausmann et al., 2021). At the supranational level, the European Commission's competitiveness agenda and the World Bank's 2024 World Development Report draw on relatedness and complexity metrics to argue for targeted, place-specific industrial policies rather than horizontal subsidies (Draghi, 2024; World Bank, 2024). In each case, the framework is used not to pick winners in isolation but to narrow the policy search space to activities that are simultaneously complex (high PCI) and feasible (high relatedness to current capabilities).

Hence, at a broad level, the product space helps policymakers assess a territory's current capabilities and the related economic activities that are more likely to thrive. The ECI is used to summarize in a single measure the degree of sophistication of a territory, while the PCI, in combination with relatedness metrics, is often used to identify place-specific diversification opportunities. Together, these analytical tools allow policymakers to move beyond generic recommendations and tailor targeted industrial strategies that align with a place's unique latent advantages.

Hausmann-Hidalgo complexity measures, however, should not be the sole basis for real-world policy design. Although they provide valuable orientation on where to begin a diversification strategy based on current capabilities, there are numerous additional aspects to consider. For instance, territories must still set realistic targets and determine their best strategy to escape diversification traps (Balland et al., 2019). There are also ongoing discussions regarding the extent to which countries should diversify into unrelated activities, as an over-reliance on relatedness may lead to lock-ins (Pinheiro et al., 2022; Boschma et al., 2023). Furthermore, policymakers must address critical questions related to the timing and location of interventions, as well as the agents who will perform them (Hidalgo, 2023). Moreover, strategies often require tailored, multidimensional interventions to address concrete local problems, rather than importing solutions to issues a region does not actually face (Hausmann et al., 2024b).

5. Future Directions

There are several promising avenues for future research. First, the empirical scope of the framework continues to widen. Complexity metrics are refined as more accurate data become available (Bustos et al., 2026) and being applied to new domains beyond trade (Juhász et al., 2026). Increasingly, scholars are also integrating data across domains (e.g., trade, technology, and science) to construct multidimensional measures that capture phenomena such as innovation (WIPO, 2026; Moscatelli et al., 2024) and inclusive green growth (Stojkoski et al., 2023). Second, the framework would benefit from stronger theoretical foundations. Clarifying the mathematical properties of complexity metrics and the assumptions underlying empirical estimates (McNerney et al., 2025; Li & Neffke, 2024) would enable integration with structural economic models (Diodato et al., 2022; Atkin et al., 2026; Schetter, 2022), help reconcile the economic complexity approach with alternative complexity frameworks (Sciarra et al., 2020), and support the development of new metrics (Valverde-Carbonell, 2025). Third, the policy implications of economic complexity deserve more systematic study, as significant questions remain about how the framework should inform the design, implementation, and evaluation of real-world interventions (Hidalgo, 2023; Hausmann et al., 2024b).

6. Conclusion

The Hausmann-Hidalgo economic complexity framework provides a flexible, data-driven way to measure the productive knowledge embedded in economies and to map the related activities into which they are most likely to diversify. Over the past decade, it has been expanded beyond export data and has moved from single-domain indices to multidimensional measures. At its core, the framework is deeply evolutionary and institutional: it portrays development not as a movement along a fixed production frontier but as an open-ended, path-dependent process of accumulating and recombining capabilities. Like the 'routines' of evolutionary economics (Nelson & Winter, 1982), these capabilities involve tacit, collectively held knowledge. They encompass not only skills and machinery, but also the institutions, organizational forms, shared norms, and other factors that make production possible and that can be difficult to diffuse across places. Novelty arises near what an economy already does, and the product space describes the constrained set of viable next steps (Neffke et al., 2011; Hidalgo et al., 2018). Hence, agents of change from elsewhere, for instance, may be necessary for diversification (Neffke et al., 2018; Hidalgo, 2023), and the task of policy is to widen the adjacent possible rather than to try to leapfrog toward predetermined ends.

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