Product Relatedness and Latent Production Potential of Green Goods in the EU: Evidence from International Trade Flows*

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Abstract

This paper exploits the AIPNET dataset on production linkages to develop a novel relatedness measure between products and to map countries' latent production capacities across 6-digit HS codes. Using Comtrade data paired with AIPNET one-degree network linkages, we propose a new proximity measure and construct two indicators of latent production potential: vertical and horizontal latency. We test ex-post our potential measures by estimating probability surfaces of RCA emergence between 2017 and 2023, finding that higher starting latency scores are associated with increasingly higher probabilities to develop revealed comparative advantages in the next 6 years. After demonstrating that these measures represent a "promise" for future competitiveness, we use them to evaluate the EU's production potential across some key green technologies and their components in 2023. We interpret our results through the lens of ongoing industrial policy debates in the European Union and suggest potential policy conclusions on clean-tech and strategic supply chains. More broadly, the proposed tool allows policymakers to identify latent production capabilities and supply-chain linkages, thereby informing targeted industrial policy, procurement decisions, and innovation support for strategic and environmental goods.

Keywords: Product Relatedness, Production Potential, Industrial Policy, Clean-Tech Goods, Supply Chains

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1. Introduction

1.1. Motivation

The European Green Deal has recently attracted fierce political and popular criticism which could harm the delivery on the pre-established net-zero objectives of the European Commission and on the transition to a greener economy. The transition is both an economic and political opportunity for the European Union. Member states can reap the economic benefits of tapping into growing international markets for cleantech products, providing a boost to European export demand and investment. In addition, the green transition represents a strategic opportunity for the bloc to reduce significantly, or altogether, its reliance on foreign trading partners in the procurement of energy or raw materials. The main criticisms revolve around the larger and uneven costs that European firms face across member states, and the additional loss of competitiveness with their international peers. This is even more so a pressing issue as some EU members are increasingly fiscally constrained and the European Commission politically struggles to increase their pool of available resources. These differences across member states have also fuelled different national support regimes to the industrial sector, further enhancing distortions in the single market. In other words, the European green transition policies are fundamentally a coordination problem.

Hence, the debate around the need for structural changes in the industrial sector of the European Union, and in fact that of any other individual country, needs to be approached strategically. The few resources available should be allocated effectively, focusing on the existing latent production capabilities of European sectors and industries. Uncovering these latent capabilities are key to understanding the bloc's existing strengths and weaknesses across and alongside green supply chains. We must know the likely EU member states are to specialize in proximate industries and sectors, as well as the potential development paths of EU's supply chains vertically and horizontally. Such considerations would yield better-designed policies, an improvement in the allocation of resources dedicated to the green transition. The approach should consider that not all EU member states are equally positioned to expand into the same green industries, meaning that "one-fit-all" policies are likely to worsen the coordination problem across member states. Ultimately, a more strategic approach may decrease the political backlash and resistance to the EU's environmental policy agenda.

Industrial policy has not been a leading topic in EU policy, however things are changing in the last years. The Recovery and Resilience Facility (RRF) has been characterized as a coordinated, albeit delegated to member states, effort to step up the climate transition, restructuring the composition of public investment towards climate transition related capital goods. On the private corporate side, the European Commission has undertaken a significant shift in its approach to state aid, moving from a strict prohibition model toward a more flexible compatibility framework particularly when measures are aligned with EU wide policy objectives. By leveraging instruments in the renewed state aid toolbox, the Commission now facilitates targeted public aid to support industrial goals, such as green technologies, innovation, and strategic autonomy. In 2025, the EC released a conference paper titled "State Aid Control as a Coordinating Instrument for EU Industrial Policy in the Internal Market" that describes this effort (Hornkohl and Pelekis [1]).

More broadly, with the launch of the Green Deal in 2019, the European Union set ambitious targets for the climate transition, aiming to make Europe the first carbon-neutral continent. The rise in energy costs following the conflict in Ukraine could have been a trigger for an accelerated transition, but other external challenges were in action: the growing success of the substantial industrial interventions in China (launched back in 2015 with the Made in China program through aggressive subsidies to domestic producers) and the large package launched in the United States (via the Inflation Reduction Act), prompted the EU to pursue a more centrally coordinated response. The recent Net-Zero Industry Act (NZIA) and the Clean Industrial Deal reflect this effort, in order to capture the full economic benefits of the green transition and to strengthen European manufacturing capacity in net-zero technologies. These initiatives aim both to accelerate the technological progress required to meet climate targets and to position the transition as a driver of economic growth and competitiveness. All these efforts represent efforts by European institutions to drive industrial policy through both demand and supply-side support. As coordinated efforts from governments in Europe, and elsewhere, increasingly pursue active industrial policies, it becomes essential to discern between established competitive advantages, latent potential and the production linkages between products and industries.

1.2. The EU's Standing in "Green" International Markets

It is difficult to define "green", "net-zero" or "clean-tech" goods because the effort to reduce greenhouse gas emissions embedded in products, processes, activities, or technologies can have multi-faceted outcomes. There are many definitions, lists, and concepts that attempt to create a modular and comprehensive definition. It is quite natural to refer to some well-defined products that easily represent the category, along with the products that are connected to them in terms of production. Following the lead of the International Monetary Fund's Climate Change Indicators Dashboard, starting from two sets of products, one dealing with low-carbon technologies and the other reflecting environmental goods, it is possible to compile a single list in which there are 224 different products identified with their corresponding 6-digit HS code, out of over 5000 products. From now on, we will focus on this set of products with the name of clean-tech goods.

Clean-tech goods, are expected to expand their share in the global consumption basket. As shown in the 2024/25 EIB's Investment Report [2], EU's export of clean-tech goods grew substantially more than the US one in the period between 2017 and 2023, but slightly less than the Chinese one, and with an extreme heterogeneity among EU member states. Focusing on the key products that feature prominently in the climate transition debate — such as solar panels, electric vehicles (EVs), wind turbines, batteries, heat pumps, and electrolysers — the picture is both complex and highly heterogeneous. For some of these products, the European Union is a major exporter. This is notably the case for electric vehicles and wind turbines, where EU firms maintain a significant presence in global markets. In other segments, however, the EU relies heavily on imports for both intermediate inputs and finished manufactured products. A large share of batteries used in electric vehicles, for example, is sourced from abroad. Dependence is even more pronounced in the case of solar panels, where the EU is almost entirely reliant on imports. It is a net importer (but also selling a lot abroad) of heat-pumps and a net exporter (but also importing a lot) of electrolysers.

Coming back to the full set of clean-tech goods, between 2017 and 2023, the European Union's exports in these products increased by more than 25%, totalling 266 billions USD in 2023 up from 212 in 2017. Export destinations are quite diversified, although three buyers really stand out: China, USA and the United Kingdom. Together, they absorb about 40% of the total volume of extra-EU clean-tech exports. The fourth largest importer in 2017 was,

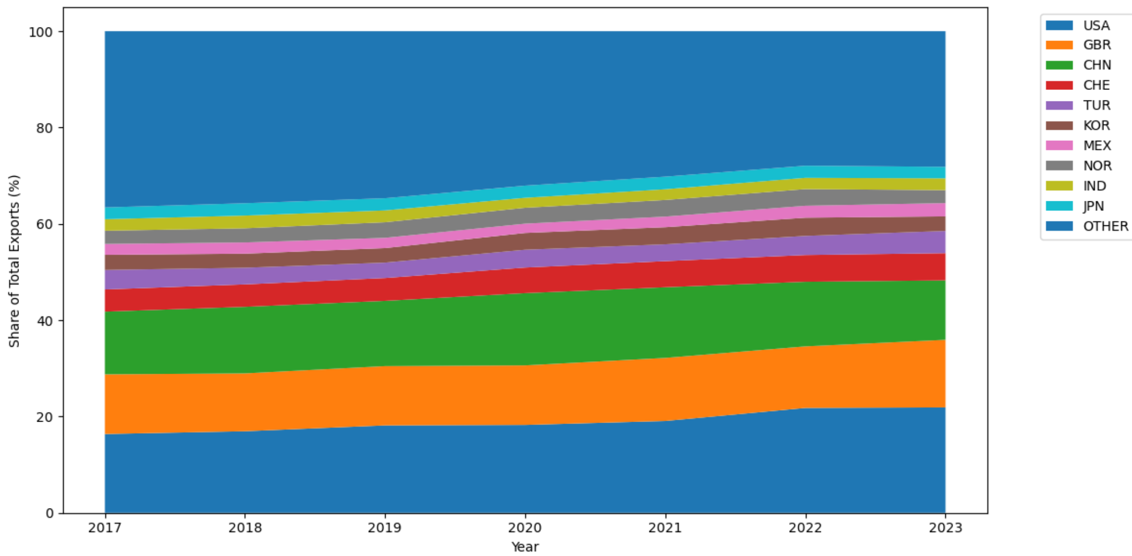


Figure 1: Shares of EU Clean-Tech Exports by Main Destination Markets (excluding Russian Federation)

somewhat surprisingly, the Russian Federation, whose direct export volumes have plummeted after 2021. In 2023, the largest importer of European clean-tech goods after the main three importers was Switzerland for a total volume of more than $17 billions. However, if one disaggregates EU flows to individual member states, it can be observed that approximately two thirds of clean-tech exports of member states stay within the European Union, highlighting the fact, ultimately, the biggest market for European environmental products is the European Union itself.

If we turn again our attention to the European bloc as an individual entity, the picture for the origin of EU imports in clean-tech goods is less varied. Between 2017 and 2023, the total value of these imports went from 147 to 243 billions in 2023 US dollars. Of these, in 2023 about 65% come from four countries: China, the US, the UK, and Japan. While increasingly less in recent years, the EU still is a net exporter for these products. Moreover, Figure 2 certifies some of the dependencies that the European still holds in such sectors, above all its reliance on China which accounts roughly for 30% of all environmental products. More than half of EU clean-tech imports come from 3 countries – China, USA, UK. EU exports well, mostly to other EU members, some dependencies on imports.

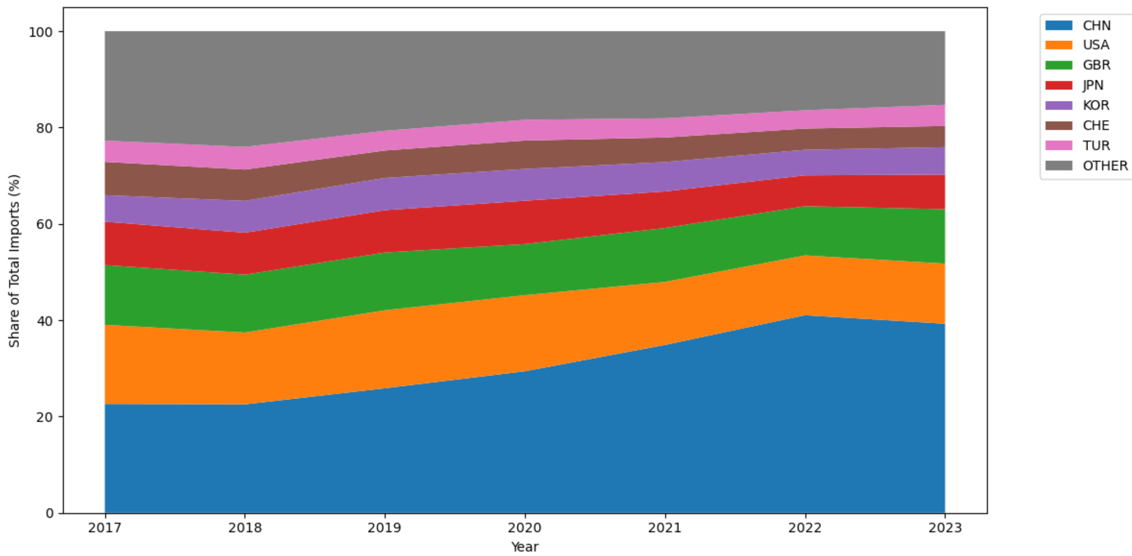


Figure 2: Shares of EU Clean-Tech Imports by Main Partners

2. Literature Review

The literature at the intersection between international trade and the climate transition is large and expanding. Starting from the former, the contributions that constitute the base of our analysis trace back to the concept of revealed comparative advantage (RCA), used to describe a country's specialization within the product space, that was introduced by Balassa [3]. The stability of these advantages over time has been examined by Proudman and Redding [4] and Brasili et al. [5]. These studies estimated the intra-distribution dynamics of RCAs across time for each country, using non-parametric techniques (such as stochastic kernels, originally applied in growth literature by Quah [6] or through mobility measures derived from transition matrices (as we do here). A key idea is that a more dynamic distribution of specialization may indicate a country's greater readiness to adopt new and pervasive technologies, required in period of intense structural transformations. Hausmann et al. [7] and Lall et al. [8] introduced the notion that not all exports are equal, suggesting that the composition of a country's export basket may be linked to its future growth trajectory. Using China as an example, they observed that by the early 2000s, its export basket resembled that of higher-income countries, demonstrating a level of sophistication exceeding domestic consumption patterns, which was interpreted as a potential driver of future growth. To quantify this sophistication, Hausmann et al. [7] proposed two indices: PRODY (at the product level) and EXPY (at the country level). The first index (PRODY) captures product sophistication. It is defined as the weighted average of the per capita GDP of exporting countries, where the weights reflect each country's revealed comparative advantage in the given product. The second index (EXPY) combines a country's trade specialisation with this measure of product sophistication. It corresponds to the weighted average of PRODY values, where the weights are given by the share of each product in the country's total exports. In the 2024/25 EIB's Investment Report [2], these concepts were applied to the clean-tech goods confirming the fact that their role in terms of share in world export is growing and their average PRODY level is growing; it shows also that the EXPY level of EU countries (limited to this subset of goods) is growing.

Hidalgo et al. [9] and Hausmann et al. [10], introduced new definitions of complexity and relatedness. They introduced a network visualisation known as the Product Space built on the structure of RCA; products are linked to each other based on the probability of being co-exported, with this probability calculated from the RCAs. Mealy and Teytelboym [11] provide a comprehensive analysis by linking an extensive classification of clean-tech exports to measures of product proximity and complexity similar to those in Hidalgo et al. [9], Hidalgo et al. [12] and O'Clery et al. [13]. Using relatedness indicators, they demonstrate how clean-tech diversification opportunities can be identified as potential targets for industrial policy. Their analysis shows that clean-tech exports did not grow faster than other product categories during the period under their review (1995-2014), but arguably, as said, this has changed in recent years. Huberty and Zachmann [14] used the concept of RCA and relatedness to analyse the prospects of clean-tech goods in Europe, concluding that supporting final consumer demand can be the right thing to do if and when the domestic supply is strong enough to support this increased demand, as happened for Denmark and Germany. This is not necessarily the case anymore; in their definition of the strength of the supporting sectors they use the same definition of proximity given by Hidalgo et al. [9] and based on the probability of competitively co-export a pair of products. Hamwey et al. [15] described the clean-tech product space for Brazil trying to identify the products for which the country was likely to become competitive in the future. They conclude that the map and the relatedness to competitive products is not the only factor determining the potential, but one should also take into account the existence of clean-tech services, production methods and resource intensities.

Another recent contribution with important policy implication is Pienknagura [16], which uses local projections to estimate the impact of trade policies in promoting imports of LCT technologies. It broadly finds that lower tariffs foster the diffusion of clean-tech goods and that more protectionist measures would impede the spread of the associated technologies. Hausmann et al. [17] focusing on South Africa, explore how policy may facilitate knowledge spillovers, learning-by-doing, and technological advancement linked with clean-tech export and production. Building on the same theoretical foundation, Pérez-Hernández et al. [18] offer industrial policy recommendations for countries in the Southern Cone (Argentina, Brazil, Chile, Paraguay, and Uruguay). In the European context, a recent report by the European Investment Bank (EIB) and the European Commission (DG GROW) (European Investment Bank and DG GROW (European Commission) [19] provides an integrated perspective using both macroeconomic and micro-level survey data, analysing trade dynamics, product complexity, global value chain adaptation, and firm-level responses. Additionally, the work in Capliez et al. [20] uses the case study of lithium batteries to analyse the positioning of the various players in the value chain for the specific technology, highlighting the significant dependencies of EU countries and suggesting ways in which it can reduce such dependencies. Our study is embedded in this strand of the literature. Its main contribution is the use of a new definition of proximity founded on the work of Fetzer et al. [21]. Their AIPNET dataset provides very granular information by enumerating the inputs required for each product on a HS 6-digit grid. The combination of this dataset with computed revealed comparative advantages allows us to define two new, different and highly granular but interrelated concepts of latent production potential.

3. Data & Methodology

We use two datasets in our methodology: UN Comtrade and AIPNET. We use Comtrade bilateral trade flows with annual frequency at the 6-digit HS code level between 2017 and 2023.

The AIPNET dataset comes from the work in Fetzer et al. [21]. It is an AI-generated production network at the 6-digit HS codes level that produces a list of all upstream and downstream linkages between products. We use their production networks to extract the upstream inputs of any HS product, so that we know "what goes into what" for any HS product in Comtrade bilateral flows data. These upstream product linkages are time-invariant vectors and they do not change over the years.

Finally, we identify clean-tech products by using the IMF list of low carbon technologies integrated with some additional codes introduced in the HS 2022 classification. The list comprehends 224 products at the 6-digit HS level which are listed by the organization as environmental goods. This will be our identifier for clean-tech goods in this work, but the methodology is flexible to different identifying strategies and is applicable to other fields of strategic industrial policy design. Using international trade flows at the 6-digit HS code level represents a trade-off: it increases the granularity of our results at the expense of the more aggregated picture. This also restricts us from using trade in value-added instead of total gross export values as a bilateral measure to estimate competitiveness between countries.

The specialization of country i in product p is measured by the ratio of its share of world exports in sector k to its share of total world exports. This measure is commonly referred to in the international trade literature as the Revealed Comparative Advantage (RCA) index. The index is bounded so that $RCA_{ip} \in [0, \infty)$, with RCAs higher than 1 indicating a comparative advantage of country i in product p. In other words, a country is considered to have a comparative advantage (relatively to other goods) in exporting (and hence producing) p if the product represents a higher share of its basket of exports than for the basket of export for the world.

$$RCA_{ip} = \frac{\frac{x_{ip}}{\sum_j x_{ip}}}{\frac{x_{ip}}{\sum_i \sum_j x_{ip}}} \tag{1}$$

This was one of the metrics used in the 2025 EIB's Investment Report to assess the position of the European Union in the trade of such goods. Overall, this will be our measure to assess whether a country is capable of producing something more efficiently than the average, hence our proxy of production performance. As shown later in Equations 3 and 4, the analysis focuses on whether RCA values exceed the threshold of one rather than on the distribution of RCA scores themselves. For this reason, we do not normalize RCA values in our calculations. Our methodology then moves to the definition of "proximity" and "relatedness". As pointed out in the previous section, we exploit the AIPNET dataset to suggest a new measure to estimate how similar any pair of goods is. In general, we consider two goods being similar and proximate in our production network in two ways:

1. Whether product j is an input of product p (vertical proximity)
2. How similar are inputs for products j and p (horizontal proximity)

While being similar, the two measures are fundamentally different. The first one, which we will call "vertical proximity" from now on, simply pairs products that are linked in the production network. In other words, vertical proximity is built on the basis of the direct upstream-downstream pairs in the AIPNET dataset, and takes the form of a binary matrix in which the cell (p, j) is set at one if the product p is one of the direct vertical inputs of j. The matrix is not symmetrical because if the product pair $(p, j) = 1$, i.e. p is a direct vertical inputs of j, the opposite cannot be true so that $(j, p) = 0$. Moreover, the matrix does not have, by construction, the diagonal matrix because at this level of disaggregation no product can be an input of itself unlike in more aggregated sources like input-output tables. Conversely, horizontal proximity takes into account the whole production network by calculating the percentage of shared inputs for any pair of 6-digit HS codes. This generates a 5612×5612 symmetric matrix with a diagonal equal to 1, since any product shares 100% of inputs with itself and given that the share of common inputs for pairs (p, j) and (j, p) are obviously identical. Because any pair of goods may have a different total number of input, we calculate the share by using as denominator the product with the most number of upstream products. It would make little sense to have different proximity scores for pair (p, j) and (j, p). In mathematical terms, the horizontal proximity matrix scores are estimated with the following formula:

$$\phi_{p,j} = \frac{|I(p) \cap I(j)|}{\max\{|I(p)|, |I(j)|\}} \tag{2}$$

where:

- (p, j) is a product pair
- $I(k)$ is the set of direct upstream inputs to any product k

In other words, two products can be "proximate" if there are directly linked or are made up by the same items. These are novel measures that we think are useful in grasping the connections between products in the network. Vertical proximity simply links pairs of goods that are directly connected in the production process, while horizontal proximity allows to compare more nuanced connections across supply chains. The two diagrams below are the graphical representation of the two proximity measures, the vertical one being a binary outcome and the horizontal one being a continuous measure bounded between 0 and 1.

Figure 3: Vertical Proximity - Binary Relationship

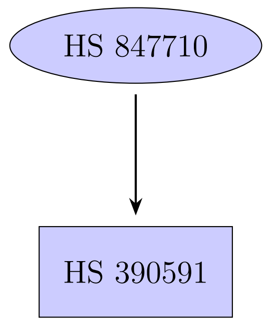
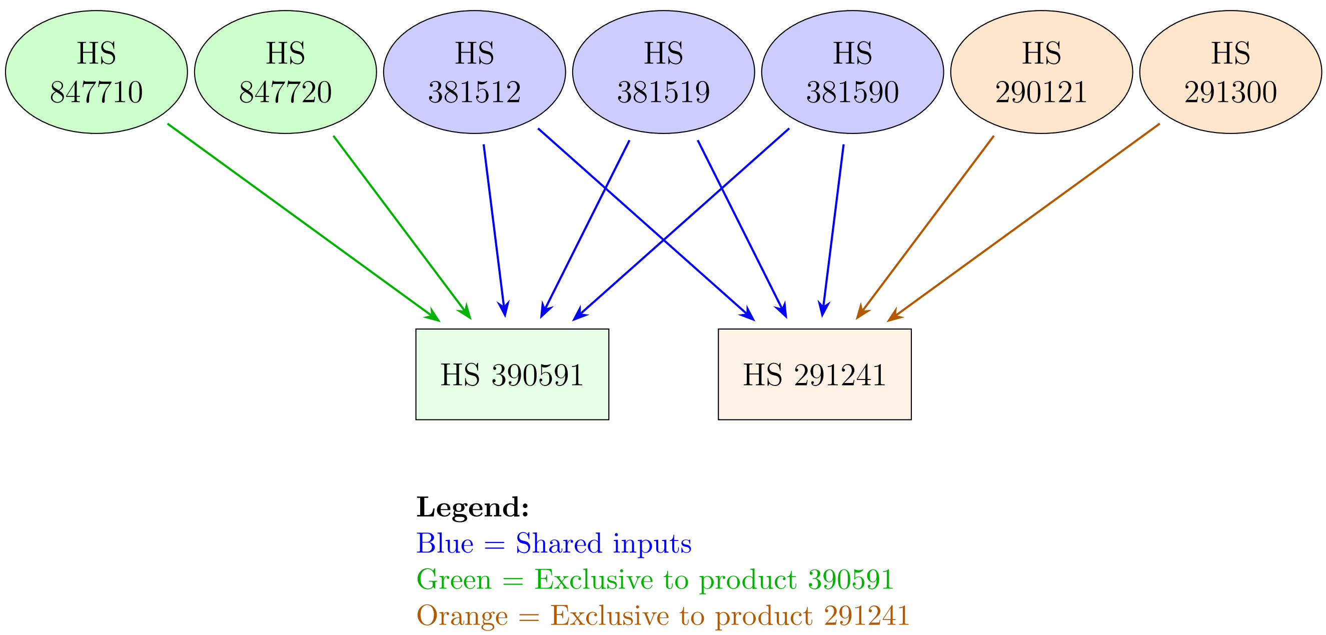


Figure 4: Horizontal Proximity - Unit Relationship



At this stage, we have a granular measure of competitiveness for each country-good pair and two measures of relatedness for any pair of goods at the 6-digit HS level. We can combine the information to estimate measures of inputs competitiveness for any country-product pair, giving us an indication on the latent production potential of country c in product p at time t. In particular, we use the binary matrix for vertical proximity to calculate the share of inputs for product p country c is competitive in. We call this measure "vertical latency" (VL), expressed in mathematical terms as:

$$L^{v}_{p,c,t} = \frac{1}{|I(p)|} \sum_{i \in I(p)} \mathbf{1}\{RCA_{i,c,t} > 1\} \tag{3}$$

Each country-product pair scores between 0 and 1, with 1 indicating that a country already competitively produces all inputs of product p. In other words, the score for vertical latency tells us something about the potential for a country to move vertically to develop new clean-tech industries. Because we are also interested in the characteristics of goods within the whole product space, we use the symmetric matrix for horizontal proximity to calculate the following "horizontal latency" (HL) measure:

$$L^{h}_{p,c,t} = \frac{\sum_{j \neq p} \phi_{p,j} \cdot \mathbf{1}\{RCA_{j,c,t} > 1\}}{\sum_{j \neq p} \phi_{p,j}} \tag{4}$$

This formulation of the latency measure yields the proximity-weighted average of RCAs for the whole product-space of any product p in country c. Each country-product pair scores between 0 and 1, with 1 indicating that a country already competitively produces all products that share at least one input with product p. The score shows a country's potential to diversify competitively across supply chains. We assign an RCA of 0 in each latency measure for any input of product p that country c does not export. It is identical to the specification of a density measure in Hidalgo et al. [9], but diverges in the chosen measure for relatedness.

This is the generalized version of our methodology that can be applied to the entire collection of 6-digit HS products and countries over the years. The last step is to introduce our identifier for clean-tech goods to single out the latent potential of countries in the production of these products. The same methodology can be exploited to study the status-quo or the development of specific countries, or bloc of countries, in the production of specific products. It can be used to study vertical and horizontal supply chains alike.

4. Results

4.1. Proximity Matrix

The proximity score proposed in the methodology can be seen as a substitute (or complementary) measure of relatedness as famously suggested in Hidalgo et al. [9]. Hidalgo's original measure of similarity between products was computed as a symmetric matrix of conditional probabilities for any product pair $\{ij\}$ in country c. In particular, Hidalgo et al. [9] assigns proximity scores by estimating the probability that country c has a revealed comparative advantage in product i given that it holds a comparative advantage for j. In mathematical terms that is:

$$\phi_{ij} = \min\{\mathbb{P}(RCA_{c,i}|RCA_{c,j}), \mathbb{P}(RCA_{c,j}|RCA_{c,i})\} \tag{5}$$

This measure was grounded in the assumption that the relatedness of any two products was highly correlated with the ability of country to export both competitively to international markets. In simpler terms, if, on average, countries specializing in the export of cotton garments tend to export competitively linen garments, then it must be there two products are similar. In our methodology, instead, we exploit the newly-developed AIPNET to abstract from the concept of revealed comparative advantage as a measure of relatedness. This relaxes the assumption that countries specialize production in individual "clusters", reducing potential outliers driven by structural or geographical characteristics of nations. Moreover, the identification of production networks through trade data is a good approximation, but not necessarily an accurate one. For instance, if a country's exports of two goods are both overwhelmingly routed to a single neighbour or hub (very concentrated partner shares) or if the same customs re-exporting centre appears in the trade paths, that pattern suggests geography or transit effects rather than shared domestic capabilities. Such methodology also allows for these relationships between products to change considerably over time, even within a relatively small time interval, which conflicts with the notion of more time-invariant relationships in a product space.

It is important to highlight that the direct linkages for any product pair in AIPNET represent a one-degree network of a single focal product. In other words, linkages between products represent direct inputs into the production of the finished product without tracing the whole supply chain, but enabling to tell something about the product space and immediate production networks around individual products. The more abstract concept of an AI-generated "upstream" or "downstream" relation between two products may help refining these proximity scores. As previously presented in Equation 2, we use AIPNET linkages at the 6-digit HS code level to estimate proximity scores between any pair of commodities. This exercise yields, just like in Hidalgo et al. [9], a symmetric 5277 x 5277 matrix for proximity scores for the whole product space which is independent of time-variant relationships and dependencies.

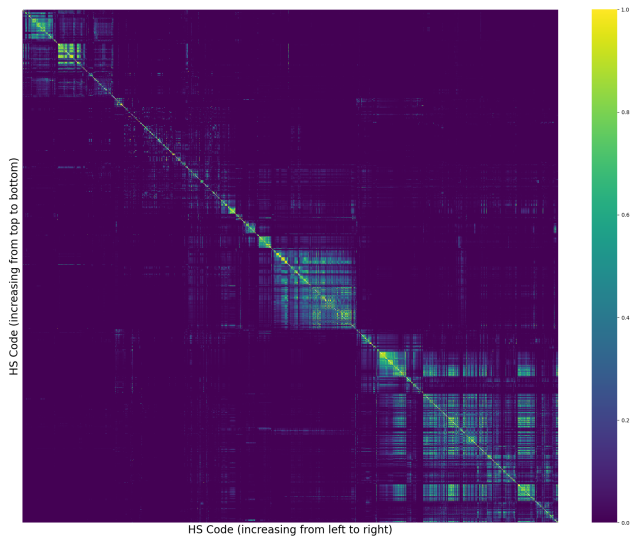


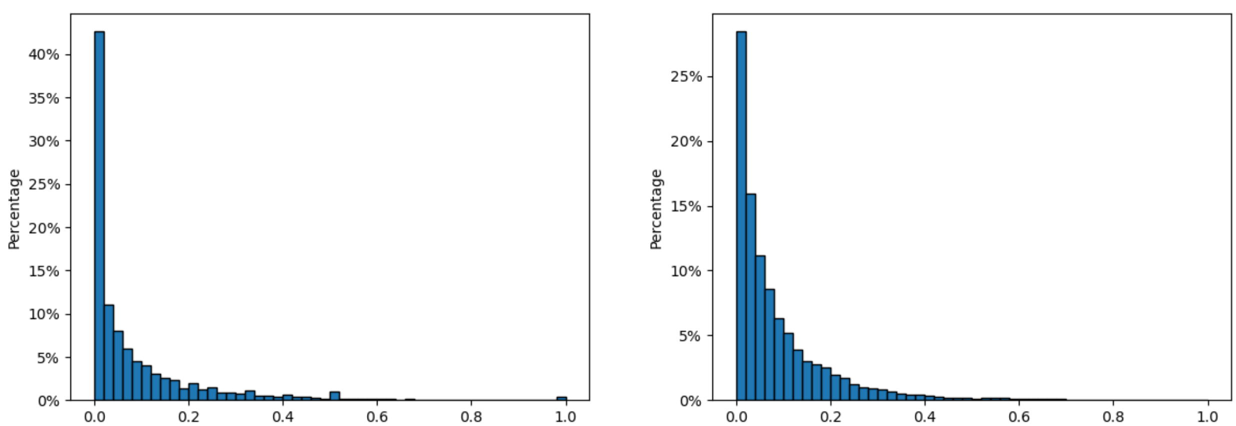
Figure 5: Proximity Matrix for 6-digit HS codes

Figure 5 shows the proximity scores distribution across the product space. Relative to that in Hidalgo et al. [9], this matrix is computed on a much higher level of disaggregation (4 to 6-digit HS codes) and the latest HS standard. The distribution of proximity scores in the product space calculated with our methodology corroborates the version in Hidalgo et al. [9]. The scores are not homogenous, suggesting that not all products are connected uniformly. Similarly, high proximity scores are not solely concentrated around the diagonal expected in a product-ladder model but they are less modular than the distribution shown in Hidalgo et al. [9] at the 4-digit level. Yet, proximity seems to be less evenly distributed than Hidalgo et al. [9] since our methodology controls for noise created by conditional probabilities, such as structural or spatial heterogeneities. Our matrix also enforces the directionality of linkages, explicitly enforcing whether product pairs share the same inputs. In our proximity matrix where scores are drawn from linkages in the AIPNET, about 75% of product pairs share no inputs. Of those sharing at least one input ($\phi_{ij} \neq 0$), the mean and median are respectively 0.13 and 0.47.

4.2. Latent Production Potential

If we know what "proximate" products are and we have a proxy of how competitively a country can produce them, we can then estimate measures for the potential of countries in the production of any good. Fundamentally, the proposed measures in this paper rely on the assumption that you are likely to have potential in any good p if you are competitive in the production of p's inputs or in the production of products similar to p. The two approaches are related, but are not identical. Vertical potential is an expression of competitiveness along the supply chain of product p, instead horizontal latency quantifies potential across similar supply chains. Both scores are, by construction, within the unit interval since they are different weighted averages of a binary outcome (RCA above or below 1)[1]. The histograms for the distribution of scores are pictured in Figure 6.

Figure 6: Distribution of Vertical and Horizontal Latency Scores in 2023



Vertical Horizontal

The distribution of scores are heavily skewed to the left, as there is a high concentration

[1]For clarity and transparency, the results reported on latency scores and RCAs in this paper treat European Union member states as an individual country. This means that trade flows between member states are discarded and exports of member states to non-EU27 countries are grouped by product to obtain European exports by product and year.

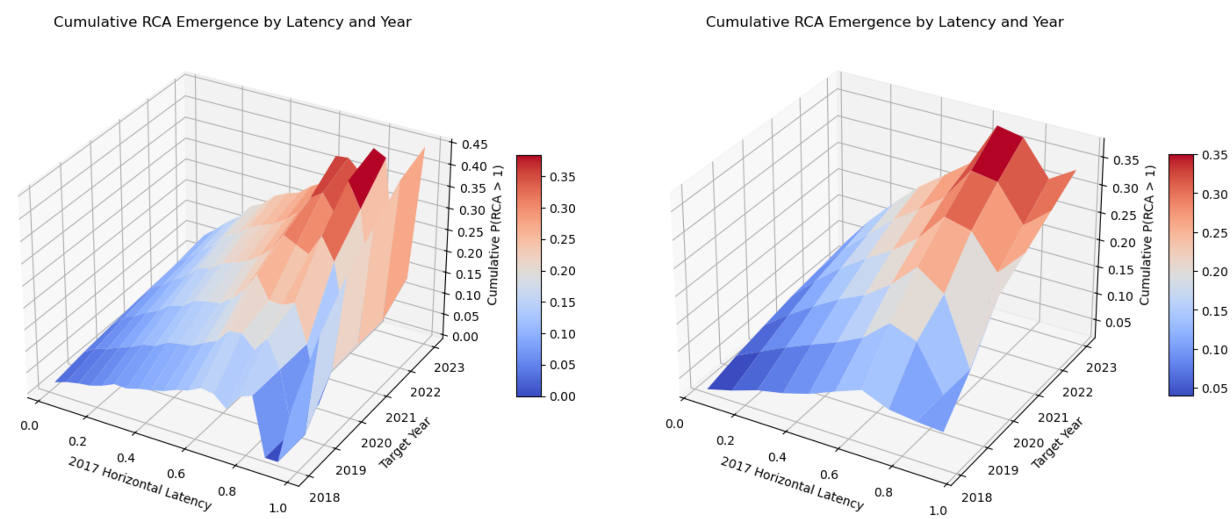
of values equal or very close to 0. This is not surprising as any country, on average, should not have latent potential in all productions. Similarly, very high potential is also a difficult feat to achieve given that countries often need high revealed comparative advantages across many products. This explains why there are plenty of values around 0 and why there are little high values. The distribution of scores for vertical latency shows a particularly strong skew to the left, unlike its horizontal equivalent. This is explained by the fact that vertical latency captures competitive advantages of direct intermediate goods, while horizontal latent potential is measured by using a the entire product space. In other words, on average, vertical latency scores are more likely to be estimated from a small pool of RCAs. In turn, this increases the likelihood of outliers, reason why there is a much larger of scores equal to 0 or 1 than in horizontal scores. Horizontal scores can instead draw from the entire product-space, leading to weighted averages of more elements. Finally, it is noteworthy pointing out that some products will, by construction, score very low in our measures. A clear example is primary raw materials, which are often inputs of many goods but rarely have product inputs.

4.3. A Promise for Competitiveness?

At this point, a legitimate question emerges: why does this matter? After all, a measure between 0 and 1 for latent potential seems a bit far-fetched and purely a methodological exercise. The scores are not normally distributed, highly concentrated around, or close to, 0 and median values are low. Moreover, it remains unclear what a high level of latent potential might be and whether there is a threshold that could distinguish between high and low potential productions. More importantly, policymakers and researchers are interested in whether these scores represent a promise for future competitiveness and within which temporal horizon. In particular, we are interested in knowing if, on average, products with a high latent potential are more likely to develop competitive advantages on international markets. Because we do not want to enforce a threshold on what constitutes a "high" latency score, we face a three dimensional problem: the unit interval of latency scores in 2017, the probability of displaying an RCA above 1, and the time horizon. Accordingly, we exploit our estimated latency and RCA scores for hundreds of thousand country-product pairs between 2017 and 2023 to plot these relationships.

Note that, by construction, latency scores in 2017 should have no relation with RCAs in consecutive years. Moreover, probabilities could indeed be affected by the time dimension, but should do so equally across starting latency scores. The probabilities are not inflated by country-product pairs that already have a revealed comparative advantage in 2017, only following over the years the "uncompetitive" pairs. This ensures that probabilities truly represent the average transition likelihood across the three dimensions. Below are the surface plots of average conditional probabilities for the competitiveness of any product with RCA smaller than 1 in 2017 (see Appendix for data).

Figure 7: 3D Cumulative Conditional Probability Surface for Horizontal Latency

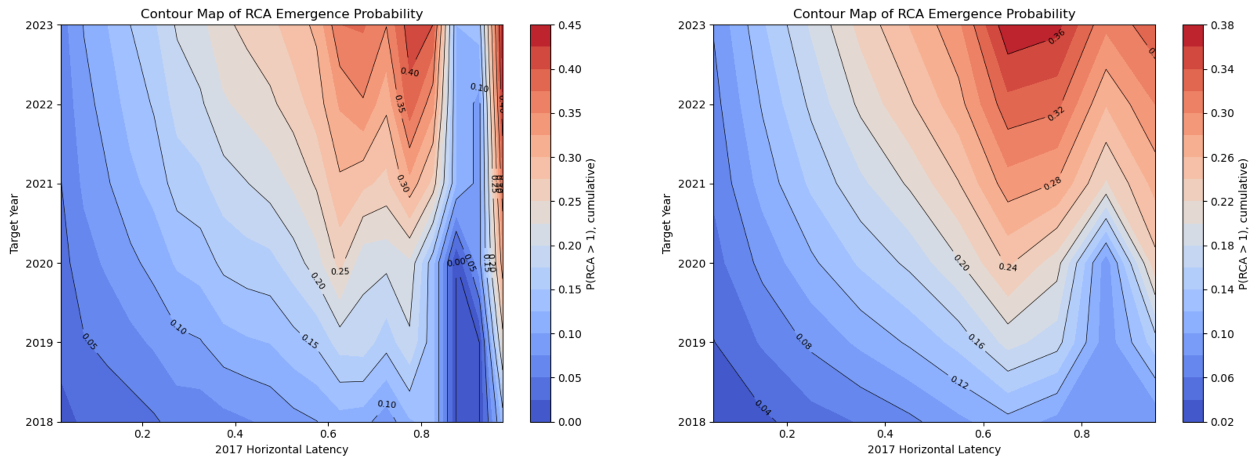


20 bins 10 bins

$$\mathbb{P}(RCA_{i,p,1:T} > 1) = \mathbb{P}\left(\bigcup_{t=1}^{T}\{RCA_{i,p,t} > 1\}\right) = 1 - \prod_{t=1}^{T}[1 - P_t] \tag{6}$$

The surface, and its corresponding 2D Contour plot, represent the average cumulative probability that any product develops a revealed comparative advantage between 2017 and 2023. If starting latency levels were not a predictor of developing competitive advantages in international trade, the surface would yield a monotonic upward slope across the time dimension, with no changes in steepness across the latency distribution in 2017. As shown in our plots, that is not the case. Products that start with a score for latent potential equal to 0 have a cumulative probability to develop a competitive advantage around 6-7%. This could be seen as the "baseline" scenario or the time trend, where "randomness" over the

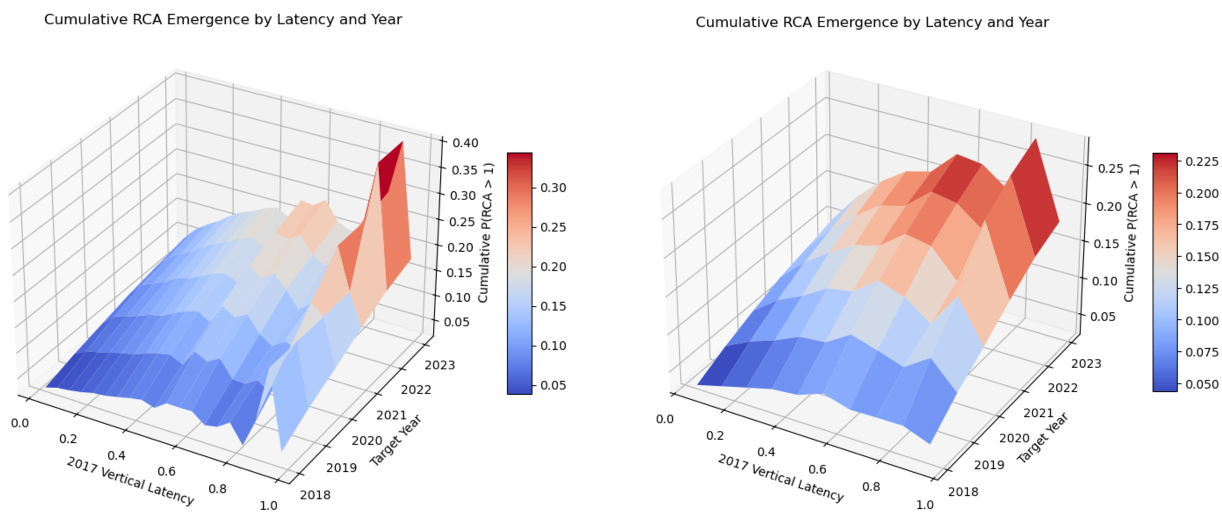
Figure 8: Contour Plots of Cumulative Conditional Probability for Horizontal Latency



20 bins

10 bins

Figure 9: 3D Cumulative Conditional Probability Surface for Vertical Latency

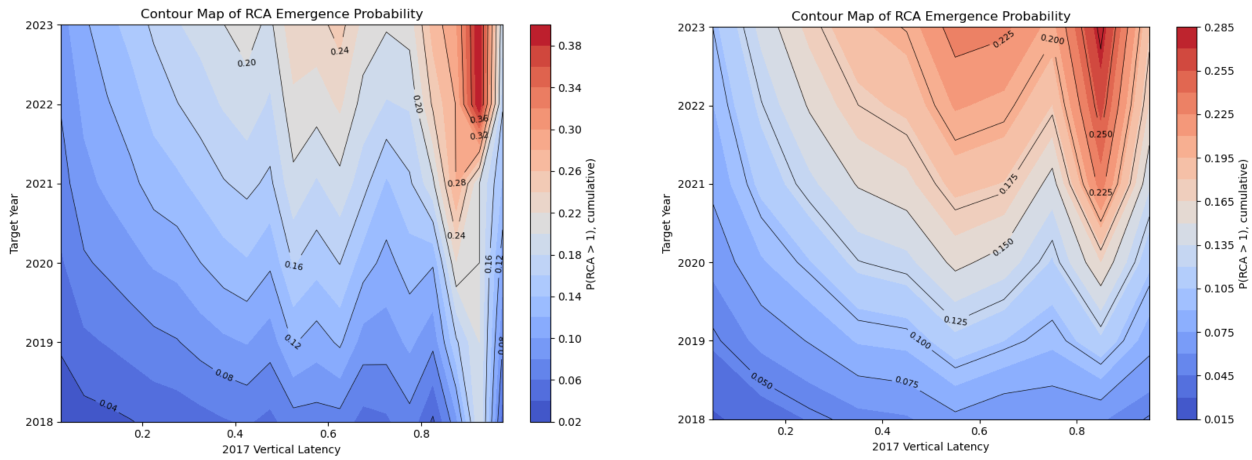


20 bins

10 bins

years pushes products to have RCAs over 1. The plots show that, instead, the steepness of the surface rises sharply along the horizontal latency distribution of 2017. In particular, more than a third of products that display scores for latent potential above 0.6 in 2017, on average, exhibit RCAs above 1 in the following 7 years, with probability rising quickly after a couple of years. Almost half of the 39 country-product pairs with a latency score above

Figure 10: Contour Plots of Cumulative Conditional Probability for Vertical Latency



20 bins

10 bins

0.95 in 2017 turned competitive up to 2023. Given the scarcely populated bins on the right tail of the latency score distribution in 2017, we present the same estimation over 10 bins instead of 20. The results remain essentially unchanged, higher starting latency scores are, on average, a promise for future competitiveness.

A similar pattern can be observed over vertical latency scores, where higher starting latent potential for direct inputs are associated with average higher cumulative probabilities over the time horizon considered. Once again, the probability surface grows faster in on the right end of the starting latency distribution. We report probabilities divided in 20 and 10 bins of the 2017 vertical latency unit interval since certain brackets are rarely populated just like in horizontal latency scores, meaning that average probabilities can lead to large outliers[2]. The smaller breakdown in 10 bins reduces volatility and increases the pool of pairs from where we draw average transition probabilities.

The higher incidence of horizontal latency scores is evidence of the strength of the product-space proposed by Hidalgo et al. [9] and the Atlas of Economic Complexity. The production capacity of economic systems is dependent on many concurrent factors outside of direct

[2]For instance, there are only 5 country-product pairs in the 0.9-0.95 vertical latency bin or only 8 pairs in the 0.85-0.9 horizontal latency bracket.

product inputs. There are, for instance, unobservable factors like service inputs (see for example Blázquez et al. [22]) and "know-how" that cannot be captured purely by drawing the one-degree production network of goods. The measure of horizontal latent potential partly attempts to account for these abilities, which can be common to clusters of similar products. Horizontal latency scores put a much heavier weight on the ability of a country, or groups of countries, to produce competitively similar products rather than do so for their direct inputs. By doing so, it becomes a measure of potential horizontally across supply chains and product clusters. Conversely, vertical latent potential takes into account the ability of an economic system to move up the supply chain and to, precisely, establish production capacities vertically.

4.4. Europe, Clean-Tech Technologies and Industrial Policy

We now apply the measures described above to the case study of European international competitiveness in key clean-tech goods. In particular, we show some of the results for a subset of clean-tech goods divided in "final products", such as electric cars, solar panel, windmills, electrolysers, heat pumps and electric batteries, and their main components, like lithium-ion batteries, electric engines, raw materials. Starting from the RCA in 2023, the map of Europe's current specialization in green reveals several areas of strength and expected shortcomings.

Figure 11 summarizes some of the comparative advantages in international trade for key clean-tech products, with brighter green identifying higher competitiveness levels. In 2023, the EU exhibits an RCA greater than 1 in 29 out of the 55 clean-tech goods singled-out, compared with 34 for China and 14 for the US. The EU is well-positioned in the production of mechanical and engineering products, as well in the production chain of electric vehicles and some of their components. The same holds for similar sophisticated products like heat pumps and exchangers, electrolysers and battery management systems. Chinese advantages in certain products are particularly pronounced; for example, the RCA for solar panels reaches 3.77 in China, compared with 0.11 in the EU and 0.01 in the US. The evidence also shows some notorious weaknesses of European supply chains in these industries, mostly lacking in key components for net-zero technologies such as magnets, silicon wafers, and lithium batteries. Likewise, the picture is particularly gloomy for other raw materials, like compounds and derivatives of lithium, manganese, nickel and cobalt.

Revealed Comparative Advantages (2023)

	CHN	EU	USA		CHN	EU	USA
Electric car	1.50	1.71	0.52	Heatpump	1.40	0.56	0.50
Lithium-ion Battery Pack	3.69	0.59	0.31	Compressor	1.95	0.82	0.79
Electric Motor	1.81	0.96	0.77	Heat Exchanger (Evaporator/Condenser)	0.90	1.60	1.09
Electronics	2.07	1.08	0.61	Pumps	1.58	1.58	0.71
Vehicle Control Unit (VCU)	0.84	1.58	0.91	Expansion Valve	0.62	1.56	1.32
Thermal Management System	0.90	1.60	1.09	Fan and Motor Assembly	1.31	1.40	0.95
Charging Port & EVSE	1.29	0.88	1.02	Electrolyser	1.43	1.34	1.32
High-Voltage Cables	2.01	0.69	0.89	Car battery	3.69	0.59	0.31
Sensors & Cameras	0.81	1.62	1.08	Parts of electric accumulators	1.56	1.03	0.66
Infotainment System	1.04	1.17	1.23	Complex fluorides	3.43	0.36	0.14
Body & Chassis	0.82	1.11	1.43	Other fluorides	1.28	0.46	2.67
Transmission (Single-speed)	0.27	1.54	1.17	Graphite-based preparations	3.40	0.68	0.27
Solar panel (Photovoltaic cells assemt	3.77	0.11	0.01	Lithium hydroxide	4.48	0.13	0.38
Photovoltaic cells not assembled	3.14	0.01	0.03	Cobalt oxides and hydroxides	0.12	0.10	0.01
Led	1.56	0.37	0.87	Manganese sulfate	1.23	0.57	0.20
Silicon Wafers	2.17	0.55	0.95	Nickel sulfate	0.45	1.03	0.21
Other (Led/photovoltaic cells)	0.43	0.79	0.70	Nickel, unwrought	0.42	0.46	0.07
Inverter grid	2.07	1.08	0.61	Nickel powders and flakes	0.45	0.68	1.06
Windmill	0.86	2.67	0.81	Manganese dioxide	3.23	0.12	0.53
Blades	1.84	1.14	1.18	Nickel chloride	1.31	0.97	0.20
Tower	0.74	1.49	0.18	Cobalt chloride	1.51	0.55	2.55
Gearbox	0.89	1.88	0.98	Other phosphates	0.75	2.07	0.55
Generator	1.23	1.86	0.99	Phosphoric acid	0.65	0.22	0.71
Hub	0.78	1.95	1.42	Aluminum foil	2.72	0.82	0.64
Control System	0.84	1.58	0.91	Copper foil	1.17	1.45	0.63
Pitch/Yaw Actuators	1.00	1.93	0.87	Separator film (PE/PP)	1.32	1.11	0.94
Permanent Magnets	3.96	0.19	0.25	Battery management system (BMS)	0.84	1.58	0.91
Heatpump	1.75	1.59	0.51				

Figure 11: Revealed Comparative Advantages for Some Clean-Tech Products in 2023

Ideally the European Commission would want to target these nodes in supply chains to boost European competitiveness and decoupling from foreign dependencies. Our measures of latent potential can tell us something more about how this could be done, or at least give an indication of how resources could be allocated, bearing in mind the probabilities estimated in the previous section. Table 12 reports our proposed measure of vertical and horizontal potential in 2023 for products and components with RCAs below 1 in Table 11. We compare them with the median values of vertical and horizontal potential calculated on a list of twenty countries that are top exporters, and with the corresponding values for the US. Among this subset of goods, the EU has a stronger potential than the US (and higher than the median) for the products highlighted in dark blue. It has a potential higher than the median but lower than the US for those highlighted in light blue, and finally it has a very low potential for at least one of the measures with respect to both the US and the median, for those not highlighted. For example, several components related to electric mobility, such as electric motors, charging ports, car batteries, and lithium-ion battery packs, show strong potential.

	Vertical Potential			Horizontal Potential		
	EU	USA	Median	EU	USA	Median
Lithium-ion Battery Pack	0.50	0.33	0.33	0.454	0.389	0.239
Electric Motor	0.51	0.33	0.28	0.692	0.321	0.189
Charging Port & EVSE	0.44	0.34	0.29	0.583	0.406	0.186
High-Voltage Cables	0.51	0.44	0.25	0.612	0.415	0.205
Solar panel (Photovoltaic cells assembled in..)	0.34	0.38	0.19	0.482	0.399	0.209
Photovoltaic cells not assembled	0.29	0.46	0.19	0.478	0.404	0.211
Led	0.30	0.37	0.20	0.492	0.413	0.217
Silicon Wafers	0.33	0.46	0.13	0.555	0.370	0.170
Other (Led/photovoltaic cells)	0.29	0.39	0.19	0.479	0.401	0.208
Permanent Magnets	0.39	0.70	0.17	0.544	0.310	0.157
Heatpump	0.59	0.38	0.28	0.618	0.372	0.192
Compressor	0.76	0.36	0.23	0.658	0.315	0.199
Car battery	0.50	0.33	0.33	0.454	0.389	0.239
Complex fluorides	0.20	0.60	0.20	0.283	0.412	0.170
Other fluorides	0.00	1.00	0.00	0.185	0.442	0.138
Graphite-based preparations	0.38	0.38	0.13	0.464	0.360	0.194
Lithium hydroxide	0.00	0.67	0.33	0.273	0.502	0.146
Cobalt oxides and hydroxides	0.25	0.75	0.00	0.822	0.381	0.207
Manganese sulfate	0.38	0.25	0.25	0.476	0.325	0.138
Nickel, unwrought	0.20	0.40	0.20	0.501	0.431	0.129
Nickel powders and flakes	0.17	0.50	0.17	0.661	0.423	0.143
Manganese dioxide	0.38	0.00	0.06	0.307	0.286	0.211
Nickel chloride	0.33	0.00	0.00	0.478	0.341	0.161
Cobalt chloride	0.50	0.17	0.17	0.445	0.313	0.122
Phosphoric acid	0.25	0.08	0.08	0.404	0.266	0.123
Aluminum foil	0.79	0.32	0.23	0.470	0.309	0.208

Figure 12: Vertical and Horizontal Potential for Components in 2023 for the EU and USA

By contrast, components related to solar panels (such as silicon wafers and other photovoltaic cells) appear, in general, less promising. As expected, for many materials located further downstream in the value chains, the potential measures tend to be lower. This is line with expectations since the production potential of raw materials and less-processed commodities overwhelmingly rely on natural endowments and relatively cheaper non-specialized labour. One other general observation is that the horizontal potential is structurally quite high in Europe, meaning that it is likely that the EU owns the know-how to be competitive in the production across similar clean-tech supply chains. If we compare these levels with the Contour plots of the probability surfaces, we know that having a horizontal latency means, on average, roughly a 30% chance to develop a competitive advantage within 6 years. For the EU production of some cobalt derivatives with a horizontal latency around 0.8, probabilities can go as high as 40%. We are not trying to argue that latent potentials will inevitably turn into competitive productions, some suffer from structural weaknesses that are difficult to address.

However, the evidence shows that the latent potential exists across many clean-tech products to different extents and any industrial policy designated to boost European competitiveness in these sectors should take into consideration the nuances of different products and supply chains.

5. Conclusions & Policy Implications

In the paper, we have put together information on international bilateral trade flows and a novel dataset on product networks at the 6-digit HS level to redefine what "similar" product are and propose a new methodological tool to quantify the production potential at a granular level. We then demonstrated that these measures are a promise for future competitiveness, as high latency scores are associated with higher probabilities to develop revealed comparative advantages on international markets within a short temporal horizon. Once established the potential of such measures in identifying latent production capabilities, we apply them to the case study of clean-tech goods in the European Union. We describe the potential of the bloc in the production of such products relative to other competitors, pointing out possible targets for European industrial policy.

Environmental goods play a growing role in the consumption basket, and hence in international trade. Industrial policies around the world are directed towards stimulating technological progress and acquiring competitive hedges. The ultimate goal of the paper is to provide policymakers and researchers with a new tool to devise strategic industrial policies that are not of the "one-fit-all" type. This is particularly true within the current context in which the European Union seems to have taken a more active role in supporting new industries, most recently with the Net-Zero Industrial Act (NZIA), and countries increasingly resort to tariff and non-tariff barriers. These instances make the transition to a green economy both a technological and strategic challenge. The heterogeneity of EU member states in their positioning within global value chains for clean-tech goods can nonetheless be viewed as an advantage if the EU is capable of bringing these latent capabilities together, breaking down the barriers that still exist between member states within the Union. Industrial policy, if properly designed, can therefore play a crucial role in fostering integration and enabling member states to capitalise on their complementary positions. In fact, the analysis shows that the EU as a whole, has advantages in many areas of clean-tech goods and significant potential (that is, know-how embedded in products that are similar or in products that are further downstream in the value chain) in many others, as shown in the previous section, thanks to its large industrial base.

Vertical latency highlights the potential for a production network to move forward along the value chain of a product, starting from the assumption that latent potential is hidden in the production of goods for which you can competitively make its immediate inputs. Hence, this measure quantifies the potential for vertical integration in the supply chain of any product. Horizontal latency shows diversification potential across related products, defined as the degree that any two products share the same nodes of their supply chains. Conversely to its vertical counterpart, horizontal latency measures the potential to move across similar supply chains, accounting for synergies and know-how that is transferable across the production of similar yet differentiated products. These measures can help the design of policies to address strengths and weaknesses in the European production network of these goods.

Targeted policies and knowledge accumulation are key ingredients in enhancing competitiveness. Given the proximity of many of the products and inputs that are part of the clean-tech set, a growing and steady demand is clearly beneficial, but it does not necessarily stimulate local production. In this respect, the way demand is structured is crucial, particularly the choice between technological neutrality or challenging specifications. These choices should be aligned with the available know-how. An anchor customer (such as public administrations, for example, large municipalities, or utilities) formulating technical standard or auctioning for specific features may help generating or reinforcing the needed technical knowledge and skills. The establishment of specialized economic areas in the production of certain goods, as planned in the NZIA, can boost technological innovation by integrating key nodes of the supply chain, but this should be done strategically. Again, this requires a comprehensive, EU-wide and integrated perspective, avoiding the straitjacket of pursuing identical industrial goals across all EU member states. Keeping an open channel between the public administration at all levels, including the EU, and the corporate sector can help in designing coordinated policy responses, such as those for public procurement tenders. Ultimately, targeted policies that stimulate these latencies and accelerate innovation can help enhancing knowledge and skills in key sectors, with likely spillovers on other industries and regions.

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Appendix

Summary data compute 3D probabilistic surfaces, including number of counts for each bin of the latency distribution in 2017. The bin number represents the upper bound. Each count is a product-country pair that has an RCA below 1 in 2017. Because we construct the time-dimension from 2017, these probabilities are calculated using HS17 codes.

Table 1: Vertical Latency, 10-bin, Probabilities

Bin	2018	2019	2020	2021	2022	2023
0.1	0.0276	0.0471	0.0636	0.0785	0.0890	0.0997
0.2	0.0368	0.0641	0.0881	0.1088	0.1240	0.1394
0.3	0.0459	0.0761	0.1041	0.1314	0.1520	0.1698
0.4	0.0547	0.0914	0.1244	0.1514	0.1749	0.1923
0.5	0.0581	0.0945	0.1304	0.1601	0.1839	0.2011
0.6	0.0708	0.1154	0.1543	0.1853	0.2117	0.2333
0.7	0.0606	0.1050	0.1430	0.1791	0.2055	0.2287
0.8	0.0613	0.0936	0.1181	0.1426	0.1794	0.2040
0.9	0.0616	0.1164	0.1644	0.2329	0.2603	0.2808
1.0	0.0485	0.0813	0.1081	0.1372	0.1633	0.1805

Table 2: Vertical Latency, 10-bin, Counts

Bin	2018	2019	2020	2021	2022	2023
0.1	129116	129116	129116	129116	129116	129116
0.2	57673	57673	57673	57673	57673	57673
0.3	32253	32253	32253	32253	32253	32253
0.4	18028	18028	18028	18028	18028	18028
0.5	9488	9488	9488	9488	9488	9488
0.6	3300	3300	3300	3300	3300	3300
0.7	1563	1563	1563	1563	1563	1563
0.8	657	657	657	657	657	657
0.9	146	146	146	146	146	146
1.0	1365	1365	1365	1365	1365	1365

Table 3: Horizontal Latency, 10-bin, Probabilities

Bin	2018	2019	2020	2021	2022	2023
0.1	0.0228	0.0392	0.0517	0.0635	0.0720	0.0811
0.2	0.0356	0.0622	0.0861	0.1074	0.1222	0.1366
0.3	0.0514	0.0841	0.1160	0.1440	0.1646	0.1832
0.4	0.0612	0.1043	0.1429	0.1753	0.2048	0.2263
0.5	0.0752	0.1231	0.1648	0.2033	0.2371	0.2608
0.6	0.0947	0.1464	0.1981	0.2391	0.2725	0.2957
0.7	0.1129	0.1869	0.2434	0.2910	0.3333	0.3757
0.8	0.0930	0.1686	0.2093	0.2791	0.3256	0.3663
0.9	0.0870	0.0870	0.0870	0.2174	0.2609	0.3043
1.0	0.0833	0.1500	0.2333	0.2667	0.3000	0.3333

Table 4: Horizontal Latency, 10-bin, Counts

Bin	2018	2019	2020	2021	2022	2023
0.1	111396	111396	111396	111396	111396	111396
0.2	74637	74637	74637	74637	74637	74637
0.3	41442	41442	41442	41442	41442	41442
0.4	17245	17245	17245	17245	17245	17245
0.5	5968	5968	5968	5968	5968	5968
0.6	2075	2075	2075	2075	2075	2075
0.7	569	569	569	569	569	569
0.8	172	172	172	172	172	172
0.9	23	23	23	23	23	23
1.0	61	61	61	61	61	61

Table 5: Vertical Latency, 20-bin Probabilities

Bin	2018	2019	2020	2021	2022	2023
0.05	0.0252	0.0427	0.0567	0.0708	0.0812	0.0914
0.10	0.0323	0.0559	0.0773	0.0939	0.1045	0.1163
0.15	0.0349	0.0612	0.0845	0.1041	0.1185	0.1331
0.20	0.0391	0.0677	0.0926	0.1146	0.1307	0.1470
0.25	0.0449	0.0744	0.1022	0.1288	0.1472	0.1641
0.30	0.0475	0.0787	0.1069	0.1353	0.1593	0.1783
0.35	0.0524	0.0882	0.1197	0.1463	0.1700	0.1871
0.40	0.0580	0.0961	0.1310	0.1586	0.1819	0.1997
0.45	0.0622	0.1009	0.1380	0.1654	0.1921	0.2076
0.50	0.0543	0.0888	0.1235	0.1554	0.1766	0.1952
0.55	0.0711	0.1221	0.1619	0.1945	0.2148	0.2350
0.60	0.0705	0.1097	0.1477	0.1773	0.2091	0.2318
0.65	0.0714	0.1235	0.1607	0.1935	0.2232	0.2485
0.70	0.0523	0.0909	0.1295	0.1682	0.1920	0.2136
0.75	0.0565	0.0891	0.1130	0.1370	0.1783	0.2022
0.80	0.0729	0.1042	0.1302	0.1563	0.1823	0.2083
0.85	0.0366	0.0854	0.1220	0.1951	0.2439	0.2683
0.90	0.0938	0.1563	0.2188	0.2813	0.2813	0.2969
0.95	0.2000	0.2000	0.2000	0.2000	0.4000	0.4000
1.00	0.0479	0.0808	0.1078	0.1370	0.1624	0.1796

Table 6: Vertical Latency, 20-bin, Counts

Bin	2018	2019	2020	2021	2022	2023
0.05	86834	86834	86834	86834	86834	86834
0.10	42282	42282	42282	42282	42282	42282
0.15	31797	31797	31797	31797	31797	31797
0.20	25876	25876	25876	25876	25876	25876
0.25	19506	19506	19506	19506	19506	19506
0.30	12747	12747	12747	12747	12747	12747
0.35	10614	10614	10614	10614	10614	10614
0.40	7414	7414	7414	7414	7414	7414
0.45	4468	4468	4468	4468	4468	4468
0.50	5020	5020	5020	5020	5020	5020
0.55	1535	1535	1535	1535	1535	1535
0.60	1765	1765	1765	1765	1765	1765
0.65	674	674	674	674	674	674
0.70	889	889	889	889	889	889
0.75	463	463	463	463	463	463
0.80	194	194	194	194	194	194
0.85	82	82	82	82	82	82
0.90	64	64	64	64	64	64
0.95	5	5	5	5	5	5
1.00	1360	1360	1360	1360	1360	1360

Table 7: Horizontal Latency, 20-bin, Probabilities

Bin	2018	2019	2020	2021	2022	2023
0.05	0.0183	0.0309	0.0401	0.0489	0.0555	0.0626
0.10	0.0279	0.0484	0.0647	0.0797	0.0905	0.1018
0.15	0.0338	0.0568	0.0791	0.0974	0.1112	0.1244
0.20	0.0376	0.0681	0.0938	0.1185	0.1343	0.1502
0.25	0.0466	0.0782	0.1085	0.1333	0.1526	0.1707
0.30	0.0593	0.0936	0.1283	0.1614	0.1841	0.2036
0.35	0.0584	0.0984	0.1357	0.1684	0.1959	0.2169
0.40	0.0665	0.1151	0.1563	0.1883	0.2213	0.2437
0.45	0.0726	0.1217	0.1634	0.1991	0.2326	0.2575
0.50	0.0796	0.1255	0.1672	0.2108	0.2450	0.2665
0.55	0.0914	0.1409	0.1870	0.2290	0.2619	0.2891
0.60	0.0993	0.1542	0.2138	0.2535	0.2874	0.3049
0.65	0.1141	0.1861	0.2581	0.2953	0.3275	0.3747
0.70	0.1098	0.1890	0.2073	0.2805	0.3476	0.3780
0.75	0.0840	0.1603	0.2061	0.2672	0.3053	0.3511
0.80	0.1220	0.1951	0.2195	0.3171	0.3902	0.4146
0.85	0.1333	0.1333	0.1333	0.2667	0.3333	0.4000
0.90	0.0000	0.0000	0.0000	0.1250	0.1250	0.1250
0.95	0.0000	0.0000	0.0909	0.0909	0.0909	0.1364
1.00	0.1316	0.2368	0.3158	0.3684	0.4211	0.4474

Table 8: Horizontal Latency, 20-bin, Counts

Bin	2018	2019	2020	2021	2022	2023
0.05	59976	59976	59976	59976	59976	59976
0.10	51420	51420	51420	51420	51420	51420
0.15	39370	39370	39370	39370	39370	39370
0.20	35267	35267	35267	35267	35267	35267
0.25	25671	25671	25671	25671	25671	25671
0.30	15771	15771	15771	15771	15771	15771
0.35	11197	11197	11197	11197	11197	11197
0.40	6048	6048	6048	6048	6048	6048
0.45	3826	3826	3826	3826	3826	3826
0.50	2142	2142	2142	2142	2142	2142
0.55	1219	1219	1219	1219	1219	1219
0.60	856	856	856	856	856	856
0.65	405	405	405	405	405	405
0.70	164	164	164	164	164	164
0.75	131	131	131	131	131	131
0.80	41	41	41	41	41	41
0.85	15	15	15	15	15	15
0.90	8	8	8	8	8	8
0.95	22	22	22	22	22	22
1.00	39	39	39	39	39	39