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Innovation on Reinert's Ladder: Economic Complexity and Innovation across Countries and Brazilian States

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Innovation on Reinert's Ladder: Economic Complexity and Innovation across Countries and Brazilian States *

Paulo Gala [1] & Rodrigo Ventura [2]

Highlights

- Reinert's Quality Index ranks activities by their capacity to innovate, but it has never been measured. This paper tests that ranking against direct measures of innovation.
- Economic complexity predicts innovation (GII) across 129 countries better than income does, and keeps a partial correlation of 0.60 when income is held constant.
- Across 27 Brazilian states, complexity has a rank correlation of up to 0.80 with the IBID, and innovation follows how widely complex activity is spread across a state's municipalities.
- Across 668 Brazilian activities, one standard deviation of complexity is associated with wages about 31 percent higher, yet most formal workers are in low-complexity activities.
- The largest deviations from the fitted line are the cases Reinert described: assembly platforms innovate less than their export baskets suggest, and resource rents buy innovation inputs without building productive structure.

Abstract

Erik Reinert ranked activities by their capacity to make nations rich, and the traits atop his Quality Index are those of innovation: steep learning curves, rapid technical change, high research content. He never measured the index. The economic complexity index is the standard proxy for an economy's position on such a ladder. This paper asks whether that position predicts innovation measured outside the trade matrix, setting complexity and income against each other as rival predictors.

Three bodies of evidence agree. Across 129 countries, complexity explains 69 percent of the variation in the Global Innovation Index (GII), against 62 percent for income per capita, and keeps a partial correlation of 0.60 net of income. Across 27 Brazilian states, which share the same national institutions, employment-based complexity reaches a rank correlation of 0.80 with the Brazil Innovation and Development Index (IBID), a subnational index aligned with the GII; its spread across municipalities tracks innovation more closely than its worker-weighted level. Across 668 activities, a standard deviation of complexity goes with wages about 31 percent higher. The exceptions are Reinert's own: assembly platforms exporting complex goods without the learning, and resource rents that buy innovation inputs without building structure. The evidence is associational, not causal.

Keywords: Quality Index of economic activities, Schumpeterian underdevelopment, innovation indices, subnational complexity, territorial diffusion, Brazil.

*** Preprint. This paper has not been peer reviewed.** This paper builds on the discussions held at the *International Conference on IP and Innovation Economics*, organized by the World Intellectual Property Organization (WIPO) and the National Institute of Industrial Property of Brazil (INPI) in Rio de Janeiro on 10–11 November 2026, on the occasion of the annual meeting of the Global Network of IP Chief Economists.

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1. Introduction

Reinert's Quality Index of Economic Activities is, at root, a theory of where innovation happens. The index places every activity on a continuum from perfect competition to monopoly, and the features that put an activity at the top are steep learning curves, rapid technological progress, high research content, imperfect information protected by patents or know-how, and the dynamic imperfect competition that follows from them (Reinert, 1994a, 2007). He calls these activities Schumpeterian. Those at the bottom, with flat learning curves and little technical change, he calls Malthusian. A nation is rich or poor according to which kind it hosts, because only in the first kind are the gains from technical change retained as wages and profits rather than passed on to foreign buyers as lower prices.

Reinert ranked activities and illustrated the ranking with cases, but he did not measure the index across the economy. The nearest measure now available comes from a different literature. Hausmann, Hwang and Rodrik (2007) attached to each product the income of the countries that export it, and Hidalgo and Hausmann (2009) extracted from the country–product matrix an index of the complexity of products and of countries. On both measures the ordering is the one Reinert described, with commodities at the bottom and chemicals, machinery and instruments at the top, and complex products are exported by rich countries and rarely by poor ones (Felipe et al., 2012). Gala, Rocha and Magacho (2018) read these results as the empirical counterpart of the structuralist tradition to which Reinert's index belongs. This paper takes a country's complexity index as its position on Reinert's ladder.

That step has a gap in it. Trade data record who exports what. They do not record learning curves, research and development, the pace of technical change or the wages paid in an activity, which are the characteristics that define a Schumpeterian activity. The complexity index can place economies on a ladder that has the shape Reinert predicted. That the ladder is ordered by innovation, as his theory requires, is an inference.

This paper tests the inference from the other side. Innovation is now measured directly and independently of the trade matrix, for countries by the Global Innovation Index (GII) of the World Intellectual Property Organization (WIPO, 2025) and for Brazilian states by the Brazil Innovation and Development Index (IBID), built by Brazil's National Institute of Industrial Property (INPI, 2025), which adapts the GII framework to subnational data. If the ladder is Schumpeterian in Reinert's sense, an economy's position on it should predict how much it innovates. The prediction is not trivial, because a rival reading is

available. If the complexity axis were only a statistical summary of co-specialization, or only another proxy for income, there would be no reason for it to carry information about patents, researchers, venture capital and creative output beyond what income already carries. The paper therefore sets complexity and income against each other as rival predictors of innovation.

The association between complexity and innovation has been studied before, and Section 3.4 reviews that work in five lines. Most of it either takes complexity as a measure of innovation, or applies the complexity method to patents, or asks which innovation inputs raise complexity. What it lacks is a theory of activities that says why the two should move together and where they should part, a test with innovation measured broadly and with income held constant, and evidence below the level of countries. Those are the three things attempted here.

The results are five. First, across 129 countries the complexity index and the innovation index have a correlation of 0.83, and complexity explains more of the variation in innovation (69 percent) than income per capita does (62 percent). Second, the association is not income in disguise: with income held constant the partial correlation between complexity and innovation is 0.60, and the association holds within each third of the income distribution. Third, the pattern repeats inside one country and with a differently constructed index. Across the 27 Brazilian states, complexity measured from formal employment has a rank correlation of 0.67 to 0.80 with the IBID ranking, and the territorial measures, the share of a state's municipalities with above-average complexity and the mean municipal index, track it more closely than the worker-weighted one. Fourth, at the level of activities the Brazilian employment records supply what the trade data lacked, the wage: a standard deviation of activity complexity is associated with wages about 31 percent higher. Fifth, the economies that depart most from the line are cases Reinert described in advance. Assembly platforms such as Mexico and the Manaus Free Trade Zone hold complex baskets and innovate less than those baskets suggest. Resource-rich economies such as Australia innovate more than their structure suggests, and oil economies such as Kuwait and Trinidad and Tobago innovate less than their income suggests.

Section 2 restates Reinert's index as a set of propositions about innovation. Section 3 places the paper in the literature. Section 4 sets out the predictions, the measures and the data. Sections 5, 6 and 7 present the evidence for countries, Brazilian states and activities. Section 8 discusses the deviations and what the evidence cannot show, Section 9 draws the implications for policy, and Section 10 concludes.

2. Reinert's index as a theory of innovation

2.1 What puts an activity at the top

The Quality Index scores an activity by the degree to which it can support a high wage for the individual and a high standard of living for the nation that hosts it. Reinert attaches to the score a list of characteristics. At the top are increasing returns, dynamic imperfect competition, steep learning curves, rapid technical change, high R&D content, learning by doing, investment in large indivisible chunks, imperfect information protected by patents or internal know-how, economies of scale and scope, high barriers to entry, branded products, stable prices, skilled labour and large synergies with other activities through linkages and clusters. At the bottom are diminishing returns, perfect competition, flat learning curves, little technical change, perfect information, low barriers, unskilled labour, few linkages and extreme price fluctuations (Reinert, 1994b, 2007).

Read as a list, most of the top characteristics are either sources of innovation or its consequences. Research content and learning curves are where new knowledge comes from. Patents and internal know-how are how it is appropriated. Barriers to entry, imperfect competition and stable prices are what appropriation looks like in a market. The index is therefore not a ranking of sectors by technology in the engineering sense. It is a ranking of activities by the pace at which they generate new knowledge and by the degree to which those who generate it can keep the gains. Figure 1 summarizes the two ends of the ladder, where the gains from technical change go, and the second dimension discussed below.

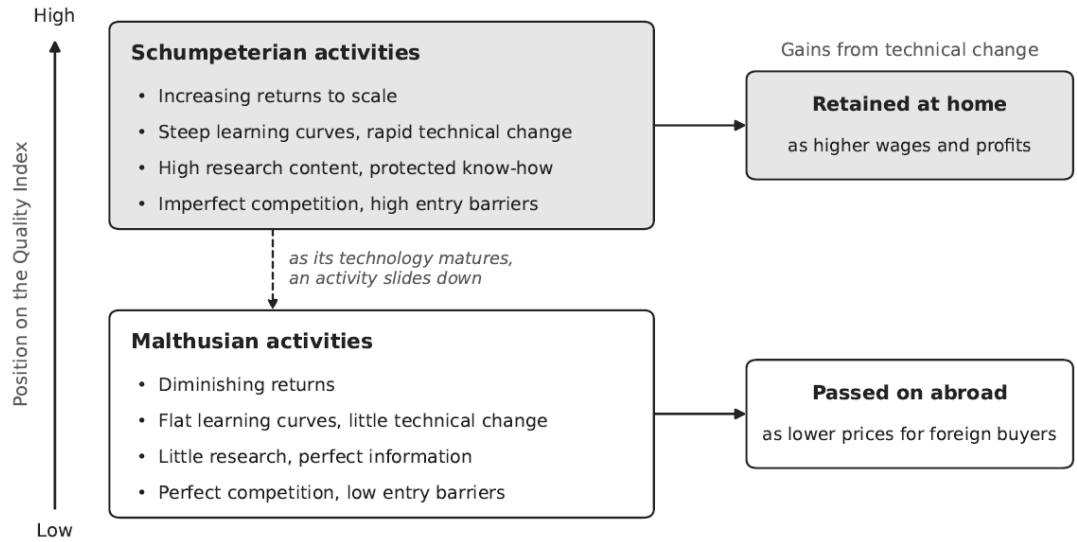

Figure 1: Reinert's ladder: what puts an activity at the top and where the gains go.

Source: authors' elaboration from Reinert (1994b, 2007) and Reinert and Riiser (1994).

2.2 Two dimensions, and why they matter for measurement

Reinert gives the index two dimensions. The first is the contrast between activities subject to increasing returns, found mainly in industry, and those subject to diminishing returns, found mainly in raw materials. The second is the technological vintage of an activity. A manufacture whose technology has stopped changing falls as low as a commodity, and mature activities are farmed out to poor countries precisely because low wages have become their decisive cost (Reinert and Riiser, 1994). The baseballs Haiti exports are manufactures. So were the garment-assembly jobs that came to the Dominican Republic without raising welfare, because the operation that underwent technical change, cutting, returned to the United States when laser cutting arrived.

The second dimension has a direct implication for any index built from trade classifications. A product heading records what is shipped, not which stage of its production took place in the exporting country. An economy can export products that sit high on the ladder while performing only the stages in which nothing is being learned. Its export basket will then overstate its position, and an independent measure of innovation should show the gap. Section 8 finds this gap where Reinert's argument says to look for it.

2.3 Resource rent and industry rent

Reinert separates the high income that comes from a scarce natural resource from the high income that comes from knowledge. Both raise the income of the exporting nation. Only the second is produced by, and reproduces, a structure of learning. Resource-rich economies should therefore depart from the line between structure and innovation, in either direction: rent can buy the inputs to innovation without building the structure or leave both untouched. The distinction can be examined at the level of countries and states, where income and structure can be compared directly as predictors of innovation.

2.4 Synergies and where they are located

The last characteristic on Reinert's list is the one most often passed over: high-quality activities create large synergies through linkages and clusters, and low-quality activities create few. The claim is spatial as much as sectoral. Knowledge of this kind is tacit, it is held by networks of engineers, suppliers and institutions, and it spreads through proximity (Jaffe, Trajtenberg and Henderson, 1993). An economy in which complex activities are confined to one enclave should therefore generate less innovation than one in which they are spread across many locations that supply and learn from each other. The Brazilian municipal data allow this to be examined, and Section 6 does so.

3. Related literature

3.1 The ladder in trade data

Two measures built from trade data order products in the way Reinert's index does. Hausmann, Hwang and Rodrik (2007) defined the income level of a product as the specialization-weighted income of its exporters and showed that the sophistication of a country's export basket predicts its later growth. Hidalgo and Hausmann (2009) derived the product and country complexity indices from the pattern of who exports what, and the Atlas of Economic Complexity (Hausmann et al., 2011) made them standard. Felipe et al. (2012) showed that the most complex products are chemicals, machinery and metals, that the least complex are raw materials, and that the first are exported by rich countries and the second by poor ones. Gala, Rocha and Magacho (2018) connected these findings to the structuralist argument that what a country produces determines how rich it can become. The complexity index is therefore used here as the available measure of position on Reinert's ladder, with the limits that Section 3.2 sets out.

3.2 What the complexity index is

The complexity indices were introduced as measures of the capabilities an economy holds, inferred from the diversity of its exports and the ubiquity of its products (Hidalgo and Hausmann, 2009; Hausmann et al., 2011). Mechanically, they are built from a single matrix: which countries export which products with revealed comparative advantage. A country scores high when it exports many products that few others export, and a product scores high when its exporters are diversified. In plain terms, the index orders countries by how closely their export baskets resemble those of the most diversified economies. A later literature established their mathematical nature. They are the leading non-trivial axis of a correspondence analysis of the country–product matrix, a summary of which countries export the same things, and they have no meaning until information from outside the matrix is attached to them (Kemp-Benedict, 2014; Mealy, Farmer and Teytelboym, 2019; van Dam et al., 2021). Nomaler and Verspagen (2024) argue that this is why the index has been found correlated with growth, inequality, emissions and much else while remaining unable to say what it is, and they propose bringing external variables in before the axes are extracted rather than afterwards.

This matters for how the present paper should be read. Correlating the complexity index with one more country variable, innovation, would on its own be the practice that literature criticizes. The difference claimed here is that the variable is not chosen for its availability. Reinert's theory names in advance the

features that should accompany a high position on the ladder, and innovation is the first of them. The exercise is a test of two predictions the theory makes about the part of itself that trade data cannot reach.

3.3 Innovation, structure and systems

That innovation depends on what an economy produces is an old proposition in the evolutionary tradition from which Reinert's index comes. Schumpeter (1934) defined innovation as new combinations, which presuppose things to combine. Pavitt (1984) showed that sectors differ systematically in where their technology comes from: science-based and specialized-supplier sectors generate it internally, supplier-dominated sectors receive it embodied in inputs. The national innovation systems literature added that innovation is produced by interaction among firms, suppliers, universities and the state rather than by firms alone (Freeman, 1987; Lundvall, 1992; Nelson, 1993), and Cohen and Levinthal (1990) that the capacity to absorb outside knowledge is built by doing related work. Fagerberg (1994) and Verspagen (1991) carried the argument to growth: catching up is conditional on capabilities that accumulate unevenly across sectors and countries.

3.4 Complexity and innovation: what has been done

The relation between economic complexity and innovation is not new ground. At least five lines of work bear on it, summarized in Table 1, and the contribution of this paper can only be stated against them.

Complexity treated as innovation. The founding papers read the complexity of an export basket as the expression of an economy's productive knowledge (Hidalgo and Hausmann, 2009; Hausmann et al., 2011), and Sweet and Eterovic Maggio (2015) use the index directly as their measure of innovation, finding that stronger intellectual property rights raise it only in countries above the average level of development. In this line the association is a premise, not a test, because the two are not measured separately.

Complexity measured on patents. A second line applies the complexity method to innovation data. Complex technologies are produced in few places and diffuse slowly (Balland and Rigby, 2017), countries climb toward related and more complex technologies (Hidalgo et al., 2018; Petralia, Balland and Morrison, 2017), and technological complexity predicts regional growth (Mewes and Broekel, 2022), concentrates in large cities (Balland et al., 2020) and has been related to investment at the sectoral level (Vrettos and Papageorgiou, 2026). These papers measure the complexity of

what is invented. They do not ask whether the complexity of what is produced predicts how much an economy innovates.

Several layers at once. A third line sets production, technology and science side by side. Technology is the best predictor of later industrial and scientific production (Pugliese et al., 2019), complexity indices computed separately for trade, patents and publications predict future growth in income, patenting and publishing (Stojkoski, Koch and Hidalgo, 2023; Hausmann et al., 2024), and causality between patenting and complexity runs both ways (Nguyen, Schinckus and Su, 2020). The layers are linked and co-evolve, but the outcome is usually growth, and innovation enters as counts of patents and papers.

Composite innovation indices. A fourth and thinner line uses composite indices of national innovation performance. Fernandez Donoso (2017) reports a correlation of 0.79 between a complexity-weighted innovation index and the Global Innovation Index. The study closest to the present one is Araújo, Azevedo and Ferreira (2025), who regress the complexity index on the five input pillars of the Global Innovation Index for 112 countries and find that only infrastructure and business sophistication are significant. Their question runs from the innovation system to complexity.

Regions, and Brazil. A fifth line takes complexity below the national level, with employment or patents in place of exports. For Brazil, complexity has been related to the growth of the federative units (Teixeira, Missio and Dathein, 2022), to the entry and retention of industries in microregions (Freitas, Britto and Amaral, 2024; Françoso, Boschma and Vonortas, 2024) and, when measured from industrial employment rather than exports, to microregional growth (Cardoso et al., 2023), which supports the employment-based index used in Section 4.3. Du and Zaccaria (2026) add a caution: at the subnational level the index can sort territories into two groups rather than along a scale. In all of this work the outcome is growth or diversification. To our knowledge no study relates the complexity of the Brazilian states to a composite index of their innovation.

Two observations cut across the five lines. The first is about theory. The method has travelled from exports to patents, papers, occupations and regions faster than its interpretation. Nomaler and Verspagen (2022) describe the index literature as "largely void of economic theory", and the theory since supplied from inside it is a model of capability endowments (Hidalgo and Stojkoski, 2025). A structuralist reading has been available since Gala, Rocha and Magacho (2018) and Hartmann et al. (2021), but neither turned Reinert's index into predictions about innovation. The second observation is about measurement. Most of this

literature measures innovation by patents. Patents record invention in the sectors and countries that patent; they say little about the adoption, design and organizational change that make up most innovation in middle-income economies, and nothing about the wage.

Table 1: The literature on complexity and innovation, and where this paper stands.

Line of work	Representative studies	What is related to what	What is left open
Complexity as innovation	Hidalgo and Hausmann (2009); Sweet and Eterovic Maggio (2015); Sweet and Eterovic (2019); Hidalgo (2021); Balland et al. (2022)	The complexity index is used as the measure of innovation	The link is assumed, not tested
Complexity of patents	Fleming and Sorenson (2001); Hidalgo et al. (2007, 2018); Balland and Rigby (2017); Petralia et al. (2017); Ivanova et al. (2017); Broekel (2019); Balland et al. (2019, 2020); Mewes and Broekel (2022); Pinheiro et al. (2022); Vrettos and Papageorgiou (2026)	Technological complexity and growth, diversification, concentration	Whether productive complexity predicts innovation
Several layers	Pugliese et al. (2019); Laverde-Rojas and Correa (2019); Nguyen et al. (2020); Lybbert and Xu (2022); Stojkoski et al. (2023); Hausmann et al. (2024)	Trade, technology and science complexity and growth	Innovation as patents and papers only; no theory of activities
Composite indices	Fernandez Donoso (2017); Lee and Lee (2020); Rubbo et al. (2021); Araújo et al. (2025)	Innovation-system inputs as determinants of complexity	Complexity as predictor, income held constant; countries only
Regions and Brazil	Gao and Zhou (2018); Operti et al. (2018); Reynolds et al. (2018); Teixeira et al. (2022); Cardoso et al. (2023); Freitas et al. (2024); Françoso et al. (2024); Du and Zaccaria (2026)	Regional complexity and growth or diversification	Regional complexity and innovation
This paper		Position on Reinert's ladder and innovation, at three scales	Direction of causation; the price–wage mechanism

3.5 What this paper adds

Against that background the paper makes four contributions, and one thing it does not.

A theory that predicts the link and its failures. The literature has shown that complexity and innovation are associated and has explained the association, where it has explained it, by capabilities: an economy that can make complex things has the knowledge to invent. That account predicts a positive sign and nothing more. Reinert's index predicts the sign and, through its second dimension and its separation of resource rent from industry rent, the places where the relationship should break: economies that perform the mature stages of complex products, and economies whose income comes from a resource. The paper tests those predictions on the residuals.

An independent and broad measure of innovation, with income held constant. Unlike the first line, the paper does not take complexity as its measure of innovation, and unlike the second and third it does not measure innovation by patents alone. The composite indices combine about eighty indicators of inputs and outputs, most of them unrelated to trade. And where Araújo, Azevedo and Ferreira (2025) ask which innovation inputs explain complexity, this paper asks the reverse of their question, the one Reinert's theory poses: whether position on the ladder predicts innovation and sets complexity against income as rival predictors. The finding that complexity explains more of innovation than income does and retains a partial correlation of 0.60 when income is held constant, is to our knowledge not in the literature.

Two scales, two constructions of the index, and diffusion. The paper repeats the test inside one country, with an index built from employment rather than exports and an innovation index (the IBID) built by Brazil's national intellectual property office on the framework of the international one. The comparison of three summaries of state complexity yields a result with no counterpart in the cross-country work: innovation follows the territorial spread of complex activity more closely than its worker-weighted level. This speaks to a debate the regional literature has opened. Balland et al. (2020) show that complex activities concentrate in large cities, and Pinheiro et al. (2022) that this deepens regional inequality. The Brazilian evidence is consistent with the view that a state innovates more when complex activity is distributed across many municipalities than when it is held in one.

The wage. The literature on complexity and innovation is almost silent on wages, and Reinert's index is defined by them. The activity-level evidence

for Brazil shows a premium of about 31 percent per standard deviation of complexity, robust to sector, convex, and absent in resource-rent activities, and it shows that the premium reaches few workers.

What the paper does not add is identification. Nguyen, Schinckus and Su (2020) find causality running both ways between patents and complexity, Pugliese et al. (2019) find long lags between the layers, and Araújo, Azevedo and Ferreira (2025) estimate the reverse relation. The present results are cross-sectional associations that a theory predicted in advance. They are consistent with co-evolution, which is also what Reinert's cumulative account implies.

4. Predictions, measures and data

4.1 Three predictions

If high positions on the ladder are occupied by activities in which innovation is concentrated and its gains retained, three things should be observed.

i. *Countries*. A country's position on the leading axis of world trade specialization should be associated with its measured innovation, and the association should survive conditioning on income per capita. Income is the obvious confounder, since rich countries both export complex goods and can afford research.

ii. *Regions*. The association should hold among the regions of a single country, where national institutions, currency, trade policy and intellectual property law are common, and it should hold when complexity is measured from a different record of economic activity than exports.

iii. *Activities*. At the level of individual activities, complexity should be associated with the wage it pays. The wage is the score that defines Reinert's index, and trade data can approach it only through the income of exporting countries. The ordering of activities should also be consistent with the research intensity of their industries, a concordance rather than a test, since research intensity is available only for broad industry groups.

Reinert's second dimension and his treatment of resource rent add two predictions about the residuals. Economies that perform only the mature stages of complex products should innovate less than their complexity suggests. And economies rich from natural resources should depart from the line in either direction: above their structure where the rent buys the inputs to innovation,

below their income where it does not. Figure 2 summarizes the design: one prediction, tested at three scales, with its failures named in advance.

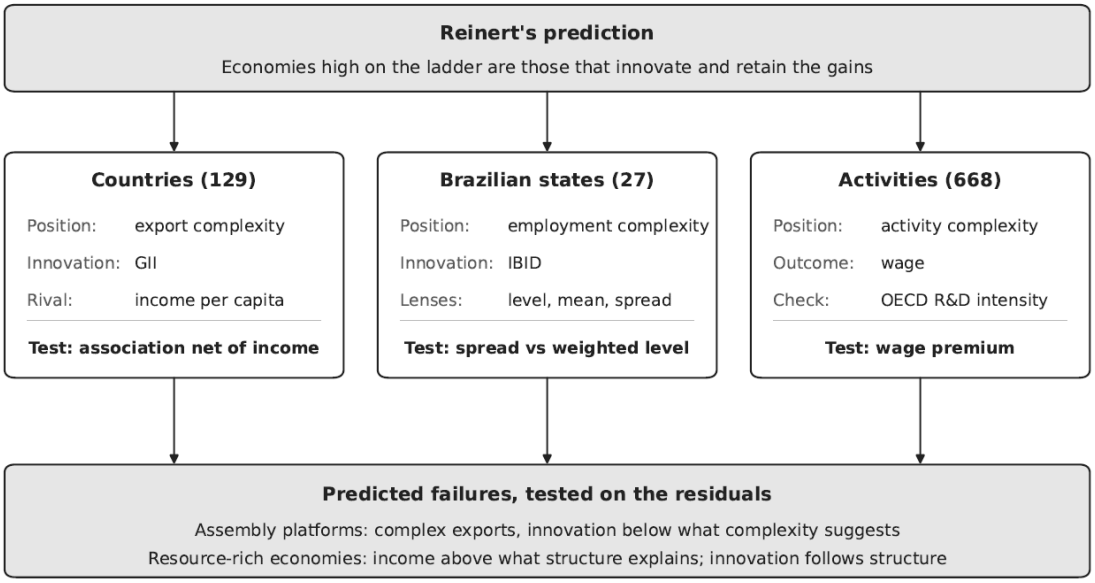

Figure 2: Research design: Reinert's prediction at three scales.

Source: authors' elaboration.

4.2 Countries

Innovation is measured by the overall score of the Global Innovation Index – GII 2025 (WIPO, 2025), which covers 139 economies on a scale from 0 to 100 and aggregates 78 indicators in seven pillars, five of innovation inputs and two of outputs. Complexity is the Economic Complexity Index for 2024 from the Growth Lab at Harvard University, computed on the 1992 Harmonized System, which ranks 145 countries. Ten economies in the innovation index have no complexity index for 2024: Barbados, Brunei Darussalam, Burundi, Cabo Verde, Iceland, Lesotho, Luxembourg, Malta, Montenegro and Seychelles. The sample is the remaining 129. Income per capita is from the Maddison Project Database (Bolt and van Zanden, 2020), in 2011 international dollars, for 2018, the last year of that series. It is available for all 129. The country index is used as published by the Growth Lab, without modification.

4.3 Brazilian states and activities

Innovation in the 27 Brazilian federative units is measured by the Brazil Innovation and Development Index –IBID 2025 (INPI, 2025), which adapts the framework of the Global Innovation Index to the states and aggregates about 80 indicators. The analysis uses each state's position in the ranking and rank correlations throughout, which do not depend on the distance between scores

and are robust to outliers such as São Paulo, whose score lies far above those of the other states.

Complexity is the regional index of the DataViva platform, developed by the Center for Development and Regional Planning of the Federal University of Minas Gerais (Cedeplar-UFMG) (Freitas et al., 2023). It is computed from formal employment in the Annual Social Information Report (RAIS) in 2025 (MTE, 2026) by five-digit activity class and municipality, for 5,570 municipalities[3]. It applies the method of reflections to the municipality–activity matrix of employment specialization, so it covers services and the domestic market, which export data omit. Three state-level summaries are used. The employment-weighted index is the complexity of the municipality in which the typical formal worker is employed. The mean index is the complexity of the typical municipality. Diffusion is the percentage of a state's municipalities whose index is positive, that is, above the national municipal average.

For activities, the same source gives a complexity index for each of 668 activity classes, standardized to mean zero and unit variance, together with employment and the wage bill, covering about 60 million formal jobs. Research intensity by industry is taken from the taxonomy of the Organisation for Economic Co-operation and Development (Galindo-Rueda and Verger, 2016), which ranks industries by business R&D relative to value added.

4.4 What is and is not independent

Two cautions belong before the results. The country and state complexity indices are built from different records, exports in one case and employment in the other, and their scales are not comparable. The paper compares patterns, not levels, between the two.

The second caution concerns overlap. The GII is not wholly independent of economic structure. Among its 78 indicators it includes production and export complexity, which is the complexity index itself, together with high-technology exports and high-technology manufacturing, all within the knowledge and technology outputs pillar. Under the index's nested averaging a single indicator of that pillar carries a weight on the order of 2 percent of the overall score, so the mechanical component of the correlations reported below is small, but it is not zero. Removing it requires the indicator-level data and is left for future work (Section 8.2). The remaining indicators, among them researchers, R&D expenditure, patent families, venture capital, university rankings, scientific

[3] The 2026 editions of both innovation indices were released after this analysis was completed: the GII 2026, in which Brazil ranks 53rd (WIPO, 2026), and the IBID 2026 (INPI, 2026). We keep the 2025 editions because their reference period is closer to that of the complexity measures used here.

publications, trademarks and creative exports, are not derived from the trade matrix.

5. Countries: complexity and innovation

Across 129 countries the correlation between the complexity index and the innovation index is 0.83, and the association is stronger than that between innovation and income.

5.1 The association

A regression of the innovation score on the complexity index has a slope of 12.6 and explains 69 percent of the variation: one point of complexity, roughly one cross-country standard deviation, corresponds to 12.6 points of innovation on the 100-point scale. The rank correlation is higher still, at 0.90. Table 2 divides the countries into quartiles of complexity.

Table 2: Innovation by quartile of economic complexity, 129 countries

Complexity quartile	Countries	Mean complexity index	Mean innovation score	Range of innovation score	Median income per capita (2011 $)
1 (lowest)	33	−1.10	18.1	11.9–28.7	3,534
2	32	−0.06	25.9	17.1–48.0	11,363
3	32	0.52	33.9	22.2–51.1	18,586
4 (highest)	32	1.15	49.0	30.5–66.0	36,146

Sources: WIPO, Global Innovation Index 2025; Growth Lab at Harvard University, Economic Complexity Index (HS92), 2024; Maddison Project Database 2020, income for 2018. Authors' calculations.

The mean innovation score rises from 18.1 in the least complex quarter to 49.0 in the most complex. The gradient steepens up the ladder. Between the first and second quartiles one point of complexity is associated with about 7.5 points of innovation; between the third and fourth, with about 24 (Figure 3). The relation is convex, as the wage premium in Section 7 is, and its flat lower end is the floor discussed in Section 8.1. The extremes do not overlap: no country in the bottom quartile of complexity scores above 28.7, and none in the top quartile scores below 30.5. Sixteen of the twenty most complex countries are among the thirty most innovative; the four that are not, Czechia, Slovenia, Hungary and Slovakia, rank between 32nd and 47th. Read from the other side, of the 27 sample countries in the top thirty of the innovation index, 21 are in

the top quartile of complexity, five in the third, one in the second and none in the bottom. Of the forty least innovative countries in the sample, thirty are in the bottom quartile of complexity and none is in the top.

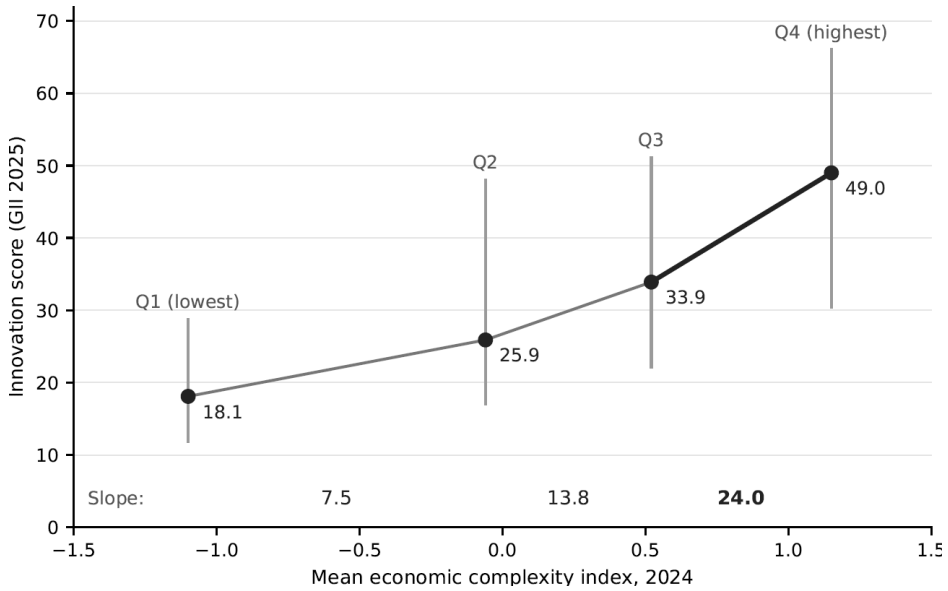

Figure 3: Innovation by quartile of economic complexity, 129 countries. Dots are quartile means, vertical lines the range of innovation scores within each quartile; the numbers at the bottom are the slopes between adjacent quartiles, in innovation points per point of complexity.

Source: authors' calculations from Table 2.

The rankings of individual countries show the same thing. Japan is first in complexity and 12th in innovation, the Republic of Korea third and fourth, Switzerland fourth and first, China tenth in both. Brazil is 59th in complexity and 52nd in innovation, and lies almost exactly on the regression line, 1.6 points below it.

5.2 Is it income?

Rich countries export complex products and can also afford laboratories, so the association could be income seen twice. Table 3 sets the two predictors side by side.

Table 3: Complexity, income and innovation (dependent variable: Global Innovation Index score, 2025)

	(1) Complexity	(2) Income	(3) Both
Economic complexity index, 2024	12.64 (0.97)		8.32 (1.16)
Log income per capita, 2018		9.65 (0.73)	4.73 (0.81)
R^2	0.686	0.617	0.755
Countries	129	129	129

Sources: as Table 2. Authors' calculations.

Note: Ordinary least squares; heteroskedasticity-robust standard errors in parentheses. All coefficients are significant at the 1 percent level. Column (1) uses complexity alone, column (2) income alone and column (3) both.

Complexity alone explains more of the variation in innovation than income alone, 69 percent against 62. When both enter, both remain significant and the complexity coefficient keeps two thirds of its size. In standardized terms the coefficient on complexity is 0.55 and that on income 0.39. The partial correlation between complexity and innovation with income held constant is 0.60; the partial correlation between income and innovation with complexity held constant is 0.47. On ranks, the partial correlation of complexity with innovation is 0.72. Complexity and log income are themselves correlated at 0.73, so the two are far from independent, but each carries information about innovation that the other lacks, and complexity carries more. Of the 75.5 percent of the variation the two predictors explain together, 13.8 points belong to complexity alone, 6.9 to income alone and 54.8 are shared. Complexity's unique contribution is twice that of income. The large shared component is what Reinert's account expects, since income earned in industry is produced by the structure itself; the unique components are the test.

The association also holds within income groups. Dividing the sample into thirds by income, the correlation between complexity and innovation is 0.68 among the 43 poorest countries, 0.70 in the middle third and 0.73 among the 43 richest. Among countries of similar income, those higher on the ladder innovate more.

This is the result the rival readings do not predict. If the complexity axis were only a summary of who exports the same things, or only a proxy for income, it would have nothing to add about researchers, patents and venture

capital once income is known. It adds a good deal. Reinert's reading predicts exactly this: income can come from a resource or from a structure of learning, and only the second should be accompanied by innovation.

5.3 Persistence

A country's position on the ladder three decades ago predicts its innovation today almost as well as its current position does. The correlation between the complexity index of 1995 and the innovation index of 2025 is 0.80, across the 125 countries with both. It is 0.81 for the index of 2000, 0.84 for 2010 and 0.87 for 2015 and 2020. In a regression of the innovation score of 2025 on both the complexity and the income of 1995, both are significant (coefficients 5.45 and 6.15, with t-statistics of 4.2 and 5.9, R^2 of 0.71).

Productive structures change slowly. Positions on the ladder are persistent, and innovation follows the position. The regression does not establish that structure causes innovation, since innovation in 1995 is not observed here and would itself predict both. What it rules out is the reading in which the two are linked only by a common contemporaneous shock.

6. Brazilian states: the same pattern inside one country

Among the 27 Brazilian states the most innovative are the most complex, and the association is stronger when complexity is measured by how widely it is spread across a state's territory than by where the typical worker is employed.

Brazil offers an unusually clean setting for this second test. Its 27 states share a currency, a legal system, trade policy, a single national intellectual property office and the same intellectual property law, yet they differ widely in development. Output per capita in 2023 ranged from R$ 22,021 in Maranhão to R$ 129,790 in the Federal District, almost six to one (IBGE, 2025), and the share of municipalities with above-average complexity ranges from 7 percent in Roraima to 86 percent in Rio de Janeiro, leaving aside the Federal District, a single municipality. Formal equality of rules coexists with deep inequality of capabilities. Brazil is also one of the few countries with a subnational innovation index built on the framework of the Global Innovation Index (WIPO, 2023). With national institutions held constant, any association that survives must come from what states produce and where they produce it.

6.1 Three lenses

The test is demanding in two ways. Because national institutions are common to all states, none of the institutional differences that separate countries can account for the pattern. And the complexity index is built from formal employment in every activity, services included, not from exports. A relationship that held only because export baskets and innovation indices both reflect integration into world trade would not reappear here.

Table 4 reports the rank correlation between each summary of state complexity and the state's position in the innovation ranking.

Table 4: Rank correlation between state complexity and the innovation ranking, 27 states

Measure of state complexity	Spearman correlation	95% interval (bootstrap)	Without the Federal District	Without the Federal District and Amazonas
Employment-weighted index	0.67	0.37–0.85	0.65	0.70
Mean municipal index	0.78	0.55–0.89	0.77	0.79
Diffusion: share of municipalities above the national average	0.80	0.60–0.89	0.80	0.81

Sources: INPI, IBID 2025 (ranking positions); DataViva regional complexity index, formal employment (RAIS) 2025, 5,570 municipalities. Authors' calculations. Intervals from 5,000 bootstrap resamples of states. All three correlations differ from zero at the 0.1 percent level.

All three correlations are large for a sample of 27, and none depends on the two states discussed below as special cases. The five most innovative states, São Paulo, Santa Catarina, Paraná, Rio de Janeiro and Rio Grande do Sul, are all among the seven most complex on every one of the three measures. Grouping the states into thirds by diffusion, the nine with the widest spread of complexity have a mean innovation rank of 5.9 and none ranks below 13th; the nine with the narrowest spread have a mean rank of 21.3 and none ranks above 15th. Appendix Table A1 lists the data for all 27 states.

6.2 Diffusion

The ordering of the three lenses is itself a result. The employment-weighted index asks how complex the place is where the typical worker is employed, and a single large and sophisticated capital can lift it. The diffusion

measure asks in how many places complex activity exists at all. Innovation follows the second more closely than the first. The mean municipal index and diffusion are themselves almost the same measure (rank correlation 0.97), and 27 states cannot separate them; the contrast that matters is between the two territorial measures and the worker-weighted one.

Two states make the contrast concrete. Santa Catarina has 295 municipalities, of which 126 have a complexity index above one and 82 percent an index above zero; its largest municipality holds 11 percent of formal employment; it is the second most innovative state in the country. Piauí has 224 municipalities, of which five have an index above one and 13 percent an index above zero; its capital holds 57 percent of formal employment; it is 18th. Neither state has a national metropolis. What separates them is whether complex activity forms a network of medium-sized industrial towns or sits in a single city (Figure 4).

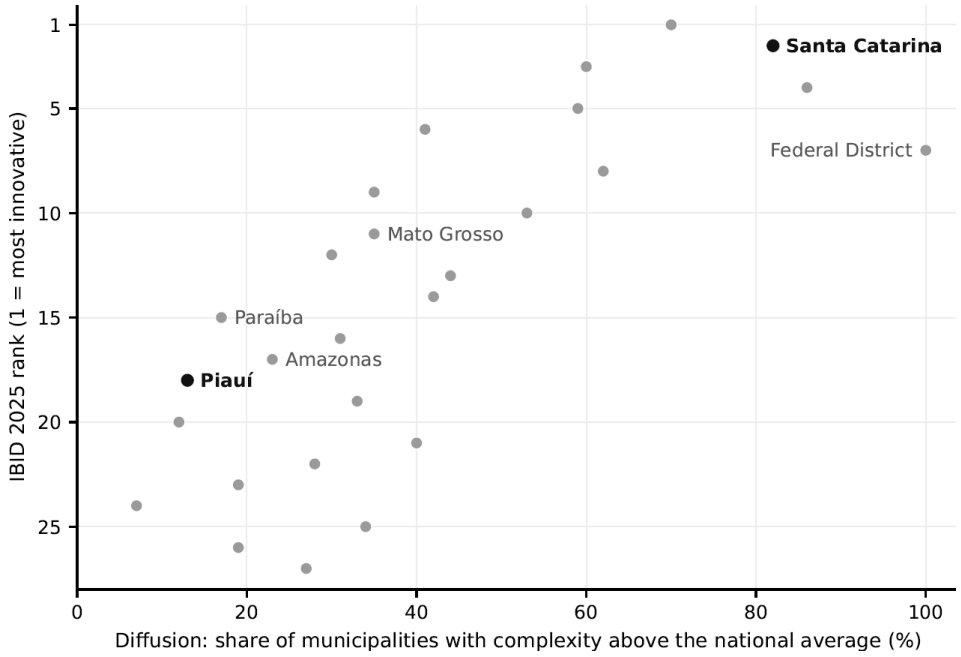

Figure 4: Diffusion of complex activity and innovation rank, 27 Brazilian states. Diffusion is the share of a state's municipalities whose complexity index is above the national municipal average.

Sources: INPI, IBID 2025; DataViva, formal employment (RAIS) 2025. Authors' calculations.

This is the territorial form of the last characteristic on Reinert's list. High-quality activities create synergies through linkages and clusters, and the knowledge behind them is tacit and spreads by proximity. A state in which many municipalities host complex activities has many sites where suppliers, skilled workers and firms meet, and the innovation index, which counts patents, firms, researchers and creative output wherever in the state they arise, registers the difference.

6.3 Exceptions that follow the rule

Amazonas ranks third among the states on the employment-weighted index and 21st on the two other measures, and it is 17th in innovation. The complexity is real and it is located in the Manaus Free Trade Zone, an assembly platform for electronics and motorcycles sustained by tax incentives. Only 23 percent of the state's municipalities have an index above the national average. The worker-weighted lens sees the enclave; the innovation index sees a state in which the complex activities are few in location and concentrated in stages of production where, in Reinert's phrase for the Dominican case, the operation that undergoes technical change takes place elsewhere.

The Federal District is first on all three complexity measures and seventh in innovation. It is a single municipality, so diffusion is trivially complete, and its complexity is that of federal public administration, the judiciary and the financial and professional services that surround them. These are activities that few places host, which is what the index rewards, but they generate little of what an innovation index measures. The case is a reminder that an index of co-specialization built from employment places high whatever is rare and co-located, and that rarity is not always the trace of a learning curve.

A third case points to the distinction between income and structure. Mato Grosso had the third-highest output per capita among the states in 2023, R$ 74,620 against a national figure of R$ 53,887 (IBGE, 2025), on the strength of soybeans, maize and cattle. It ranks 26th on the employment-weighted complexity index, tied for 13th on the other two measures, and 11th in innovation. Its innovation is close to what its structure predicts and well below what its income would.

7. Activities: what the ladder pays

Sections 5 and 6 show that economies higher on the ladder innovate more. Reinert's index, however, ranks activities, not economies, and it is defined by a wage. This section moves to the level at which the index is defined: first the wage, then research content.

7.1 The wage

Reinert's score is a wage, and trade-based measures reach it only through the income of the countries that export a product. Whether activities higher on the scale pay more is part of the hypothesis rather than a measured fact. Brazilian employment records allow the link to be examined directly within one country. For each of 668 activity classes they give a complexity index and the average

monthly wage across about 60 million formal jobs in 2025. Table 5 reports the regressions.

Table 5: Activity complexity and wages, 668 Brazilian activity classes, 2025 (dependent variable: log average monthly wage)

	(1) Complexity only	(2) With sector indicators	(3) Weighted by employment
Complexity (standardized)	0.274 (13.8)	0.270 (11.7)	0.003 (0.0)
Sector indicators	No	Yes	No
Weighted by employment	No	No	Yes
R^2	0.25	0.25	0.01
Activity classes	668	668	668

Source: DataViva, formal employment records (RAIS) for 2025; authors' calculations.

Note: Complexity is standardized to mean zero and standard deviation one across the 668 activity classes. t-statistics based on heteroskedasticity-robust standard errors in parentheses. Columns (1) and (2) are unweighted, so each activity class counts once; column (1) uses complexity alone; column (2) adds indicators for agriculture, industry and services; column (3) repeats column (1) with each activity weighted by its formal employment.

In column (1) of Table 5 the coefficient on complexity is 0.274: since wages are in logs and complexity is standardized, an activity one standard deviation more complex pays about 31 percent more (exp(0.274) − 1 = 0.31). Complexity alone accounts for a quarter of the variation in wages across activities (R^2 = 0.25), which corresponds to a correlation of 0.50. With sector indicators, in column (2), the coefficient is practically the same (0.270), and the R^2 does not rise. The premium is therefore not the wage gap between sectors; it is found, on average, among activities of the same sector. A specification not shown in the table adds the square of complexity: the squared term is positive (0.090, t = 6.0) and the R^2 rises to 0.30, so the premium grows toward the top of the scale. Across activities, then, the property that defines Reinert's score rises with position on the complexity axis, inside a single labour market with common institutions. These are associations. Part of the premium reflects the schooling of the workers that complex activities employ, which in Reinert's account is part of what such activities demand rather than a confounder to be removed.

Three qualifications sharpen the reading, and each is one Reinert would recognize.

The first is resource rent. The extraction of oil and gas pays among the highest wages in the country, R$ 26,001 a month, with a complexity index of only 0.14. The wage is anchored in the rent of the resource and the scale of capital, not in the

sophistication of the activity. Within agriculture the relation between complexity and wages is flat to negative (correlation −0.25), against 0.43 in industry and 0.51 in services. The premium found on average within sectors in column (2) is thus carried by industry and services.

The second concerns what the employment-based index places at the top. The most complex activities in Brazil by this measure are financial: leasing, reinsurance, investment banking, the central bank. The most complex industrial activities, compressors, trucks and buses, and railway equipment, come just below. Finance is not research-intensive: it is in the lowest group of the OECD taxonomy (Section 7.2). It is, however, an activity of high barriers to entry, scale and imperfect competition that pays high wages, which is a reminder that Reinert's index is a ranking by industry rent, of which research is the main source but not the only one.

The third is where people work. When each activity is weighted by its employment the premium disappears: in column (3) of Table 5 the coefficient falls to 0.003 and the R^2 to 0.01. Among the activities that employ most Brazilians, complexity does not sort wages. Employment is also concentrated at the bottom of the scale. Four fifths of formal jobs, 80.6 percent, are in activities of below-average complexity, and 3.0 percent are in activities more than one standard deviation above it. The complexity of the activity in which the typical Brazilian worker is employed is −0.85. The ladder exists inside Brazil and pays as Reinert said it would, and most of the workforce stands on its lower rungs. That is Schumpeterian underdevelopment described from within a country, and it is the structural counterpart of Brazil's position at 52nd in the GII.

7.2 Research content: a concordance

Research content is the one characteristic on Reinert's list for which a systematic measure by activity exists. The OECD taxonomy of economic activities based on R&D intensity (Galindo-Rueda and Verger, 2016), reproduced in Appendix Table A2, ranks the industries of every sector, services and primary production included, by business R&D as a percentage of value added, averaged over 29 economies for 2011. Its range is the premise of an index that ranks activities: research intensity runs from 31.69 percent of value added in aircraft to 0.01 percent in real estate, more than three orders of magnitude. Its ordering is Reinert's: aircraft, pharmaceuticals, electronics, vehicles, machinery and chemicals at the top, agriculture (0.27) and mining (0.80) near the bottom. It also reproduces his second dimension. Textiles (1.73), wearing apparel (1.40) and furniture (1.17) are manufactures, yet they sit in the medium-low group beside mining and far below machinery: these are the mature manufactures he described as farmed out to poor countries once their technology stops changing.

Intensities also vary across countries within the same industry, which is the statistical form of the assembly-platform case examined in Section 8.

Set beside the Brazilian complexity scale, the taxonomy agrees at the ends. The most complex industrial activities, compressors, trucks and buses, and railway equipment, belong to machinery (7.89), motor vehicles (15.36) and railroad equipment (5.72), all in the medium-high group; soybeans, cereals and cattle belong to agriculture (0.27). The two scales part in services, where finance is at the top of the complexity index and in the lowest group of research intensity. This is a concordance of extremes, not an estimated relationship: a correlation would require mapping activity classes onto the taxonomy's industries, which this paper does not do. The taxonomy also measures research performed, not technology used, as its authors warn. An industry can absorb technology embodied in its inputs while doing little research of its own, which is Pavitt's (1984) supplier-dominated sector and Reinert's activity whose technical change is passed on to buyers.

8. Deviations from the line, and what the evidence cannot show

8.1 The residuals are Reinert's cases

The countries furthest from the regression line fall into groups that the theory names (Table 6).

Table 6: Selected countries: rank in complexity and innovation, and distance from the fitted line

Country	Complexity rank (of 145)	Innovation rank (of 139)	Residual, complexity only	Residual, complexity and income
Japan	1	12	+1.6	+3.3
Rep. of Korea	3	4	+9.7	+10.8
Switzerland	4	1	+15.9	+14.7
China	10	10	+10.4	+15.2
United States	18	3	+17.4	+14.7
Mexico	27	58	−11.5	−9.2
India	42	38	−0.8	+4.6
Brazil	59	52	−1.6	−1.1
Australia	73	22	+16.2	+9.8

Source: Growth Lab, Atlas of Economic Complexity (HS92, 2024); WIPO, GII 2025; authors' calculations.

Note: Residuals are in points of the innovation score, from columns (1) and (3) of Table 3. A positive residual means more innovation than complexity alone, or complexity and income together, predict. Other countries discussed in the text are reported there with the residual of the specification cited.

Assembly platforms. Mexico ranks 27th in complexity and 58th in innovation, 11.5 points below the line. Its export basket of vehicles, electronics and machinery is that of a far more innovative economy, and much of it is assembled for the United States market with design, engineering and research performed abroad. This is Reinert's second dimension: products high on the ladder, tasks low on it. It is the same configuration as Amazonas among the Brazilian states, and the same as his Dominican and Haitian cases.

Inherited structures. Belarus and Bosnia and Herzegovina, 14.5 and 15.1 points below the line in the regression on complexity alone, hold industrial baskets built under planning. The products remain; the innovation systems that would renew them are weak. Complexity measured from exports is a stock that outlasts the capacity that created it.

Resource rent that buys inputs. Australia ranks 73rd in complexity and 22nd in innovation, 16.2 points above the line. Its exports are ores, coal and gas, and its income supports universities, a venture capital market and

high scores on the input pillars of the index. Conditioning on income removes two fifths of the residual, which falls to 9.8. Income from resources can purchase the inputs to innovation; the export structure shows that those inputs have not yet been converted into a different set of activities.

The multidimensional indices of Stojkoski, Koch and Hidalgo (2023) show the same thing from the other side: Australia ranks 76th in trade complexity and among the leaders in the complexity of its technology and research. Their reading is that trade understates the country's capabilities. Reinert's adds that the capabilities are being paid for by a rent and have not yet become a productive structure.

Resource rent that does not. In the regression with both predictors the largest negative residuals belong to Trinidad and Tobago (−15.7), Belarus (−13.7) and Kuwait (−12.8). Belarus is the inherited structure above. The other two are hydrocarbon exporters whose high incomes raise the innovation the regression predicts, and they innovate far less. Income earned from a resource does not carry innovation with it, which is the difference between resource rent and industry rent stated with country data.

Above the line at the frontier. The United States, Sweden, Switzerland, the United Kingdom, the Netherlands and Finland lie 13 to 17 points above the line in the regression on complexity alone. All have large shares of activity in software, finance, research and business services that merchandise exports do not record. The export-based index understates their position on the ladder.

China. China is tenth on both rankings and 15.2 points above what its complexity and income together predict, the second-largest positive residual in that regression. Its innovation is high for its structure and far higher for its income, consistent with an economy whose structure is still moving up, the compressed catch-up that the Republic of Korea, also well above the line, went through earlier (Lee and Kim, 2024).

Brazil. Brazil sits on the line: 59th in complexity, 52nd in innovation, less than two points below it in both specifications. The country innovates as much as its productive structure predicts. Section 7.1 showed what that structure is.

One feature of the fit is not a case but a shape. At the bottom of the complexity scale several countries, among them Nigeria, Mongolia and the Republic of the Congo, lie 15 to 20 points above the line in the

regression on complexity alone, because the innovation score has an effective floor between 12 and 20 while the complexity index of oil and mineral monocultures falls very low. The relationship is flatter at the bottom than a straight line allows, which is why the rank correlation (0.90) summarizes it better than the linear fit.

The states. The same reading can be applied to the Brazilian states, with the two measures of Section 6 that differ most: the diffusion of complex activity and its employment-weighted level (Table 7). With 27 observations and rank positions only, the gaps are differences of position, not regression residuals, and they are read as cases, not as estimates.

Table 7: Selected states: rank in innovation and in two measures of complexity, and the gap between them

State	Innovation rank (IBID 2025)	Diffusion rank	Gap, diffusion	Employment-weighted rank	Gap, employment-weighted
Federal District	7	1	−6	1	−6
Amazonas	17	21	+4	3	−14
Mato Grosso	11	13.5	+2.5	26	+15
Rio Grande do Norte	12	18	+6	12	0
Paraíba	15	24	+9	16	+1
Piauí	18	25	+7	20	+2
Tocantins	20	26	+6	13	−7
Rondônia	21	12	−9	23.5	+2.5
Alagoas	25	15	−10	23.5	−1.5
Acre	27	20	−7	14	−13

Source: INPI, IBID 2025; DataViva, formal employment records (RAIS) for 2025; authors' calculations from Appendix Table A1.

Note: Ranks among the 27 federative units; tied ranks are averaged. Gap = complexity rank minus innovation rank. A positive gap means the state ranks higher in innovation than in complexity; a negative gap, lower. Diffusion is the share of municipalities with a complexity index above zero.

Two cases are already familiar. Amazonas is the assembly platform of Section 6.3: 14 positions lower in innovation than on the employment-weighted index and close to its position on diffusion. The Federal District ranks first on both measures and seventh in innovation. As a single municipality its diffusion is 100 percent by construction, and its complex employment includes the central bank and the head offices of federal financial institutions, activities that Section 7.1 places at the top of the complexity index and at the bottom of research intensity. Its gap is industry rent that does not come from research.

Paraíba, Piauí and Rio Grande do Norte rank six to nine positions higher in innovation than in diffusion, but within two positions of their rank on the employment-weighted index. In these states complex activity and innovation are both concentrated in the capital, where federal universities and research institutes are located, and a measure that counts municipalities misses them. They are the mirror image of Amazonas: there the worker-weighted lens overstates the structure behind innovation, here the territorial lens understates it. Whether their innovation rests on inputs, such as universities financed from the national budget, more than on outputs can be checked with the IBID's input and output sub-indices. Alagoas and Rondônia show the opposite pattern: a third or more of their municipalities clear the low threshold of the diffusion measure, which counts the presence of complex activity and not its depth, and both states sit close to the line on the employment-weighted index.

No single measure fits every state. This is what the near-identity of the territorial measures and their overlap with the worker-weighted index in Section 6.2 imply, and the cases show what each lens sees.

8.2 What the evidence does not show

The results establish that position on the ladder and measured innovation move together at three scales. They do not establish which moves the other, and Reinert's theory does not say that the causation runs one way. Activities with steep learning curves generate innovation, and innovation is how economies enter such activities. The accumulation is cumulative and circular, as in Kaldor (1967), and a cross-section cannot separate its two halves. Section 5.3 shows persistence, not direction.

Several limits of the data should be kept in view. The innovation index includes the complexity index among its 78 indicators, together with two indicators of high-technology production and trade, so a small part of the country correlation is built in. Income is measured in 2018 and innovation in 2025. The country measure is the published complexity index, a summary of export baskets and not a direct score of the quality of activities. The state analysis has 27 observations, uses ranking positions rather than scores, and has no control for state income; the Mato Grosso case suggests what such a control would show but does not replace it. The state comparison in Section 8.1 rests on differences of rank, not on residuals. The IBID may itself contain indicators of productive structure. The wage evidence is for formal employment in one country. And the research-intensity comparison is a concordance of extremes.

The state results also need to be read against the caution of Du and Zaccaria (2026), who find that the complexity index computed for Brazilian

subnational units can correlate negatively with output per capita. The three summaries used here are built from municipal indices rather than from a state-level matrix, and the Mato Grosso case shows that income and complexity do diverge among Brazilian states. That divergence is part of the argument, since it is innovation and not income that the state index is asked to predict, but it means the state-level index should not be assumed to behave as the country index does.

The mechanism at the centre of Reinert's theory also remains untested. Whether productivity gains in activities high on the ladder are retained as wages and profits while those low on it are passed on as lower prices is a question for sectoral data on prices, costs and wages across countries. The innovation evidence makes that mechanism more plausible, since it shows that the ladder is ordered by the thing the mechanism requires. It does not observe the mechanism.

Four extensions follow directly. The first is to replace the complexity index with a product-level score of activity quality, such as the income of a product's exporters (Hausmann, Hwang and Rodrik, 2007), and to ask whether a score based on the poorest exporters predicts innovation better than one based on the average. The second is to separate the input and output sub-indices of the innovation index and to remove the structural indicators. The third is a panel: the GII has been published annually since 2007, and changes in complexity can be related to later changes in innovation. The fourth is to add state income and the municipal distribution of patents to the Brazilian analysis, so that the diffusion result can be tested at the level at which it is claimed.

9. Implications for policy

The results are associations drawn from cross-sections, and Section 8.2 sets out what they cannot show: they do not identify the effect of any policy instrument. They do show which configurations of structure and innovation stay on the line, and which fall off it, and that is enough to say which policy designs work with the evidence and which work against it. Four implications follow, each from one of the paper’s results: the fit across countries and its exceptions, the diffusion result among the states, the resource-rich cases, and the common institutions of the Brazilian states.

Structure and laboratories are complements, not alternatives. The evidence does not say that research spending is wasted. It says that research spending converts into innovation where there are activities to absorb it. Australia shows inputs to innovation running ahead of

structure; Mexico and Amazonas show structure running ahead of learning. Both configurations fall off the line. Policies that pair the supply of knowledge with productive demand for it, such as procurement for missions, support conditioned on local engineering and design, and the absorptive capacity that Cohen and Levinthal (1990) describe, work with the grain of the evidence. Policies that fund either side alone work against it.

Where complex activity is located matters as much as how much of it there is. Among Brazilian states, innovation follows the territorial spread of complex activity more closely, on average, than its worker-weighted level. Santa Catarina and Paraná, the two states that closed most of their distance to São Paulo in the IBID between 2015 and 2025, both have complex production spread over most of their municipalities. The evidence points regional policy aimed at innovation toward networks of medium-sized industrial towns rather than isolated enclaves. The Manaus Free Trade Zone shows the limit of incentives tied to location alone: they secured complex products, not the stages in which learning takes place. Incentives conditioned on local linkages, such as suppliers, engineering and research performed in the region, are the instrument the evidence favours, provided they are judged by the capabilities they build rather than by the sums they move.

Resource rent is a source of finance, not of structure. Resource-rich economies can buy the inputs to innovation, and Brazil's agricultural and mineral exports, including the critical minerals of the energy transition, will generate such rents. Owning a resource is not the same as mastering the technologies that transform it. Reinert's distinction between resource rent and industry rent implies that the rent should finance the move into processing, equipment and engineering services, the activities in which it can be converted into structure.

Intellectual property protection works where capabilities exist. The 27 Brazilian states share one intellectual property law and a single national intellectual property office, yet output per capita differs almost six to one among them and innovation follows the spread of complex activity (Section 6). Uniform rules do not produce uniform outcomes. This is consistent with evidence that stronger intellectual property rights raise economic complexity only above a threshold of development (Sweet and Eterovic Maggio, 2015). Intellectual property offices can also contribute beyond granting rights. Subnational innovation indices such as the IBID, and the municipal geography of patent, trademark and design filings, show where complex activity and inventive capacity are spreading and

where they stall. They can serve as an early-warning system for industrial and regional policy.

10. Conclusion

Reinert ranked economic activities by their capacity to make nations rich and placed at the top those in which knowledge is created quickly and its gains can be kept. The complexity index places economies on a ladder of that shape but cannot show that the ladder is ordered by innovation. This paper tested that with innovation measured independently, and the prediction holds at three scales.

Across countries, the complexity index explains 69 percent of the variation in the Global Innovation Index, more than income does (62 percent), and remains strongly associated with innovation among countries of the same income. Across Brazilian states, where the index is built from employment rather than exports and institutions are common, the rank correlation with innovation is between 0.67 and 0.80. Across Brazilian activities, complexity is associated with a wage premium of about 31 percent per standard deviation, which is the outcome Reinert's index was defined by, and the one trade data could approach only through the income of exporting countries. The premium holds across activity classes but not among the activities where most Brazilians work.

Two findings go beyond confirmation. The first is diffusion. Among the states, the territorial measures of complexity, the share of municipalities in which complex activity is present and the mean municipal index, track innovation more closely than the complexity of the place where the average worker is employed. Complex activity concentrated in an enclave, whether a free trade zone or a federal capital, is associated with less innovation than the same activity spread across a network of towns, although 27 states cannot fully separate the territorial and worker-weighted measures (Sections 6.2 and 8.1). This gives empirical content to the synergies Reinert listed among the characteristics of high-quality activities, and it has no counterpart in the country data.

The second is the pattern of exceptions. Economies that assemble complex products without designing them innovate less than their baskets suggest. Economies rich from resources innovate above their structure where the rent buys the inputs to innovation, as in Australia, and far below their income where it does not, as in Kuwait and Trinidad and Tobago. These are Reinert's second dimension and his distinction between resource rent and industry rent, recovered as residuals from a regression he never ran.

For the reinterpretation of economic complexity the implication is specific. The recent literature has shown that the complexity index is a statistical

summary of co-specialization that needs a theory from outside the matrix to be read. A theory earns that place by predicting things the matrix does not contain. Reinert's predicts that the axis should be ordered by innovation, beyond income, and the data agree. A capabilities reading would predict the same sign, so the result does not discriminate sharply between the two; what Reinert's account adds is the prediction of where the relationship fails, and it fails there.

For policy the implication is the one Reinert drew from history: research spending converts into innovation where there are activities to absorb it, and Section 9 sets out what follows. An economy that wishes to innovate more has to learn to produce more of the things in which innovation occurs.

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Appendix: state-level data

Table A1: Innovation ranking and three measures of complexity, 27 Brazilian federative units

State	Innovation rank (IBID 2025)	Employment-weighted complexity	Mean municipal complexity	Diffusion (% of municipalities above zero)
São Paulo	1	2.60	0.67	70
Santa Catarina	2	2.10	0.81	82
Paraná	3	2.02	0.27	60
Rio de Janeiro	4	2.57	1.03	86
Rio Grande do Sul	5	1.99	0.32	59
Minas Gerais	6	1.67	−0.06	41
Federal District	7	3.03	3.03	100
Espírito Santo	8	1.72	0.40	62
Goiás	9	1.44	−0.24	35
Mato Grosso do Sul	10	1.26	0.04	53
Mato Grosso	11	1.18	−0.24	35
Rio Grande do Norte	12	1.56	−0.42	30
Pernambuco	13	1.88	−0.06	44
Ceará	14	1.69	−0.08	42
Paraíba	15	1.44	−0.70	17
Bahia	16	1.44	−0.24	31
Amazonas	17	2.58	−0.39	23
Piauí	18	1.34	−0.83	13
Sergipe	19	1.21	−0.26	33
Tocantins	20	1.55	−0.77	12
Rondônia	21	1.25	−0.08	40
Pará	22	1.15	−0.26	28
Amapá	23	1.39	−0.35	19
Roraima	24	1.39	−0.50	7
Alagoas	25	1.25	−0.38	34
Maranhão	26	1.26	−0.64	19
Acre	27	1.50	−0.36	27

Source: INPI, IBID 2025; DataViva regional complexity index, formal employment records (RAIS) for 2025; authors' calculations.

Note: The Federal District is a single municipality, so its three measures coincide.

Table A2: The OECD taxonomy of economic activities by R&D intensity (business R&D as a percentage of gross value added, 2011)

Group	Manufacturing	Other activities
High	Air and spacecraft (31.69); pharmaceuticals (27.98); computer, electronic and optical products (24.05)	Scientific research and development (30.39); software publishing (28.94)
Medium-high	Weapons and ammunition (18.87); motor vehicles (15.36); medical and dental instruments (9.29); machinery and equipment (7.89); chemicals (6.52); electrical equipment (6.22); railroad and other transport equipment (5.72)	IT and other information services (5.92)
Medium	Rubber and plastics (3.58); ships and boats (2.99); other manufacturing (2.85); non-metallic mineral products (2.24); basic metals (2.07); repair and installation of machinery (1.93)	—
Medium-low	Textiles (1.73); leather (1.65); paper (1.58); food, beverages and tobacco (1.44); wearing apparel (1.40); fabricated metal products (1.19); coke and refined petroleum (1.17); furniture (1.17); wood (0.70); printing (0.67)	Professional and technical services (1.76); telecommunications (1.45); mining and quarrying (0.80); publishing (0.57)
Low	—	Finance and insurance (0.38); electricity, gas, water and waste (0.35); audiovisual and broadcasting (0.32); wholesale and retail trade (0.28); agriculture, forestry and fishing (0.27); construction (0.21); administrative and support services (0.18); arts and other services (0.11); transportation and storage (0.08); accommodation and food services (0.02); real estate (0.01)

Source: Galindo-Rueda and Verger (2016), Table 1.

Note: Business expenditure on R&D as a percentage of gross value added, by industry of the International Standard Industrial Classification (ISIC Rev. 4). Averages over 27 OECD countries, Singapore and Chinese Taipei for 2011, weighted by value added; industries are sorted into five groups by intensity. Unlike earlier OECD classifications by technology, the taxonomy covers services and primary production as well as manufacturing. A dash means no industry of that kind falls in the group.