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Mapping Economic Opportunities in Global Clean Energy Supply Chains

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The energy transition offers countries that can manufacture clean energy technologies substantial opportunities for sustainable economic growth. This paper provides a framework for context-aware industrial policy by applying economic complexity theory to a newly constructed dataset of twelve key clean energy supply chains (CESCs). We find that CESCs are diverse but highly interdependent; they are also growing faster and are more concentrated than other industries. CESCs exhibit substantial entry, exit and competitive churn, and countries are more likely to enter CESC industries that are related to their existing productive capabilities. We also explore changing global competitiveness and country positioning in these industries, and draw out implications of these patterns for industrial policymakers.

Keywords: clean energy, supply chain, principle of relatedness, economic complexity, industrial policy

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Global decarbonization necessitates rapid deployment of clean energy technologies, like solar, wind, and electrolyzers (Pehl et al. 2017) (International Renewable Energy Agency (IRENA) 2024). This demand growth creates significant economic opportunities for regions that can produce clean energy technologies and products in their supply chains (which we refer to as Clean Energy Supply Chains or 'CESCs') (Bowen and Hepburn 2014; Gernaat et al. 2021; Schmidt and Huenteler 2016; Swilling et al. 2022; Yap et al. 2022; Lennon et al. 2022; Owen et al. 2022; Hausmann 2022).

Many countries seek to capture this economic opportunity with industrial policy to promote manufacturing of energy technologies or their inputs (Liang and You 2023; Foster et al. 2024; Kolcava et al. 2022). Yet policymakers lack clear guides to capitalize on their opportunities in CESCs, leading to one-size-fits-all industrial policies, which can be wasteful and ineffective.

This paper helps fill this void, offering a perspective on industrial policy around manufacturing clean energy technologies, encompassing selection of important industries, assessing dynamics of these industries, and assessing places' context in these industries.

This paper's approach allows us to say several useful things about CESCs that help policymakers create contextually-aware industrial policy. We find that CESCs are diverse and interdependent: they involve many intermediate products, and several inputs are common across supply chains. While many of these supply chain products are widely available, some present serious concerns around risk and supply chain security. CESC industries have fewer exporters than importers, and production in CESCs is more concentrated geographically than in other industries. CESC industries are also growing faster than other industries on average and exhibit substantial competitive entry and exit. That said, some countries (like China and Vietnam) are broadly gaining competitiveness within CESCs, while other countries (like the US and Germany) are broadly losing their competitiveness in CESCs.

This paper situates its perspective within a theory of economic growth called economic complexity (Balland et al. 2022), which posits that regions tend to diversify into industries that are similar to those they already possess (Balland et al. 2022; Hausmann et al. 2022) (a prediction which this paper validates for CESC industries). Diversifying into more, and more complex industries drives growth. Complex industries are industries in which fewer regions can compete: these industries tend to emerge in rich economies with many capabilities, or from countries that control a critical resource (Hausmann et al. 2014). Industrial policymakers seeking economic growth should therefore aim to help their regions diversify into more and more complex industries in CESCs, taking account of which industries are related to their region's current industrial structure.

This paper therefore offers a coherent perspective on how policymakers can create industrial policy around manufacturing clean energy technologies to drive economic growth, that is sensitive to industry and regional context. It also demonstrates a set of analytical tools that industrial policymakers can use in other industries. Alongside this paper, we have developed a data tool, Greenplexity, that aims to help policymakers formulate industrial policy in CESCs.

CESC Selection and Dataset

We create a dataset of twelve supply chains: nine energy technologies which will need to be deployed in very large numbers to decarbonize the world during the energy transition (and their inputs), and three value chains for common intermediate inputs to energy technologies including semiconductors, magnets, and critical minerals. Critical features of our CESCs for industrial policymakers are that these are manufactured goods (and their inputs), for which demand is expected to increase rapidly. Our list of CESCs is neither closed nor comprehensive: policymakers can extend our analysis to other technologies that we have not mapped, and there are other technologies that are important in the energy transition.

Previous research has often focused on sets of industries that are either too narrow or too broad to guide green industrial strategy. Research often focuses on specific product supply chains (Meckling and Hughes 2017; Surana et al. 2020; Helveston et al. 2022; Cheng et al. 2024; Rosenow and Mealy 2024), which can be informative industry studies, but overlook inter-dependencies across chains and synergies arising from multiple complementary technologies. Other research uses lists of products deemed broadly 'green' for different reasons by organizations like the OECD, WTO, and APEC (Mealy and Teytelboym 2022). These lists of 'green' industries are often over-broad, including products that are low-carbon, sustainable, or 'green' in some general sense (like hemp tote bags and bicycles), alongside clean energy technologies. These lists do not focus on manufactured products (and their inputs) for which demand will increase rapidly in the energy transition.

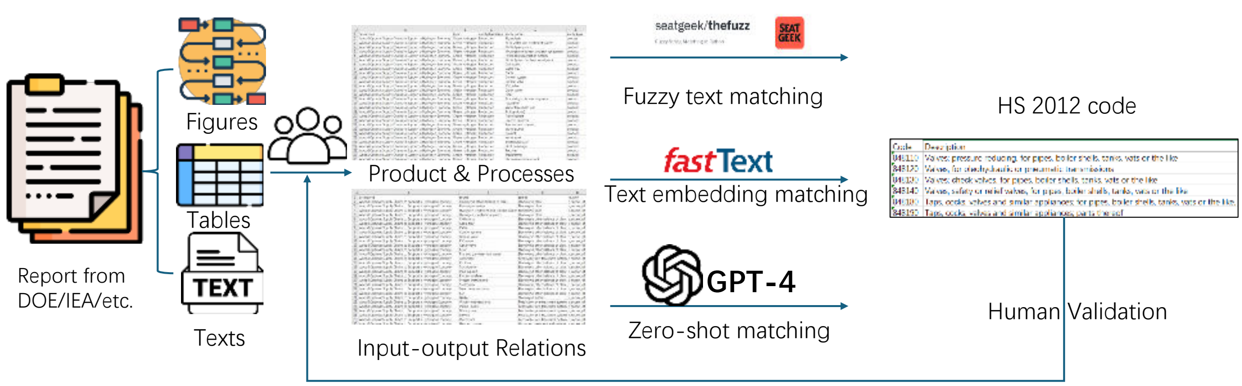
We map value chains for Platinum Group Metals (PG), Carbon Capture (CC), Semiconductors (SC), Electric Grid (EG), Large Capacity Batteries (BT), Heat Pumps (HP), Electrolyzers, Fuel Cells And Green Hydrogen (HY), Solar (SL), Neodymium Magnets (NM), Nuclear Power (NP), Wind (WI), and Hydropower (HD).

We map these value chains using reports from government agencies and industry associations, such as the US Department of Energy and the International Energy Agency. We relate these data to standard Harmonized System (HS) 2012 codes, with the help of experts with subject matter knowledge, and machine learning tools, including ChatGPT and Claude (See Methods and Fig. 1 for details).

Our dataset covers 313 products at the six-digit HS-2012 code level, and 725 input-output directed links to show inputs to clean energy technologies. CESCs involve complex products with many inputs.

In addition to our list of CESCs, we also consider a list of critical minerals (which is largely a subset of our CESC dataset, as inputs to manufactured technologies).

Figure 1: Mapping CESCs through unstructured data



Notes: This figure shows how we built CESCs. We start with published reports from the US Department of Energy and the International Energy Agency for different CESCs. We identified products, processes and input-output relations. Using machine learning and AI techniques and human validation, we arrive at the Harmonized System Codes (2012 edition) for products.

Analyzing Production Patterns in CESCs

CESCs are Highly Interdependent

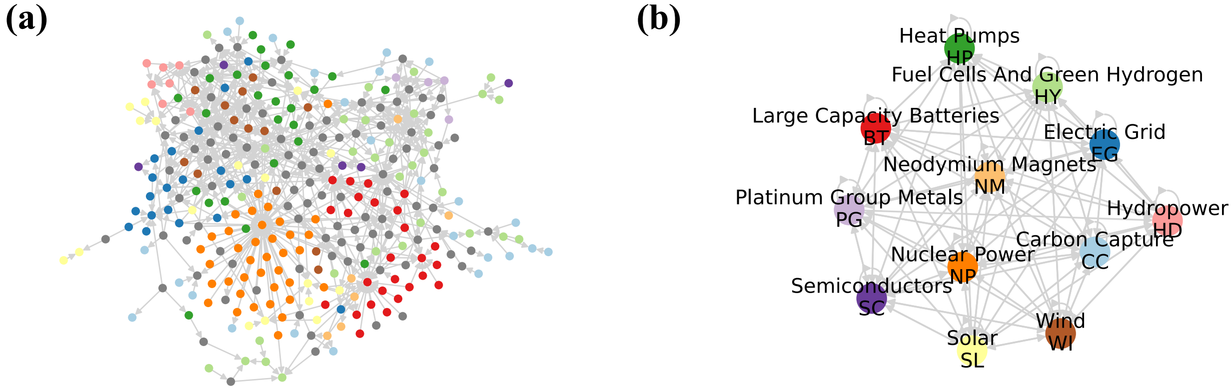
CESC products are closely connected and interdependent. Each CESC shares products with at least one other CESC, and CESC input-output relations are sometimes cross-chain. Fig. 2a illustrates these products and their supply chain linkages as a network diagram. The network in Fig. 2a has an average degree of 2.3 (implying that only 0.7% of the potential pairs of nodes are connected), which indicates a sparse network. The average path length between CESC products is 3.02 and the network diameter is 8, which suggests that most products within CESCs are closely connected to each other: on average there are about three edges or links between any pair of products in CESCs. Put another way, each CESC product is typically connected to each other CESC product by an average of two intermediaries. Overall, this suggests a sparse but well-connected network, with many 'bridging' products, common inputs, capability spillovers and critical dependencies. Fig. 2b shows these interdependencies with edge weights representing the overlap between different chains, highlighting interdependencies across each pair of chains (Lei et al. 2023).

This has implications for industrial policymakers: because CESCs are very interdependent, policymakers should consider CESCs as a whole when assessing industrial policy, rather than focusing on any single energy technology or CESC in isolation. This interdependence implies that there are capability spillovers and risk propagation channels between green supply chains.

CESCs Have Fewer Exporters Than Importers

Manufacturing in CESCs is more concentrated than consumption. On average, fewer countries competitively produce in CESCs than purchase CESC technologies and their components. Fig. 3b shows this nested structure, by visualizing countries' export and import values of CESC products as heatmaps. CESC products are more nested in their production and more widely demanded, and CESC industries are also more concentrated in their production than the average industry (See caption for Fig. 3b).

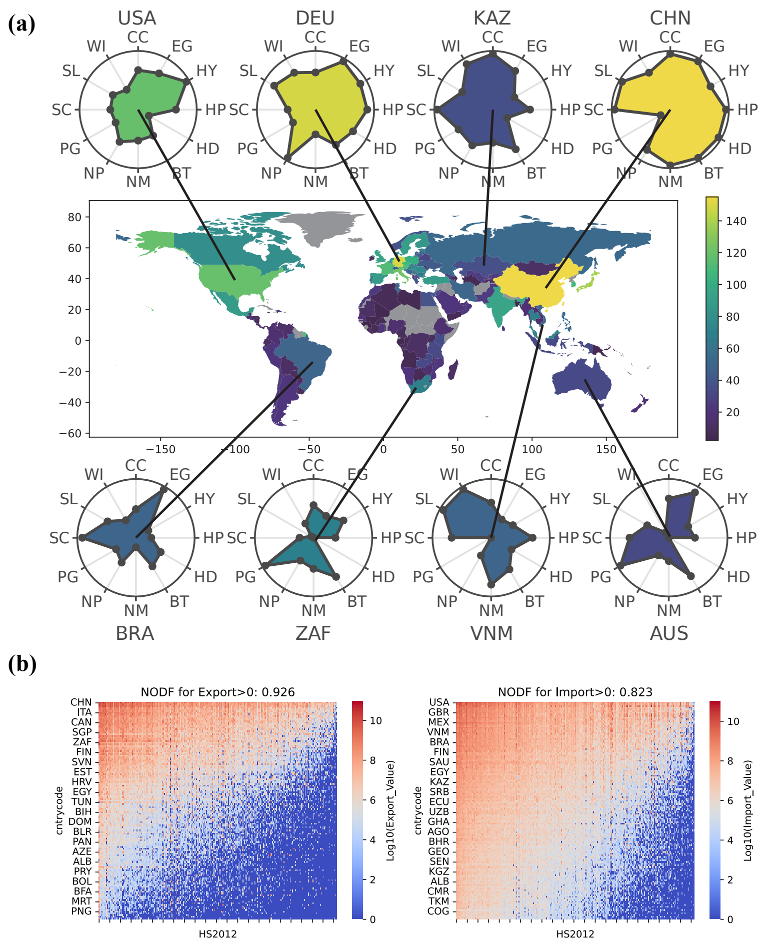
Figure 2: CESC Product Networks



Notes: (a) Visualization of CESCs. Supply chain relationship between identified clean energy supply-chain products. Each node is a product, and products are connected if they have a supply chain relationship. Colors reflect supply chains (grey for multiple chains). Detailed visualization for each chain is in the supplementary information Fig. S4. (**b)** Interdependency of the CESCs. Relationship between CESCs based on shared products. Each node is a supply chain and edges indicate common products and up/downstream relationships between these supply chains. Colors same as in (a); labels including full name and abbreviation.

This suggests that few countries have competitive manufacturing industries across many parts of CESCs, and that more countries may demand these products than will supply them. It also suggests that countries should not seek to become self-sufficient in production across CESCs as a whole: because production is more concentrated than consumption, industrial policymakers should focus on localizing production in the parts of CESCs where their region can realistically be competitive, while procuring most CESC products from globally competitive suppliers. High export nestedness means latecomers tend to enter a subset of 'easier' products first; only a few countries sit at the diversified apex.

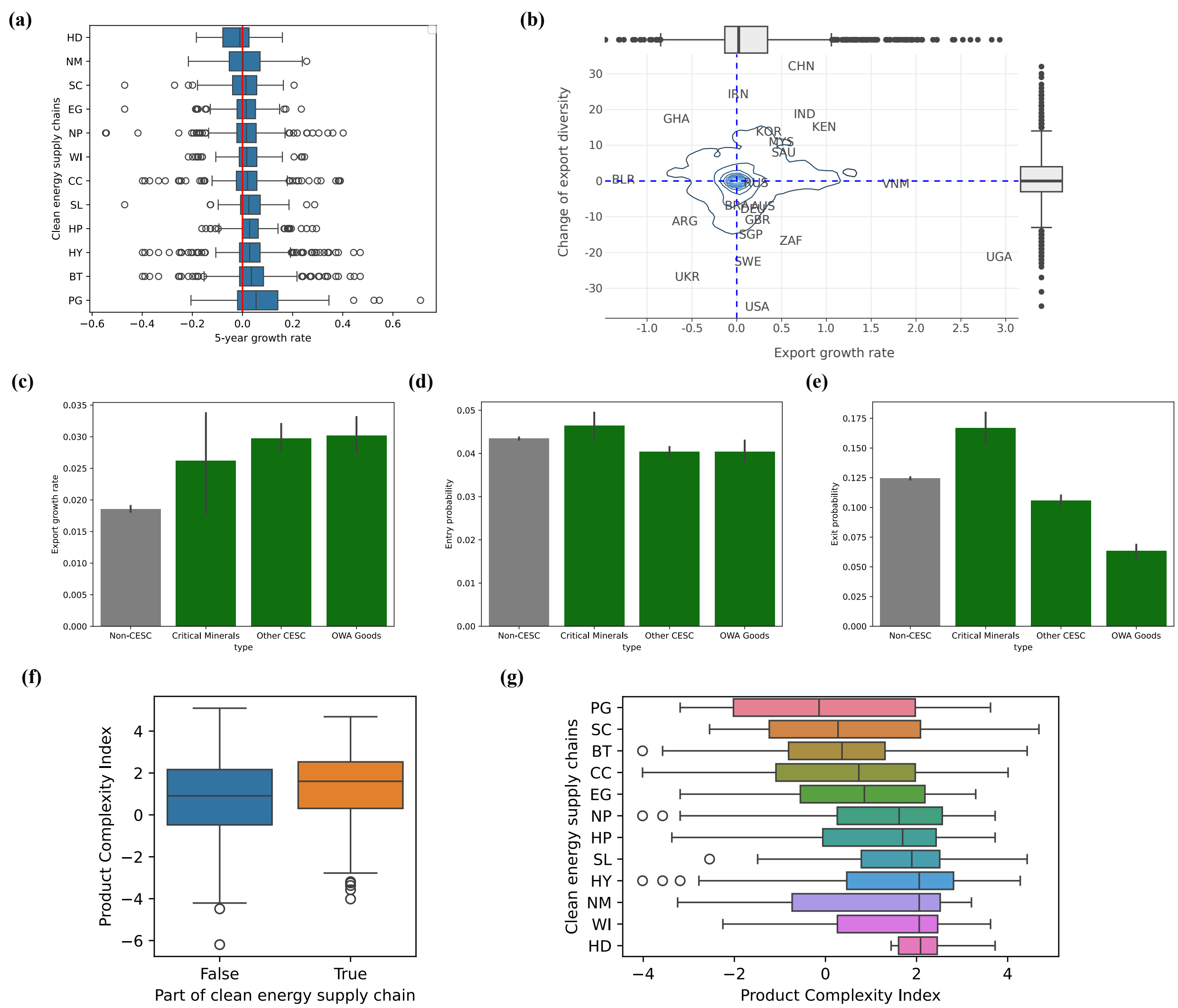
Figure 3: CESC Diversity and Concentration



Notes: (a) Map and radar plot of CESC diversity. In the world map, countries are colored based on the number of CESC products with RCA > 1. In the radar map, we show country and supply chain specific participation in CESCs. Each CESC is normalized with the country with maximum products present in that supply chain. (**b)** Nestedness of CESC trade. The NODF metric, commonly used in ecology and economic complexity research (Mariani et al. 2019) quantifies this nestedness pattern (Almeida-Neto et al. 2008), taking a value between 0 and 1, with higher values indicating a more nested pattern. NODF values are 0.926 and 0.823, for export and import patterns respectively. This export NODF value is higher, and import value lower, than for non-CESC products (which take values 0.898 and 0.888 respectively), indicating that CESC products are more hierarchical in their production and more widely demanded.

These patterns are unsurprising: More complex countries can competitively produce many CESC products, while less complex countries can produce fewer CESC products. CESCs, like many manufacturing industries, exhibit increasing returns in production arising from economies of scale and learning effects, leading to path dependence (Bücker et al. 2025; Zaussinger et al. 2025), and industries where a few regions become more competitive than most others (Autor et al. 2023). We also expect more complex parts of CESCs to locate only in the few regions that have the right capabilities to support these industries (Balland et al. 2022).

Figure 4: Dynamics of CESC Products



Notes: **(a)** 5 year growth rate of trade value across CESCs in international trade data. **(b)** Export volume growth vs change in diversity. Diversity is calculated as the number of products above RCA of 1. **(c)** Export growth rate over 2017-2022. (**d**) Entry probability between 2017 and 2022. Entry is defined as going from an RCA of below 0.05 in an industry to an RCA of above 0.25 five years later. **(e)** Exit probability between 2017 and 2022. Exit amounts to a country's RCA declining from above 1 to below 0.25 five years later. **(f)** Comparison of Product Complexity Index (PCI) distribution of CESC products and the rest of the products. PCI values are calculated as described by (Hausmann et al. 2014). **(g)** Distribution of PCI of products in each supply chain. Abbreviations of CESCs as in Figure 2 (b).

Growth Rates and Complexity

CESC industries are attractive industrial policy targets because they are growing fast, and many countries have opportunities to participate in CESCs, because CESCs encompass a diverse range of industries.

CESC industries are growing faster than non-CESC industries, making these value chains strategic economic development opportunities (Fig. 4c). Nonetheless, some CESCs, and CESC products, offer better growth opportunities than others: mature CESCs, like the Hydropower supply chain, are growing slowly, while emerging supply chains are growing faster (Fig. 4a).

CESCs involve a diverse range of high, medium and low complexity products, implying many countries have capabilities to diversify into some parts of these chains. CESC products are of similar complexity to traded products outside CESCs (Fig. 4f), according to the Product Complexity Index (PCI) (César A. Hidalgo and Hausmann 2009), with substantial variation within and across chains (Fig. 4g).

Diversification in CESCs

Related Diversification Shapes CESC Evolution

Countries are more likely to enter CESC industries that are related to their existing industrial bases (Table 1a). These findings are consistent with the literature on related diversification (Balland et al. 2022; Hausmann et al. 2022; César A. Hidalgo 2023).

We assess how similar a country's industrial base is to a new industry using a metric called 'density' (C. A. Hidalgo et al. 2007). The density of a product in a country is defined as the average prevalence of all other industries in the country, weighted by their relatedness to the product of interest.

Table 1a shows that density predicts countries' growth and entry across many industries, with slightly better predictions for CESC products than for non-CESC products (see Methods for regression calculations). On the intensive margin, a one standard deviation increase in density is associated with an approximately 14% higher growth rate for CESC products, and of 13% for non-CESC products over five years; on the extensive margin, a one standard deviation increase in density is associated with an approximately 11% higher entry probability for CESC products, and 12% for non-CESC products. These differences between CESC and non-CESC products are not statistically significant.

Density more strongly predicts whether a country enters or grows its presence in CESC industries than upstream, downstream, input-output linkages, or other supply chain relationships (Tables 1b and 1c).

Role of Input-Output and Supply Chain Relationships in CESC Diversification

Having other industries in the same supply chain, upstream industries, or input-output relationships also correlates with growth of industries in CESCs, but the effect sizes are small (Table 1b). Input-output relationships may also be weakly associated with whether a country enters new CESC products.

This supports previous work, which finds that density more strongly predicts diversification than do supply chain relationships (Bahar et al. 2019). This work also found that countries have a statistically significant likelihood of moving up a supply chain by producing inputs to products they already competitively produce. By contrast, our results suggest that countries have a statistically significant likelihood of moving down a supply chain by producing products downstream of those they already produce. Our sector-specific CESCs capture much more granular relationships than aggregated input-output data tables used in previous literature, which may explain this difference.

Implications for Industrial Policy

Economic complexity research has found that countries tend to diversify into products related to their existing industrial base (Balland et al. 2022; Hausmann et al. 2022). This context therefore shapes countries' optimal industrial strategy in CESCs: policymakers may optimally target diversification into clusters of similar industries within CESCs, rather than aim to diversify vertically up and down a single CESC. They should also design industrial strategy that leverages existing domestic capabilities (where available), or attracts and develops new capabilities (if few related capabilities are available domestically).

Table 1: Growth, Entry and Exit into CESC Products

a: Documenting related diversification for CESC and non-CESC products

Dependent Variables:	growth			entry		
Model:	all	CESC	non-CESC	all	CESC	non-CESC
Variables						
logexp0	-0.4132***	-0.4309***	-0.4139***			
	(0.0122)	(0.0187)	(0.0124)			
density	0.1291***	0.1390***	0.1287***	0.1257***	0.1086***	0.1260***
	(0.0110)	(0.0179)	(0.0111)	(0.0095)	(0.0239)	(0.0097)
Fixed-effects						
HS2012	Yes	Yes	Yes	Yes	Yes	Yes
cntrycode	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	343,132	23,182	319,950	411,127	21,735	389,392
R^2	0.20003	0.20993	0.20052	0.05822	0.07686	0.05788
Within R^2	0.13243	0.14026	0.13249	0.00569	0.00317	0.00575

b: Growth of CESC products

Dependent Variable:	growth									
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables										
logexp0	-0.3656***	-0.4309***	-0.3687***	-0.4328***	-0.3693***	-0.4337***	-0.3663***	-0.4311***	-0.3699***	-0.4336***
	(0.0173)	(0.0187)	(0.0172)	(0.0187)	(0.0173)	(0.0187)	(0.0173)	(0.0187)	(0.0174)	(0.0188)
density		0.1390***		0.1373***		0.1378***		0.1384***		0.1372***
		(0.0179)		(0.0178)		(0.0179)		(0.0179)		(0.0179)
log(n_io+1)			0.0040***	0.0034***						
			(0.0009)	(0.0009)						
log(n_upstream+1)					0.0041***	0.0038***				
					(0.0008)	(0.0008)				
log(n_downstream+1)							0.0015**	0.0009		
							(0.0007)	(0.0007)		
log(n_samechain+1)									0.0154***	0.0125***
									(0.0041)	(0.0041)
Fixed-effects										
HS2012	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
cntrycode	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics										
Observations	23,182	23,182	23,182	23,182	23,182	23,182	23,182	23,182	23,182	23,182
R^2	0.19717	0.20993	0.19839	0.21081	0.19868	0.21120	0.19740	0.21002	0.19821	0.21061
Within R^2	0.12638	0.14026	0.12770	0.14121	0.12802	0.14164	0.12662	0.14036	0.12750	0.14100

c: Entry into CESC products

Dependent Variable:	entry								
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables									
density	0.1086***		0.1073***		0.1091***		0.1070***		0.1086***
	(0.0239)		(0.0237)		(0.0237)		(0.0239)		(0.0239)
log(n_io+1)		0.0022***	0.0020**						
		(0.0008)	(0.0008)						
log(n_upstream+1)				0.0013*	0.0013*				
				(0.0008)	(0.0008)				
log(n_downstream+1)						0.0014	0.0011		
						(0.0009)	(0.0009)		
log(n_samechain+1)								0.0006	0.0004
								(0.0017)	(0.0017)
Fixed-effects									
HS2012	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
cntrycode	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics									
Observations	21,735	21,735	21,735	21,735	21,735	21,735	21,735	21,735	21,735
R^2	0.07686	0.07445	0.07731	0.07413	0.07708	0.07419	0.07702	0.07394	0.07687
Within R^2	0.00317	0.00056	0.00365	0.00021	0.00341	0.00028	0.00334	0.00001	0.00317

*For all regressions, clustered (HS2012 & cntrycode) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Density regressions for evolution of CESC products. Dependent variable *growth* is logged yearly growth rate (2014-2019), *entry* is 1 if country has RCA < 0.05 in 2014 and RCA > 0.25 in 2019, otherwise 0. Variable logexp0 is logged export value in 2014, *density* calculated based on 2014 trade data, *n_upstream* / *n_downstream* are the number of direct upstream / downstream products with RCA ≥ 1 for focal product, *n_io* is the sum of both upstream and downstream products, and *n_samechain* is the number of product in the same supply chain of the focal product. All dependent variables are mean-standardized.

Supply chain relationships may be weakly relevant to industrial policy in CESCs, but the effect sizes are small and directions are ambiguous, both in our analysis, and in the literature. Industrial policymakers may sometimes be able to diversify into upstream or downstream industries in CESCs, but whether doing so is advisable likely depends on contextual considerations that may not be captured in our analysis.

Analyzing Country Context in CESCs

Country Positioning within CESCs

Some countries are better positioned than others in CESCs. We use Balassa's Revealed Comparative Advantage (RCA) measure to assess countries' positioning in CESCs: RCA measures in which CESC products a country has a comparative advantage. Fig. 3a shows the number of CESC products each country has a comparative advantage in with RCA larger than 1, which we refer to as the 'diversity' of a country in CESC products.

Countries may be stronger in some supply chains and weaker in others. Fig. 3a shows eight countries' relative strengths across the twelve CESCs that we map, using radar maps. These maps demonstrate, for example, that China has high diversity in almost all chains, but South Africa is better positioned in the Platinum Group Metals chain.

Changing Country Competitiveness Within CESCs

As CESC industries are generally growing fast, absolute growth rates can mask strategic weakness or deteriorating competitiveness across CESCs as a whole.

Many countries are growing their total exports of CESC products (i.e., intensive margin growth), shown in the x-axis of Fig. 4b. But some countries are gaining (and some are losing) comparative advantage in CESC products (i.e., divergent extensive margin growth), shown in the y-axis of Fig. 4b. While growth in exports in CESCs is valuable (x axis), a country's diversity in CESC products (y axis) represents a proxy for the country's competitiveness in CESCs as a whole. This gives four different strategic diagnoses:

1. Countries on the top-right quadrant of Fig. 4b are both scaling and broadening their presence in CESCs. They are winners in the energy transition.
2. Countries in the bottom-right quadrant are scaling and narrowing their presence in CESCs. They are specializing and risking lock in.
3. Countries on the top-left quadrant are broadening without scaling their presence in CESCs. They are diversifying, but not yet at competitive scale.
4. Countries in the bottom-left quadrant are losing ground: narrowing and not scaling their presence in CESCs.

Diversity across CESCs matters because diversifying into more, and more complex industries drives growth. The economic complexity literature suggests that countries with a lower diversity of different, complex industries face more challenging economic growth paths. Policymakers in countries that experience declining diversity across CESCs may wish to design industrial strategy to build and maintain competitiveness in more complex CESC industries, to reverse their decline in diversity of CESC industries, even if their exports in CESCs as a whole are growing absolutely.

CESC industries exhibit substantial churn, with countries regularly gaining and losing competitiveness over time. Churn rates are broadly comparable to non-CESC industries. In the extensive margin, countries have a roughly four percent probability of entering a CESC industry in any given five-year period (see Fig. 4d). Trade data suggests entry into both CESC and non-CESC industries became harder during the six years from 2017 to 2022. Countries also have around a ten percent probability of losing competitiveness in any given CESC industry over a five-year period (see Fig. 4e). Entry and exit rates are broadly similar for non-CESC products, while critical minerals have slightly higher entry and exit probabilities, and varying growth rates compared to other CESC products (Fig. 4d and 4e). Critical mineral mining therefore offers good, but volatile, development opportunities.

These churn rates suggest that opportunities in clean energy value chains are still very much open to countries that are able to develop capabilities to compete in these industries.

Conclusion

This paper offers a perspective on a distinct type of green industrial policy: manufacturing high-growth energy technologies and their inputs. It situates this perspective within a well-supported theory of economic growth called economic complexity: that places tend to diversify into industries related to the ones they already host, which share common underlying capabilities, and that diversifying into more and more complex industries drives growth.

To operationalize this perspective, this paper generates a dataset on clean energy supply chains (CESCs), analyzes the structure of CESCs, and outlines implications for industrial policymakers who seek to evaluate economic opportunities in these industries.

Key takeaways are that policymakers should consider CESCs together in industrial strategy: focusing on a single chain would overlook opportunities and risks that arise from CESC interdependencies. Building an industrial base across several CESCs might be synergistic, while risks in one supply chain might suggest vulnerabilities in another, connected chain.

CESC industries are very diverse, are growing healthily, and have substantial entry and exit. This suggests that CESC industries are good industrial policy targets, and that they continue to present many industrial opportunities for regions with a wide range of different industrial structures.

Some countries are broadly gaining competitiveness across CESCs, while other countries are losing competitiveness. Countries are likely to diversify into parts of CESCs that are related to their existing productive structure, and these adjacencies in productive capabilities matter more than supply chain relationships in shaping diversification.

Industrial policymakers should consider their region's context in CESCs when forming industrial policy. A region's existing diversity across CESCs, and whether it is gaining or losing industries in CESCs as a whole, should shape industrial policy priorities. Low or declining diversity across

CESCs suggests policymakers should support their region in becoming competitive across more (and more complex) CESC industries, as diversifying into more and more complex industries drives growth. Since countries are likely to diversify into related CESC industries, and relatedness of CESC industries matters more than supply chain relationships, industrial policymakers should target ‘clusters’ of related CESC industries, rather than primarily aim to move up or down a single value chain.

Methods

Identifying CESCs from unstructured data

In published reports from the US Department of Energy and the International Energy Agency, experts have collectively depicted rich details of various CESCs. However, the knowledge of CESCs was scattered in figures (esp. flowcharts), tables (esp. material list) and texts, which are hard to utilize and not unified across chains.

In our work, research assistants with subject matter knowledge identified "entities" of processes and products and the input-output "relations" between entities mentioned in these reports, to create a knowledge graph in "property graph" representation. The graph contains 961 nodes of processes and products, and 1217 directed edges that indicate the direction of material flows.

This knowledge graph was further standardized using the HS2012 product classification, which unifies entities from different chains (e.g. ``Polysilicon" in Semiconductor chain but ``polycrystalline silicon" in Solar PV) and with different granularity (e.g. ``Stainless Steel 441" as a subset of ``Stainless Steel"), and enables analysis using existing international trade and other datasets. Standardization used full product descriptions of HS 6-digit codes to conduct fuzzy matching by strings and semantic matching by *Fasttext* embedding vectors, together with a GPT-4-based few-shot prompt, which returned the top-5 candidates for each entity. Research assistants would manually review each option and decide if the candidate HS codes were a valid option. The original knowledge graph was then reduced to a HS 6-digits code-based graph and further validated through manual review to correct missing and erroneous entities/links. The finalized network is shown in Fig. 2a.

International trade data and complexity metrics

With HS codes of CESCs identified, the analysis relies on processed international trade data, publicly available at the Atlas of Economic Complexity website and the Harvard Dataverse (The Growth Lab At Harvard University 2024), which uses a mirroring methodology to clean raw UN Comtrade data. Trade data with HS2012 classification was used for analysis throughout for consistency across years.

Revealed comparative advantage (or the Balassa index/location quotient) is a common way to evaluate the prevalence of a product in a country's export basket:

$$\mathrm{RCA}_{cp} = \sum_{c} \frac{X_{cp}/X_{.p}}{X_{c.}/X_{..}} \tag{1}$$

The prevalence measure RCA_{cp} can be binarized with a cutoff value. The product with a higher RCA than the natural threshold 1 is usually considered competitive in the global market. We refer to these values with M_{cp}:

$$M_{cp} = \begin{cases} 1 \text{ if } \mathrm{RCA}_{cp} > \text{cutoff} \\ 0 \text{ otherwise} \end{cases} \tag{2}$$

The relatedness between products can be measured in numerous ways (Li and Neffke 2024). The most widely used way is based on the co-occurrence of products with comparative advantage at the country level, where proximity is defined as the minimum conditional probability of observing a product conditioning on the existence of another product:

$$\phi_{pq} = \min\{P(M_{cp} = 1 | M_{cq} = 1), P(M_{cq} = 1 | M_{cp} = 1)\} = \frac{\sum_c M_{cp} M_{cq}}{\max(\sum_c M_{cp}, \sum_c M_{cq})} \tag{3}$$

Density is a commonly used metric in economic complexity analysis, which captures the capability needs of a product and the capabilities present in a location. It is calculated by the weighted sum of the related products present in the region of interest, c for a product p:

$$d_{cp} = \frac{\sum_{q \in I_{p,k}} \phi_{pq} \mathrm{M}_{cp}}{\sum_{jq \in I_{p,k}} \phi_{pq}} \tag{4}$$

where $I_{p,k}$ is the set of k most closely related (i.e., *nearest neighbor*) products to product p, and ϕ_{pq} is the relatedness between product p and q. In some cases, the continuous RCA metric is used instead of the prevalence metric, M.

Analyzing the evolution of CESC products with density regressions

In the growth regressions, we use the following specification:

$$\log \frac{E_{cp,t+\Delta}}{E_{cp,t}} = \beta_1 \log E_{cp,t} + \beta_2 d_{cp,t} + \beta_3 X_{cp,t} + \delta_c + \delta_p + \epsilon_{cp,t} \tag{5}$$

where $E_{cp,t}$ is the export value of product p in country c in year t, Δ is the time horizon (we often take it to be 5 years), $d_{cp,t}$ is the density in year t, $X_{cp,t}$is a set of controls, δ_c is the country fixed effect and δ_p is the product fixed effect. In growth regressions, we limit our sample set to country product pairs with $E_{cp,t+\Delta} > 0$ and $E_{cp,t} > 0$.

For the extensive margin, **product entry regression** follows:

$$I_{c,t,t+\Delta}^{entry} = \beta_1 d_{cp,t} + \beta_2 X_{cp,t} + \delta_c + \delta_p + \epsilon_{cp,t} \quad \text{if} \quad \text{RCA}_{cp,t} < 0.05 \text{ and } p \notin P_{nat} \tag{6}$$

where $I_{c,t,t+\Delta}^{entry}$ is equal to 1 if $\text{RCA}_{cp,t+\Delta} > 0.25$ while $\text{RCA}_{cp,t} < 0.05$ and P_{nat} is the set of natural resource products. We control for the natural resource products since entry into these products is partly related to geographical presence of resources rather than capability accumulation. And the **exit regression** follows:

$$I_{c,t,t+\Delta}^{exit} = \beta_1 \log E_{cp,t} + \beta_2 d_{cp,t} + \beta_3 X_{cp,t} + \delta_c + \delta_p + \epsilon_{cp,t} \quad \text{if} \quad \text{RCA}_{cp,t} \geq 1 \tag{7}$$

where $I_{c,t,t+\Delta}^{exit}$ is equal to 1 if $\text{RCA}_{cp,t+\Delta} < 0.25$ while $\text{RCA}_{cp,t} \geq 1$.

The regressions are estimated with 2-way fixed effects and clustered standard errors, using the *fixest* package (Bergé 2018) in R, as reported in Table 1.

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Data Availability: Data will be made available upon request.

Code availability: The analysis in this study was done using Python and the code is available upon request.

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