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PAPER

Bringing links back: economic complexity as network centrality in the Product Space

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Keywords: economic complexity, Product Space, network centrality

Abstract

This paper reframes economic complexity metrics as centrality values in the Product Space. Instead of searching for the 'best' algorithm to calculate a superior complexity index, I propose utilizing different centrality values in a complementary fashion to explain export diversification and income. The linear economic complexity index, the non-linear country Fitness, and network degree and closeness centralities share a large common component, yet each retains a distinct aspect of a country's position in the network. As a result, country income, diversification, and growth are each best explained by different centrality metrics. The paper argues that the explanatory power of complexity metrics stems from the connections an export basket holds in the Product Space. The centrality approach can strengthen the network implications of the Product Space for developing countries. Since the current location and opportunities of each developing country differ, a centrality approach can better provide country-specific development targets and policy prescriptions.

1. Introduction

Almost two decades ago, strong objections were raised against the classical prescription that developing countries should keep producing what they already do best. The 'What You Export Matters' argument differentiated products by the income level of exporting countries and linked the resulting basket index to growth [1]. The policy message was to produce what the rich produce. In the authors' words, 'Rich countries are those that have latched on to 'rich-country products,' while countries that continue to produce 'poor-country' goods remain poor. Countries become what they produce.' The argument was compelling but circular, with significant endogeneity and no clear path for how a country could reach 'rich-country products'.

A network-based breakthrough addressed this gap by introducing the Product Space, a proximity network of products with a dense core of highly connected products and a sparse periphery of products scattered across remote areas [2]. Developed countries occupy the core, while developing countries risk being stuck in the periphery. The vast implications of the Product Space for economic growth and development were based mainly on the links. If a developing country lacked the necessary connections, it would be impossible to reach the fruitful core. Hence, the connections a country's products or the current position of its export basket in the Product Space have a significant impact on its development trajectory. Countries are repeatedly found to diversify into related products in the Product Space [3, 4], leading to a trade-off for developing countries: central products with many connections are further from their current export baskets. A structural transformation in the direction of development required the reversion of the trade-off, denying the current export structure to some extent and leaping towards the center of the Product Space [5, 6].

The emphasis on what countries export motivates product- and country-level measures that can be linked to growth and development. In that regard, the concept of economic complexity has primarily been used to explain why some countries outperform others in terms of growth and development [7].

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Countries with a high economic complexity index (ECI) have been found to be richer, grow faster, and even have lower CO_2 emissions [7–10].

Alternatives were proposed not only for the interpretation of economic complexity but also for the metric itself. The non-linear product complexity and country fitness pair has been claimed to outperform ECI and PCI and widely used as a substitute [11]. Linear or non-linear complexity metrics have been individually used to explain a wide variety of phenomena, from economic to environmental variables, from successes in the Olympics to the citation performance of academic journals. Yet the search for one superior complexity metric has overshadowed their network roots and narrowed their implications.

A product's 'value' in the Product Space comes from its connections. Each new link increases the chance of moving into additional products and making further steps in development. No matter what formula is used or how the theory is framed, any complexity metric connects to income and growth only to the extent that it captures these product connections. In this sense, complexity metrics belong to a broader family of measures, each reflecting a different aspect of how products are interconnected. In network terms, these measures are called 'centrality'.

Building on these network roots, this paper reevaluates complexity metrics as centrality measures in the Product Space and examines their commonalities and distinctions. Instead of seeking a 'best-performing complexity metric', the paper asks which centrality measure explains which aspect of export diversification, income, and their growth. Since PCI is an eigenvector centrality in the Product Space, ECI can be viewed as the average eigenvector centrality of an export basket. Although not itself a centrality metric, Fitness, F, increases as a country's products occupy more central positions. Beyond these two complexity metrics, I use the average degree and average closeness centralities (ADC and ACC) of products in a country's export basket.

The analysis shows that a major part of the variation in these centrality metrics can be captured by a single component that best explains diversification and income. However, each centrality metric has its individual strength in explaining different aspects of diversification and income. Consequently, the analysis highlights the importance of focusing on the network structure of the Product Space when studying diversification patterns and income differences. Rather than ranking complexity measures as inherently 'superior' or 'inferior,' they can be evaluated within a centrality framework, where each metric reflects both a common centrality aspect and a distinct facet of network position and opportunity.

The rest of the paper is organized as follows: section 2 reviews the relevant literature on Product Space, complexity metrics, and their alternative interpretations. Section 3 theoretically discusses the connection of centrality to diversification and income. Section 4 defines the variables and centrality measures. Section 5 describes the data and reports the empirical results. Finally, section 6 concludes the paper.

2. Relevant literature

Countries are likely to diversify into related products that are closely connected to their current export baskets in the Product Space [3, 4]. This result is validated at various levels, from country to firm[1] [13] and by multiple techniques, including machine learning [14–16]. Being far away from the core of the Product Space, developing countries experience a negative correlation between the nearness and complexity of external products, leading to a trade-off [5, 6]. Successful structural transformation cases, such as Korea's, have witnessed a reversal of the negative correlation between nearness and complexity into a positive one [5, 17]. The trade-off between nearness and complexity raises the question of how combining these dimensions to find optimal products or strategies for export diversification helps the diversification of less diversified [6, 18–20]. All this research shows that gaining access to complex or central products is a necessary part of the development path.

Economic complexity is conceptualized through the 'capabilities model' [7]. Countries with broad capabilities can export diverse, sophisticated products, while such capabilities are concentrated among a few economies. However, the capabilities model theorization of ECI and PCI [7, 21] is not the only interpretation of the metric. Formally, both indices are eigenvectors derived from country-country and product-product similarity matrices [22, 23]. In addition, ECI and PCI are shown to be equivalent to outputs of a spectral clustering algorithm applied to the similarity networks of countries or products [24]. In this view, the ECI essentially partitions countries into groups based on the resemblance of their

[1] The fitness metric operates differently at the firm level compared to the country level [12].

export profiles [25] or long-run patterns of structural change [26], rather than measuring their underlying capabilities. The observed link between ECI and GDP per capita could reflect the fact that countries with similar export structures also tend to have similar income levels [27]. Contributing to the discussion, complexity metrics are shown to behave similarly to clustering algorithms in the presence of another dominant variable, but merely indicate complexity without the dominance of that variable [28].

As an alternative to the linear ECI and PCI, a non-linear metric has been proposed to measure the economic complexity of countries and products [11]. A country's fitness increases if it exports many complex products, whereas a product's complexity decreases non-linearly when low-fitness countries export it. The non-linear country Fitness metric is found to be strongly correlated to the first eigenvector of the country-country proximity matrix [22], and almost all variation in country Fitness is found to be explained by its export diversification [29]. Of course, there are other attempts to improve the linear metric for economic complexity, such as correcting for the difficulty of exporting [30], or using value-added exports instead of gross exports [31].

Whether it is the linear ECI or non-linear country Fitness, the concept of economic complexity has been widely used to explain a variety of economic and social phenomena, extending beyond trade patterns. ECI and Fitness have been linked to key outcomes, such as GDP per capita, long-term economic growth, and even output volatility [7, 32–35]. Beyond macroeconomic outcomes, economic complexity has been applied to explain regional development patterns [36, 37], unemployment [38], and environmental performance [10, 39–41]. Changes in economic complexity have been found to be persistent and linked to structural change [42–45]. That persistence was even dated back to ancient Roman times [46]. It is not only the complexity of products that matters, but also the complexity of services [47, 48]. Scholars also have explored the relationship between economic complexity and social outcomes, such as inequality, suggesting that complexity not only shapes what economies produce but also how societies distribute opportunities and resources [49]. Economic complexity has been used as a dependent variable as well to find out, for example, whether the ability to create sophisticated jobs matters to improve long-run economic complexity [50]; or FDI helps countries diversify into complex products [51].

The ideas of Product Space and economic complexity have been applied to various other fields. Product Space can be constructed for agricultural products to analyze specialization patterns and implications for food security and sustainability [52, 53]. Products have also been differentiated by their skill content, showing that high- and low-skill-intensity products appear at opposite ends of the Product Space [54]. A 'citation space' framework has been developed to map the technological capabilities of countries using patent citation data [55]. Similarly, other studies have assessed the scientific complexity of nations, demonstrating that countries tend to diversify into related scientific domains [56–58]. A network of scientific research fields has also been constructed based on data on countries' research outputs [59]. In the realm of technology, a 'Technology Space' has been created by connecting technologies through patent data [60]. Extending this network approach, a 'sports space' has been built using Olympic medal counts to map countries' sports capabilities [61]. A similar logic has been applied to online chess data, showing that highly rated players tend to favor chess openings with a greater complexity index [62]. The proximity network of the Sustainable Development Goals and the complexity indices of the goals and countries that achieve them have also been analyzed [63]. Similarly, a 'Poverty Space,' a network of poverty indicators, has been proposed to identify the central indicators that are key to reducing poverty [64]. In another recent study, ECI and PCI have been applied to author-journal networks in scientific publications to construct an Author Complexity Index and a Journal Complexity Index [28].

There have been few studies approaching economic complexity from the perspective of centrality. Mexico's southern states have been analyzed using employment data to build an industry proximity network, showing that industries with high betweenness centrality act as critical bridges to more complex sectors, and that states specializing in such industries achieve greater diversification [65]. A version of degree centrality has been used as a proxy for product complexity, suggesting that countries targeting products with greater combinations of product nearness and centrality can increase export diversification [6]. The fitness complexity metric has also been modified and interpreted as a centrality measure applicable to general networks [66].

Closer to the ideas in this study, ECI has been interpreted as an eigenvector centrality-type metric [24]. Moreover, Fitness has been shown to be linked to the first, size-relevant eigenvector, while ECI is associated with the second [22]. More broadly, widely used complexity metrics have been divided into two groups: Fitness-type metrics are associated with diversity, and ECI-type metrics with product composition, supporting the view that complexity metrics complementarily explain different dimensions of the production structure [26].

These papers have therefore already established a close connection between complexity metrics and network centrality, as well as the idea that different complexity measures should be interpreted

in a complementary manner. Building on this perspective, the present paper compares the empirical behavior of complexity metrics with that of standard network centrality measures that do not rely on a complexity or capability-based interpretation. The results show that many empirical patterns previously attributed to complexity metrics also emerge for traditional centrality measures, suggesting that an important part of their explanatory power stems from how they summarize a country's position in the Product Space. In addition, the findings indicate that the performance of these metrics is not restricted to the commonly emphasized income-composition (ECI) versus size-diversification (Fitness) distinction. In some specifications, average centrality measures such as ECI, average degree, and average closeness display comparable or stronger associations with diversification outcomes than Fitness, while Fitness can supersede the others in explaining income.

Hence, this paper contributes to the existing literature by framing complexity metrics as network centrality measures and comparing their performance to alternative centrality measures. Complementing studies that highlight the centrality interpretation of complexity indices, this study shows that different centrality metrics capture distinct aspects of diversification and income, and that standard complexity metrics lie within this broader centrality spectrum. By emphasizing that each centrality metric has strengths and weaknesses in different settings, the paper advocates using multiple centrality measures for different purposes rather than searching for a single 'best' index. This perspective helps recover the network implications of the Product Space for development.

3. Why would links lead to greater income?

In this section, I will elaborate on the theoretical foundations of the relationship between centrality in the Product Space and income and income growth. The links in the Product Space solely denote the relatedness between products [2]. As mentioned above, if two products are related, a successful transition from one to the other is more likely [3, 4]. Diversification into related products is easier and with lower costs because they share overlapping labor skills [13, 67], require similar institutional and organizational routines [68], draw on common input suppliers and infrastructure [69], and benefit from knowledge spillovers enabled by cognitive proximity between producers [70].

Hence, in general, related products share a larger set of capabilities, and the additional capabilities gathered by producing one make producing related others possible [5]. The returns to additional capabilities follow a convex shape: for a country with many capabilities, a new one can complete the puzzle for many products related to each other. On the other hand, a country with few capabilities may not diversify and fall into a quiescence trap as a new capability does not find new products to complete the puzzle [8]. Therefore, countries whose export basket occupies a central, densely connected neighborhood benefit from all three channels of learning spillovers, shared inputs, and transferable skills simultaneously. As a result, including central products or occupying a central position in the Product Space helps countries diversify into many other related central products [2, 7].

The empirical relationship between diversification and income is evident [71–73]. Low-income countries suffer from being dependent on a small set of ubiquitous products to export, while high-income countries successfully export many central and exclusive products. Countries with higher complexity possess more capabilities, which enable them to produce a wider range of sophisticated products [1, 7]. This broader productive base leads to export diversification, which in turn drives structural transformation as countries enter new product markets and shift toward higher-value-added activities. Countries whose complexity exceeds what their income level would predict tend to grow faster, converging toward the income implied by their capabilities [8]. In that regard, centrality in the Product Space leads to higher income and income growth by enabling access to strongly connected sophisticated product clusters that compound capability accumulation and accelerate structural transformation.

It should be noted that the relationship between complexity metrics and income is subject to endogeneity concerns, as richer countries may develop more complex export baskets rather than the reverse. The literature has addressed this through IV estimation, such as country size as instruments [1] or replacing country complexity with averages of similar non-neighboring countries [40]. Nevertheless, the endogeneity of complexity metrics with respect to income remains an open challenge that no study has fully resolved. The present paper follows the standard approach by using country fixed effects in within regressions. More importantly, the paper's central contribution is not a causal claim about complexity driving income, but the demonstration that the explanatory power of complexity metrics stems from their role as centrality measures in the Product Space, a reinterpretation that holds regardless of the direction of causality.

A related concern is whether regressing income on centrality constitutes a tautology, given that both variables pertain to a country's export structure. The distinction between this approach and the PRODY/EXPY framework is instructive [1]. PRODY is defined as the weighted average GDP per capita of countries exporting a given product, while EXPY represents the average PRODY of a country's export basket. By design, EXPY incorporates country income directly, making the regression of income on EXPY nearly tautological. In contrast, centrality measures in the Product Space are fundamentally different. These measures are derived from the binary country-product matrix without incorporating income information. A product attains centrality not because of its association with wealthy exporters, but because it is strongly connected to numerous other products in the network. For instance, crude oil exhibits high PRODY because high-income countries export it, yet it has low centrality in the Product Space since oil is weakly connected to other products and occupies a peripheral position in the network.

4. Model variables and definitions

Let C be the set of countries, P the set of products, and T the set of years. The primary data is the set of export values X_{cpt} for each country c, product p, and year t. From this, I compute the Revealed Comparative Advantage (RCA) index:

$$\mathrm{RCA}_{cpt} = \frac{X_{cpt}/\sum_{p\in P} X_{cpt}}{\sum_{c\in C} X_{cpt}/\sum_{c\in C, p\in P} X_{cpt}}. \tag{1}$$

The revealed comparative advantage is the share of a product in a country's total exports over the share of the product in all world exports. Hence, it provides a measure of the country's specialization in the product relative to the product's weight in global trade.

A country is said to have a comparative advantage in product p if $\mathrm{RCA}_{cpt} \geqslant 1$. The set of products for which this holds defines country c's export basket, which is denoted by B_c.

I define a binary matrix $R_{cpt} \in \{0,1\}$ such that

$$R_{cpt} = \begin{cases} 1 & \text{if } \mathrm{RCA}_{cpt} \geqslant 1 \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

The diversification of a country, denoted D_{ct}, is defined as the number of products in its export basket:

$$D_{ct} = \sum_{p\in P} R_{cpt}. \tag{3}$$

A product proximity matrix Φ is defined to capture similarity between products based on co-export patterns. Each entry is defined as

$$\Phi_{pp'} = \min\left(P(p|p'), P(p'|p)\right) \tag{4}$$

where $P(p|p')$ is the probability that a country exports p given that it exports p', estimated from the matrix R.

The degree centrality of a product p in year t, denoted DC_{pt}, is a weighted degree centrality that measures how connected it is to other products:

$$\mathrm{DC}_{pt} = \sum_{p'\in P} \Phi_{pp'}. \tag{5}$$

DC values are z-standardized within each year.

For each country c, the average degree centrality (ADC) is defined as the mean degree centrality of the products in its export basket:

$$\mathrm{ADC}_{ct} = \frac{1}{D_{ct}} \sum_{p\in B_c} \mathrm{DC}_{pt}. \tag{6}$$

I also compute closeness centrality of products, denoted CC_{pt}, based on average shortest path lengths from a product to others in the product network with pairwise distances set as $\frac{1}{\Phi_{pp'}}$. CC values are z-standardized within each year.

Table 1. Correlation matrix of key measures.

	D	ECI	F	ADC	ACC
D	1.0000				
ECI	0.7511	1.0000			
F	0.9158	0.7930	1.0000		
ADC	0.7885	0.8115	0.6624	1.0000	
ACC	0.8192	0.8754	0.7267	0.9874	1.0000

The average closeness centrality of a country, ACC_{ct}, is the average of CC_{pt} over its export basket:

$$\mathrm{ACC}_{ct} = \frac{1}{D_{ct}} \sum_{p \in B_c} \mathrm{CC}_{pt}. \tag{7}$$

Economic complexity index, ECI, and product complexity index, PCI, are determined as a result of recursive equations where ECI is the average PCI, while PCI is the average ECI [7]. The values are calculated by the method of reflections. R_{cpt} being the country-product matrix at time t, at iteration n,

$$\mathrm{PCI}_{pt}^{(n)} = \frac{1}{U_{pt}} \sum_{c \in C} R_{cpt}\, \mathrm{ECI}_{ct}^{(n-1)}, \tag{8}$$

and, analogously,

$$\mathrm{ECI}_{ct}^{(n)} = \frac{1}{D_{ct}} \sum_{p \in P} R_{cpt}\, \mathrm{PCI}_{pt}^{(n-1)}, \tag{9}$$

where $D_{ct} = \sum_{p \in P} R_{cpt}$ is country diversification and $U_{pt} = \sum_{c \in C} R_{cpt}$ is product ubiquity. ECI and PCI values are z-standardized within each year.

In addition, following [11], the non-linear 'fitness-complexity' metrics are defined. Country fitness F_{ct} and product complexity Q_{pt} are iteratively defined by

$$F_{ct}^{(n)} = \sum_{p} R_{cpt} Q_{pt}^{(n-1)} \tag{10}$$

$$Q_{pt}^{(n)} = \frac{1}{\sum_{c} R_{cpt} / F_{ct}^{(n-1)}} \tag{11}$$

with normalization at each iteration. High-fitness countries tend to export more complex products, while complex products are those that are typically exported by high-fitness countries.

These variables together allow us to quantify the structure and sophistication of countries' productive structures and to trace their evolution through time.

5. Results

For the empirical analysis, I use international trade data from the BACI database [74], which covers all bilateral trade flows at the HS 6-digit level for 1995–2023. To enhance robustness and limit noise, I aggregate products to the HS 4-digit level. To avoid the effects of the COVID-19 pandemic, the analysis window is restricted to 1995–2019. To gather country characteristics such as GDP per capita and population, I use the Penn World Table database [75]. I use a similar strategy to the literature to decide which countries to include in the empirical analysis [32]. Countries that exist in the Penn World Table database, have a population greater than 1 million in 2019, and have a sample average export value greater than 1 million dollars are included in the analysis. This leaves us with 131 countries, 1241 products, and 25 years. For each year, a Product Space network is constructed via the proximity matrix, and country statistics are calculated accordingly. Hence, each observation in the sample has a value for each of the country, product, year, GDP per capita, diversification, ECI, Fitness, ADC, and ACC.

The first striking observation is that our network variables are strongly correlated with each other (table 1). ECI, ADC, and ACC are very strongly correlated, all above 0.8, with almost a perfect correlation between the last two. The correlation between F, the fitness, and the other three is lower. The main reason is that all ECI, ADC, and ACC represent average centrality values for products in the export basket. In contrast, F accumulates as the number of products increases, making it distinct from the average.

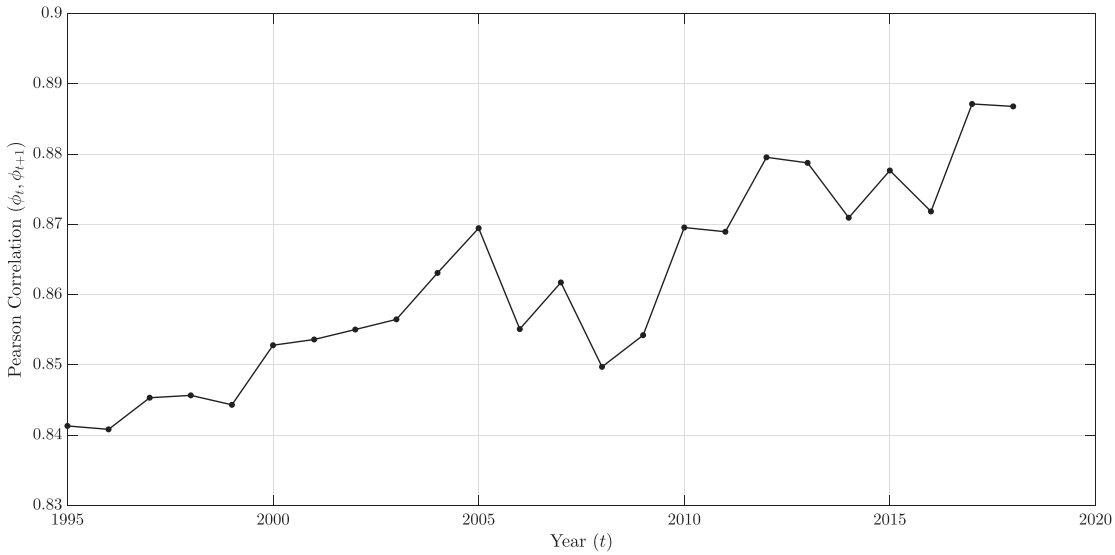


Figure 1. Pearson correlations between proximity values in consecutive years (1995–2018).

Since centrality measures here depend on the yearly networks of pairwise product proximities, the stability of the network structure must be addressed. Figure 1 reports the Pearson correlation of the product proximity values in consecutive years, t and $t+1$. The correlations consistently range between 0.84 and 0.89, indicating a high degree of persistence of proximities in the Product Space. Hence, changes in a country's centrality over time reflect actual changes in its position in the Product Space, not noise from the network structure. With network stability established, I now turn to how centrality relates to diversification.

As discussed in section 3, all centrality metrics are strongly correlated with diversification (D), the number of products in the export basket, with F having the highest value. The non-linear relationship between centrality metrics and diversification shown in figure 2 resembles a power law. Such a power law between diversification and centrality metrics not only exists (figure 3) but is also stable across time and country groups (figures 4 and 5). To make centrality values positive for the log-log and power-law analyses, I apply a quantile normalization within each year across countries. Analogous to preferential attachment in networks, the inclusion of new products in country export baskets is not random. Central products attract other central products; countries occupying the central areas in the Product Space become more diversified. Consistent with the correlations, the power-law exponent varies across metrics. As visible in figure 3, the scatter around the fitted line is tightest for Fitness and loosest for ECI, with ADC and ACC in between. Over the sample period (figure 4), Fitness maintains the highest exponent (approximately 0.95–1.15) and R^2 (consistently above 0.90), while ECI has the lowest exponent (approximately 0.60–0.80) and R^2 (between 0.40 and 0.60). ADC and ACC occupy the middle ground with exponents around 0.80–0.95 and R^2 values between 0.65 and 0.80.

Figure 2 raises a question: if the four metrics present such similar curves with respect to diversification, are they effectively measuring the same underlying quantity, and does comparing them provide any information? The principal component analysis and orthogonalization exercises later in this section are designed to answer this directly by separating the large shared component from the metric-specific components and testing whether each centrality metric retains independent explanatory power. As will become clear, a single component captures most of the common variation, but the residual differences are far from noise and remain informative.

To better understand how centrality metrics individually or collectively explain diversification and income, I will next use regression models. The first set of regression models examines diversification and its growth using our network centrality measures[2]. While most of the literature focuses on the effect of complexity metrics on GDP per capita and its growth, the mechanism runs through diversification. In the Product Space framework, central products tend to open paths to other products through their dense

[2] The strong correlation coefficient among our variables of interest leads to a potential problem of multicollinearity. Before determining the model specifications, it is necessary to check the VIF (Variance Inflation Factor) for different groups of variables. Table 2 shows that the problem of multicollinearity is not excessive; all VIF values are below 10, unless ADC and ACC are used together. Hence, I will run regression models without ADC and ACC together as independent variables.

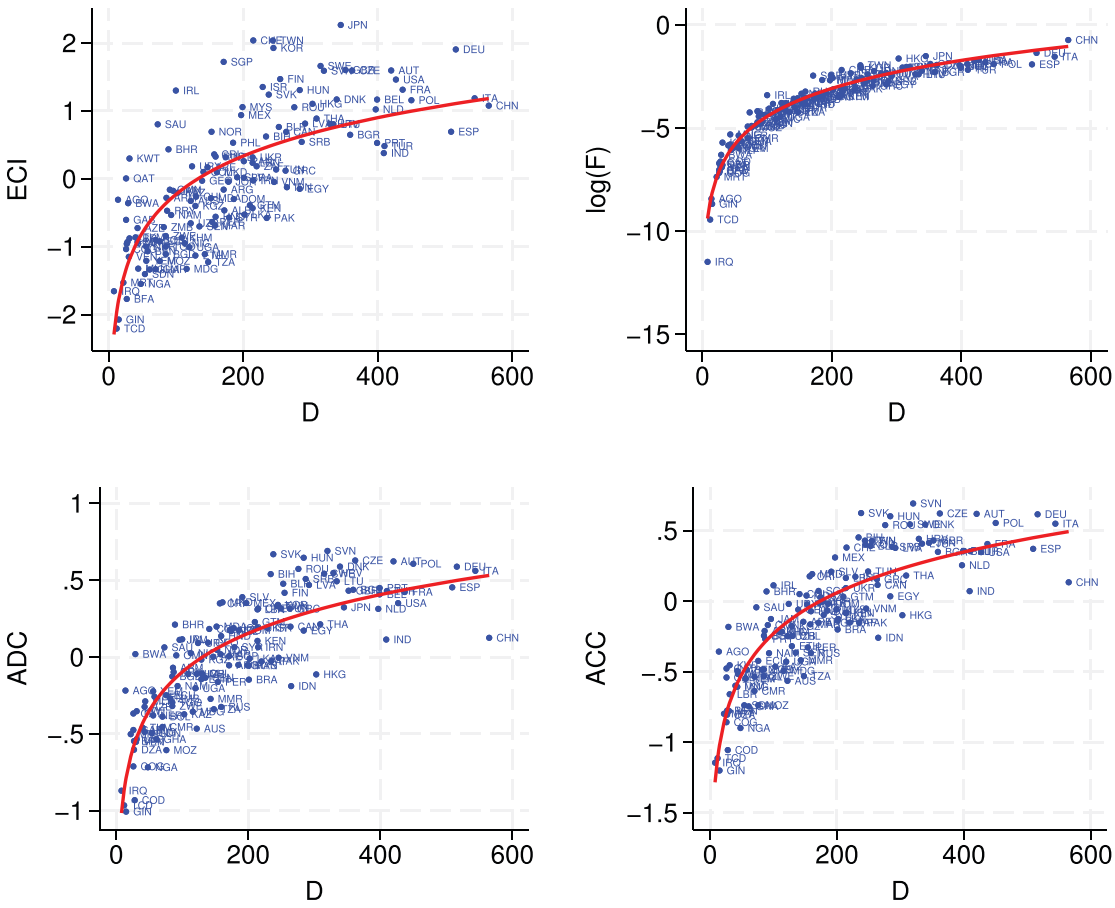


Figure 2. Centrality vs diversification (2019).

connections. Therefore, a country that holds a central position in the network is expected to display a more diversified export basket. To test this expectation, I regress the logarithm of the number of products, $\log(D)$, on the centrality metrics.

The results in table 3 show that ADC and ACC are stronger predictors of diversification than either ECI or Fitness. Specifications including ADC or ACC yield higher R^2 values than models with ECI and F, and their coefficients are more significant across all estimators. This pattern holds even when country and year fixed effects are controlled for. The interpretation is straightforward: ADC and ACC directly capture how tightly connected a country's export basket is, and baskets with denser links are more likely to be diversified. Their strong positive coefficients highlight the role of network connectivity, even though they are average measures.

Another striking observation is that ECI has a negative impact on $\log(D)$ for a given level of F and ADC or ACC. A possible reason is the high penalty by the ECI metric for diversification due to averaging with respect to the number of products in the basket. The highest-ECI Asian economies have medium levels of diversification. Moreover, oil-exporting Gulf countries have high ECI relative to their low levels of diversification. These are two clusters of countries violating the positive correlation between diversification and the ECI. The clustering interpretation of ECI fits these results in the sense that as these two clusters of countries export similar products, their ECI is similar and high relative to their level of diversification. On the other hand, we cannot observe such cases for ADC or ACC (figure 2) as they do not partition countries based on clusters. For these reasons, ECI has a negative impact on diversification when F and ADC or ACC are kept constant. Moreover, the country fitness, F, has a more significant positive impact than the economic complexity index, ECI. As said before, F is not an average metric; it sums over the products in the basket, while ECI is an average. That is the main reason behind the dominance of F over ECI for the impact on logged diversification.

Table 4 presents regression results for the 5-year change in logged diversification explained by the network variables. The significant negative impact of current diversification on future change is expected: already diversified countries tend to diversify significantly less. ECI has a significant negative impact, and F has a significant positive impact on the log change of diversification. ADC and ACC mostly

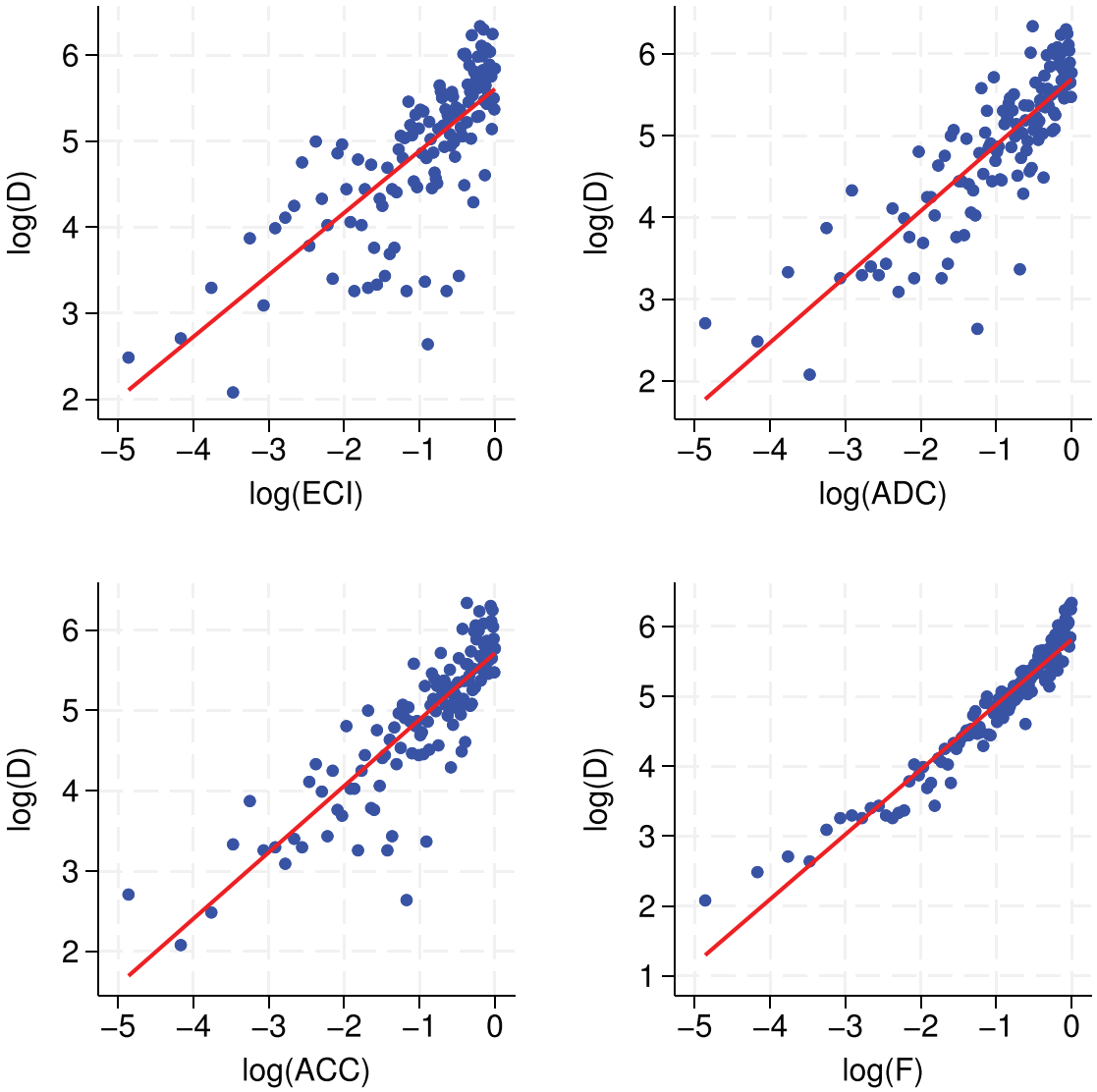


Figure 3. Log-log plots of centrality measures vs diversification (2019).

impact similarly to ECI, with much less significance. The reason why ECI has a negative impact on the future diversification growth is similar to the previous one. When controlled for past diversification and other centralities, the clustering effect of ECI that penalizes current and future diversification takes the stage. On the other hand, a diversification-friendly metric, F, relates positively to future changes in diversification.

The regression results for the level of income, measured as the logarithm of GDP per capita, are reported in table 5. The first striking result is that the ECI is significantly and positively associated with income in OLS specifications, confirming the well-documented complexity-income nexus. However, this significance largely disappears once country fixed effects are introduced, suggesting that ECI primarily captures cross-country differences rather than within-country income dynamics over time. In contrast, diversification ($\log(D)$) has a negative coefficient in almost all specifications, indicating that once the centrality of the export basket is controlled for, simply having more products is not associated with higher income levels. Fitness, F, has mixed results: while its impact is negative or insignificant in OLS models, it turns significantly positive in fixed-effects models. This suggests that once basket size, country, and year fixed effects are accounted for, the fitness of a country's export basket contributes to higher income levels. In this setting, fixed effects absorb the pure scale component of export size, leaving Fitness to capture relative basket composition conditional on size.

Interestingly, ADC and ACC behave very similarly to ECI in explaining income levels individually. While they show positive and highly significant coefficients in OLS specifications, their significance largely weakens in fixed-effects regressions, like ECI, as their explanatory power is driven mainly by cross-country variation rather than by within-country dynamics over time. The results of the income

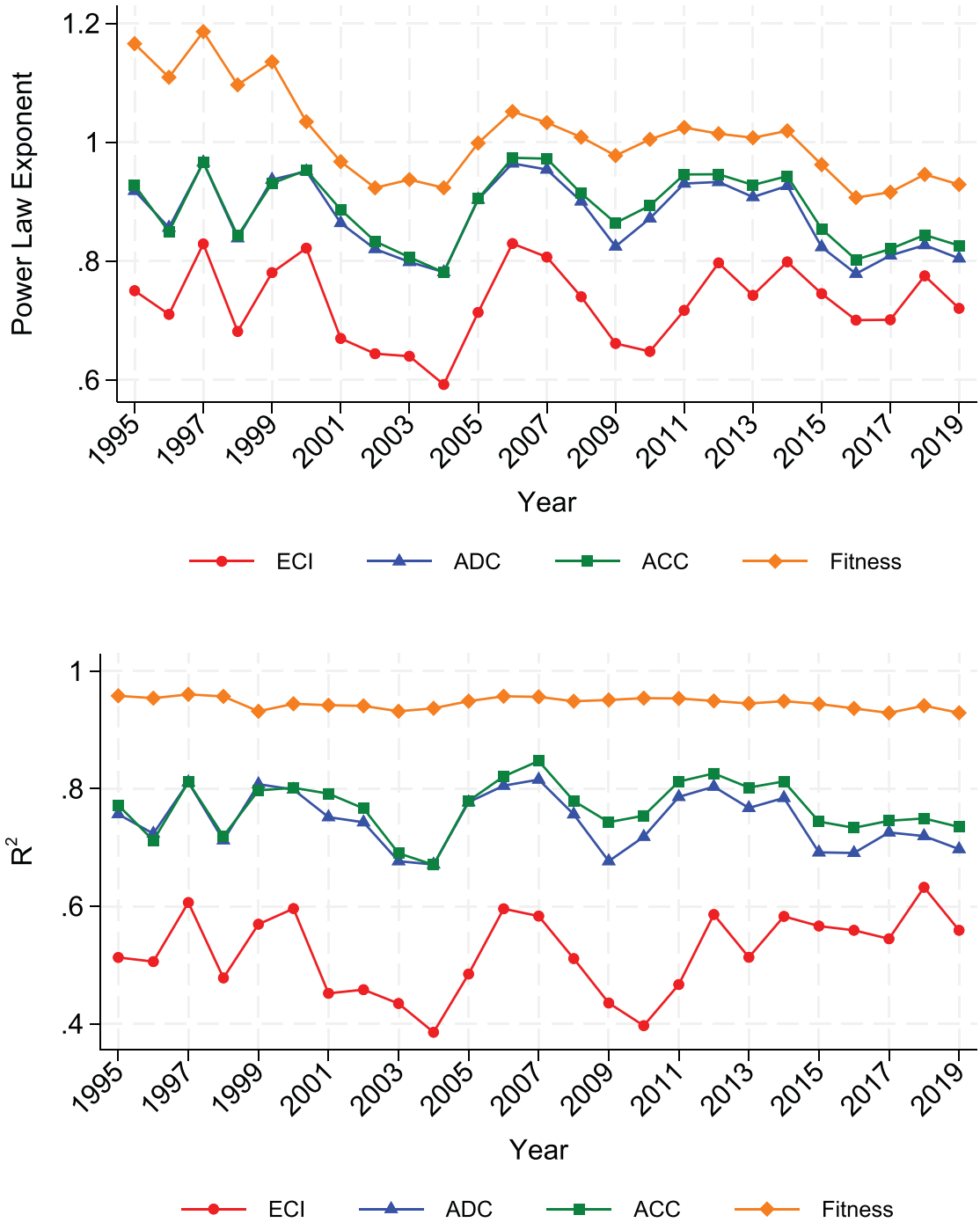


Figure 4. Power-law exponents and R^2 of log-log regressions over time.

regressions show that ECI and *F* are not the only measures capturing income differences. Rather, they are part of a broader set of centrality metrics, none of which dominate across all specifications, but each of which gains or loses explanatory power depending on the model and context.

Turning to the dynamics, table 6 reports the results for 5-year growth in GDP per capita. The strongest and most consistent predictor is the initial income level, which has a negative impact, as expected from income convergence. The results for centrality variables are more mixed. ECI enters positively in OLS models but turns significantly negative in fixed-effects specifications. This pattern indicates that while higher complexity is associated with cross-country income growth, within-country changes in ECI do not necessarily translate into faster growth. Fitness, *F*, also changes sign across estimators: it is negative or insignificant in OLS but becomes strongly positive under fixed effects, suggesting that its contribution is mainly observed in within-country dynamics. ADC and ACC play a secondary role, with

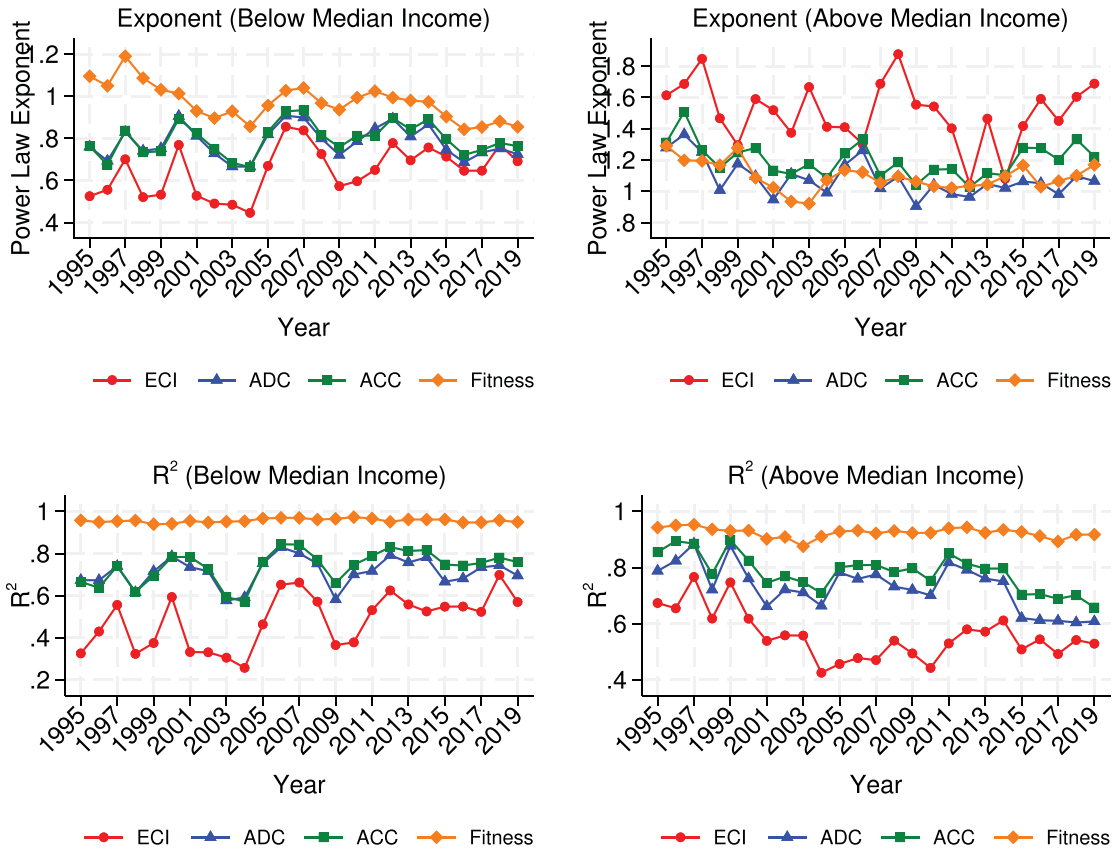


Figure 5. Power-law exponents and R^2 of log-log regressions by income group.

Table 2. Variance inflation factors by specification.

	Model 1	Model 2	Model 3
log(D)	4.72	4.92	
ECI	4.65	6.24	8.48
F	3.36	3.26	2.97
ADC	5.82		83.45
ACC		8.93	122.75
Mean VIF	4.64	5.84	54.41

Table 3. Results of regression models with dependent variable log diversification (log(D_t)).

	OLS Models					FE Models				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ECI_t	0.37***			−0.21***	−0.38***	0.40***			0.04	−0.03
	(4.18)			(−2.96)	(−5.12)	(9.05)			(1.03)	(−0.84)
F_t	5.86***			5.31***	4.66***	2.80***			2.76***	2.65***
	(4.97)			(6.62)	(6.43)	(2.84)			(3.99)	(4.21)
ADC_t		1.99***		1.83***			1.30***		1.15***	
		(19.35)		(10.74)			(19.13)		(12.05)	
ACC_t			1.74***		1.96***			1.20***		1.16***
			(19.51)		(11.81)			(19.94)		(14.72)
R^2_{Within}						0.34	0.52	0.53	0.56	0.56
R^2_{Between}						0.58	0.77	0.78	0.79	0.80
R^2_{Overall}	0.58	0.74	0.75	0.79	0.57	0.51	0.75	0.76	0.78	0.78
Observations	3265	3265	3265	3265	3265	3134	3265	3265	3265	3265

Notes: t-statistics in parentheses. OLS models (1)–(5); FE models with country fixed-effects and year dummies in (6)–(10). Constant terms are included, and standard errors are clustered at the country level.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4. Results of regression models with dependent variable 5-year growth in diversification ($\log(D_{t+5}) - \log(D_t)$).

	OLS Models					FE Models				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\log(D)_t$	−0.07***	−0.03*	−0.04*	−0.07***	−0.07***	−0.88***	−0.84***	−0.87***	−0.88***	−0.90***
	(−5.10)	(−1.84)	(−1.81)	(−4.08)	(−3.62)	(−11.09)	(−12.68)	(−12.60)	(−11.85)	(−11.51)
ECI_t	−0.05**			−0.05***	−0.05**	−0.04			−0.04	−0.06
	(−2.44)			(−2.64)	(−2.46)	(−0.77)			(−0.63)	(−0.93)
F_t	0.95***			0.95***	0.95***	1.73**			1.73**	1.79**
	(3.22)			(3.50)	(3.44)	(2.28)			(2.28)	(2.34)
ADC_t		−0.06		0.00			−0.05		0.00	
		(−1.24)		(0.03)			(−0.60)		(0.05)	
ACC_t			−0.05		0.01			0.01		0.09
			(−1.10)		(0.11)			(0.09)		(0.80)
R^2_{Within}						0.50	0.50	0.50	0.50	0.50
R^2_{Between}						0.03	0.03	0.03	0.03	0.03
R^2_{Overall}	0.06	0.04	0.04	0.06	0.06	0.04	0.04	0.04	0.04	0.04
Observations	2610	2610	2610	2610	2610	2610	2610	2610	2610	2610

Notes: *t*-statistics in parentheses. OLS models (1)–(5); FE models with country fixed-effects and year dummies in (6)–(10). Constant terms are included, and standard errors are clustered at the country level.
$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5. Regression results: dependent variable log GDP per capita (log(GDPPC)).

	OLS Models					FE Models				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\log(D)$	−0.27**	−0.28	−0.57***	−0.36**	−0.40**	−0.06	0.01	−0.06	−0.05	−0.11
	(−2.21)	(−1.52)	(−3.13)	(−2.39)	(−2.48)	(−0.98)	(0.08)	(−0.85)	(−0.64)	(−1.32)
ECI	1.12***			1.05***	0.98***	0.09			0.09	0.05
	(10.89)			(9.00)	(7.61)	(1.12)			(1.02)	(0.49)
F	−0.76			−0.33	−0.30	1.81***			1.78**	1.91***
	(−0.60)			(−0.25)	(−0.23)	(2.73)			(2.55)	(2.81)
ADC		2.22***		0.34			0.08		−0.04	
		(6.45)		(1.15)			(0.69)		(−0.27)	
ACC			2.59***		0.49			0.23*		0.15
			(8.81)		(1.58)			(1.84)		(1.00)
R^2_{Within}						0.56	0.55	0.56	0.56	0.56
R^2_{Between}						0.51	0.31	0.46	0.51	0.50
R^2_{Overall}	0.58	0.33	0.44	0.58	0.28	0.16	0.08	0.13	0.28	0.28
Observations	3215	3215	3215	3215	3215	3215	3215	3215	3215	3215

Notes: *t*-statistics in parentheses. OLS models (1)–(5); FE models with country fixed-effects and year dummies in (6)–(10). Constant terms are included, and standard errors are clustered at the country level.
$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

weaker and less stable coefficients, though they sometimes show positive effects, especially in fixed-effects models.

The high correlations among the centrality metrics (table 1) raise the question of how much they overlap and how much they differ. Principal component analysis (table 7) shows that 86% of the total variation in centrality metrics is captured by one component and 96% by two components. This shows that most of what these metrics capture is common, supporting the claim that they should be used complementarily instead of searching for a single superior metric. It is also interesting to see that all four metrics contribute to the first principal component in a similar way. Hence, the first principal component captures the overall centrality of a country's export basket in the Product Space with all four metrics contributing equally. The second principal component, which captures 10% of the total variation, mostly distinguishes between the cumulative metric Fitness and the average degree and closeness centralities, while ECI falls in the middle. In that way, the second principal component captures the distinctiveness of these centrality metrics. Table 8 presents the previous regressions with the first

Table 6. Regression results: dependent variable 5-year income growth $(\log(\text{GDPPC})_{t+5} - \log(\text{GDPPC})_t)$.

	OLS Models					FE Models				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\log(\text{GDPPC})_t$	−0.07***	−0.06***	−0.06***	−0.07***	−0.07***	−0.58***	−0.58***	−0.58***	−0.58***	−0.59***
	(−5.24)	(−4.55)	(−4.82)	(−5.31)	(−5.30)	(−13.10)	(−12.82)	(−12.76)	(−13.51)	(−13.61)
$\log(D)$	0.01	−0.00	−0.00	−0.00	0.01	0.13	0.03	0.06	0.02	0.03
	(0.42)	(−0.15)	(−0.10)	(−0.03)	(0.32)	(0.94)	(0.38)	(0.56)	(0.16)	(0.26)
ECI	0.05***			0.04*	0.05*	−0.07			−0.15**	−0.17***
	(2.59)			(1.70)	(1.82)	(−1.88)			(−2.57)	(−2.90)
F	−0.27			−0.22	−0.26	1.40**			1.74***	1.68**
	(−1.19)			(−0.92)	(−1.14)	(1.99)			(2.72)	(2.48)
ADC		0.09*		0.04			0.20*		0.39***	
		(1.79)		(0.64)			(1.93)		(2.58)	
ACC			0.08*		0.01			0.12*		0.35***
			(1.83)		(0.13)			(1.69)		(3.00)
R^2_{Within}						0.40	0.39	0.39	0.41	0.40
R^2_{Between}						0.04	0.05	0.05	0.04	0.04
R^2_{Overall}	0.06	0.05	0.05	0.06	0.06	0.05	0.05	0.05	0.05	0.05
Observations	2570	2570	2570	2570	2570	2570	2570	2570	2570	2570

Notes: t-statistics in parentheses. OLS models (1)–(5); FE models with country fixed-effects and year dummies in (6)–(10). Constant terms are included, and standard errors are clustered at the country level.
$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 7. Principal component analysis of centrality measures.

Panel A: Eigenvalues				
Component	Eigenvalue	Difference	Proportion (%)	Cumulative (%)
PC1	3.43	3.02	85.81	85.81
PC2	0.41	0.26	10.23	96.04
PC3	0.15	0.15	3.84	99.88
PC4	0.00		0.12	100.00
Panel B: Eigenvectors (Loadings)				
Variable	PC1	PC2	PC3	PC4
ECI	0.51	0.15	−0.84	0.13
F	0.46	0.78	0.43	0.03
ADC	0.51	−0.50	0.32	0.63
ACC	0.52	−0.35	0.13	−0.77

Notes: Principal Component Analysis is applied to the four centrality measures pooled across all country-years ($N = 3215$).

two principal components. It is not only the first component that has a significant coefficient; in some model setups, where the distinction between Fitness and ADC/ACC is more important, only the second component is significant, or both are. Hence, it is not only the common component that explains some aspects of diversification and income; centrality metrics also have explanatory power on their own. This finding is supported by residualized regressions where F, ADC, and ACC are sequentially orthogonalized with respect to preceding metrics (table 9). Each successive residual explains less, yet there are models where even the orthogonalized ACC, which is residual to all others, has a significant coefficient. These exercises clearly show that although these four centrality metrics have much in common, they can also explain different aspects of diversification and income.

Table 8. Regression results using principal components of centrality measures.

	$\log(D)$		$\Delta^5\log(D)$		$\log(\text{GDPPC})$		$\Delta^5\log(\text{GDPPC})$	
	OLS (1)	FE (2)	OLS (3)	FE (4)	OLS (5)	FE (6)	OLS (7)	FE (8)
$\log(D)_t$			−0.04**	−0.88***	−0.68***	−0.08	−0.01	0.07
			(−2.19)	(−12.75)	(−3.94)	(−1.08)	(−0.37)	(0.59)
$\log(\text{GDPPC})_t$							−0.07***	−0.58***
							(−4.85)	(−12.69)
$PC1_t$	0.44***	0.34***	−0.01	0.03	0.73***	0.11***	0.02**	0.03
	(18.49)	(17.93)	(−0.83)	(1.36)	(10.51)	(2.95)	(2.35)	(0.84)
$PC2_t$	−0.14**	−0.07**	0.04**	0.07*	0.03	0.10***	−0.01	−0.01
	(−2.27)	(−2.33)	(2.27)	(1.74)	(0.28)	(2.70)	(−0.88)	(−0.21)
R^2_{Within}		0.54		0.50		0.56		0.39
R^2_{Between}		0.76		0.03		0.50		0.05
R^2_{Overall}	0.74	0.74	0.05	0.04	0.53	0.28	0.05	0.05
Observations	3215	3215	2570	2570	3215	3215	2570	2570

Notes: *t*-statistics in parentheses. *PC*1 and *PC*2 are the first two principal components of ECI, *F*, ADC, and ACC. FE models include country fixed effects and year dummies. Constant terms are included, and standard errors are clustered at the country level. Δ^5 denotes 5-year growth.
$^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 9. Regression results using orthogonalized centrality measures.

	$\log(D)$		$\Delta^5\log(D)$		$\log(\text{GDPPC})$		$\Delta^5\log(\text{GDPPC})$	
	OLS (1)	FE (2)	OLS (3)	FE (4)	OLS (5)	FE (6)	OLS (7)	FE (8)
$\log(D)_t$			−0.07***	−0.90***	−0.40**	−0.08	0.01	0.02
			(−3.55)	(−11.98)	(−2.46)	(−0.94)	(0.38)	(0.18)
$\log(\text{GDPPC})_t$							−0.07***	−0.58***
							(−5.23)	(−13.14)
ECI_t	0.68***	0.58***	−0.00	0.07**	1.17***	0.21***	0.04*	0.07
	(19.26)	(14.88)	(−0.04)	(2.00)	(10.58)	(3.24)	(1.92)	(1.33)
$F_t^{\perp}$	5.84***	3.21***	0.95***	1.92**	0.01	2.19***	−0.26	1.81***
	(8.07)	(4.99)	(3.49)	(2.50)	(0.01)	(3.07)	(−1.02)	(2.62)
$\text{ADC}_t^{\perp}$	1.83***	1.16***	0.00	0.02	0.41	−0.03	0.02	0.39***
	(11.35)	(12.31)	(0.06)	(0.24)	(1.40)	(−0.22)	(0.36)	(2.62)
$\text{ACC}_t^{\perp}$	2.10***	0.57*	0.07	0.60	2.05	1.48***	−0.47	−0.14
	(3.56)	(1.84)	(0.26)	(1.49)	(1.64)	(3.50)	(−1.55)	(−0.31)
R^2_{Within}		0.56		0.51		0.57		0.41
R^2_{Between}		0.80		0.03		0.44		0.04
R^2_{Overall}	0.80	0.79	0.06	0.05	0.59	0.29	0.06	0.05
Observations	3215	3215	2570	2570	3215	3215	2570	2570

Notes: $F^{\perp}$, $\text{ADC}^{\perp}$, and $\text{ACC}^{\perp}$ are sequentially orthogonalized: each is the residual from regressing the original metric on ECI and all preceding orthogonalized metrics. *t*-statistics in parentheses. FE models include country fixed effects and year dummies. Constant terms are included, and standard errors are clustered at the country level. Δ^5 denotes 5-year growth.
$^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

6. Conclusion

This paper revisits economic complexity indices in their network roots, treating ECI and Fitness as centrality measures in the Product Space, and compares them with degree (ADC) and closeness (ACC) centralities. A large share of the variation across ECI, Fitness, ADC, and ACC is captured by a single common component, yet each metric retains its own explanatory power. ADC and ACC best explain diversification levels, ECI best explains cross-country income differences, and Fitness best captures within-country diversification growth. No single metric dominates across all outcomes.

The key message is that each index reflects a different aspect or location in the network, explaining different portions of diversification and income. They should therefore be used in a complementary manner, guiding policy toward moving export baskets into denser, more accessible neighborhoods of the Product Space, rather than ranking products or countries by a single 'best' score.

The findings and perspectives in this paper have the potential to strengthen the implications of the Product Space for economic growth and development. Each country has a different position and different opportunities in the Product Space to journey towards the core. To guide developing countries, country-specific strategies, even country-specific centrality measures, can be created instead of suggesting products ranked by a single 'superior' complexity metric.

The framework developed in this paper opens several directions for future research. While figure 1 shows that the Product Space is highly persistent over our sample period, the post-2019 period is likely to bring structural shifts that require further research. The COVID-19 pandemic, the wars in Ukraine and the Middle East, and the rapid expansion of strategic sectors such as artificial intelligence and semiconductors are reshaping global trade patterns. A natural next step is to embed the centrality framework in an explicit model of network evolution, in which both the underlying Product Space network and country positions co-evolve. Such a framework would allow us to understand how the network, country positions, and product centralities respond to global shocks that affect trade patterns.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: www.cepii.fr/CEPII/en/bdd_modele/bdd_modele_item.asp?id = 37 [74].

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