Economic Complexity and the Green Economy*

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Abstract

This paper studies countries' productive capabilities relevant to the green economy. We pool all existing environmental goods classifications to create a new, comprehensive dataset of 293 green products traded between 1995 and 2014. We match these products to export data and analyse resulting patterns in the trade network using the *economic complexity* methodology. We construct the *Green Complexity Index* (GCI), which ranks countries in accordance with the number and complexity of green products they export competitively and show that countries with higher GCI have higher environmental patenting rates, lower CO_2 emissions, and more stringent environmental policies. We then look at each country's *Green Adjacent Possible* (GAP), which represents the set of technologically proximate green products that a country could potentially become competitive in. Using the GAPs, we construct a measure of each country's *Green Complexity Potential* (GCP), which we show is predictive of countries' future competitiveness in green products. The strong correlation between GCP and GCI suggests path dependence in the accumulation of green production capabilities and shines a light on policy discussions around green industrial policy.

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1 Introduction

The transition to the green economy will undoubtedly involve a transformation of production structures and economic activities around the world. This shift has the potential to alter the global competitive landscape and reshape countries' comparative advantages in production (Fankhauser et al., 2013). In this paper, we tackle two questions: (1) which countries are currently best placed to become leaders in the green economy, and (2) how might countries re-orient their industrial structure to become more competitive in green (or environmentally friendly) products.

To address these questions, we draw on country export data to systematically estimate countries' current *capabilities* (e.g. productive knowhow, market and institutional infrastructure) and future *potential* (diversification opportunities) for success in the green economy.

A key challenge in measuring green production capabilities on the basis of exports is the current lack of a universally accepted definition of environmental goods and services. Although efforts have been underway since 2001 when the World Trade Organisation (WTO) instigated a mandate to reduce or eliminate tariffs on environmental goods and services, progress towards this has slowed since the 2016 negotiations on the Environmental Goods Agreement stalled in December 2016.

To address these data gaps, we pool all existing environmental goods classifications available from the WTO, the Organisation for Economic Cooperation and Development (OECD), and the Asia-Pacific Economic Cooperation (APEC) into a comprehensive dataset of green traded products. Merging this with export data allows us to analyse country trade in green products over the 1995-2014 period.

On the basis of this dataset, we investigate countries' green production capabilities by drawing on the economic complexity methodology (Hidalgo et al., 2007; Hidalgo and Hausmann, 2009; Hausmann et al., 2014).[1] This approach aims to infer information about countries' productive capabilities and industrial structure

[1] This methodology has received significant attention in recent years and there is a healthy scientific debate about the best way to infer capabilities relevant to economic growth from export data.(Tacchella et al., 2012, 2013; Cristelli et al., 2013; Zaccaria et al., 2014; Cristelli et al., 2015; Albeaik et al., 2017; Gabrielli et al., 2017; Albeaik et al., 2017)

by making relative comparisons across country export baskets. We first calculate the Product Complexity Index (PCI) for each green product. The PCI aims to estimate the complexity of capabilities required to export a product *competitively*,[2] and has been used as a measure of technological sophistication (see, for example, Felipe et al., 2012; Poncet and de Waldemar, 2013). We find that green products relating to concentrated solar power, environmental monitoring and analysis tend to have the highest PCI scores, while environmentally preferable products (many of which are made from vegetable material) receive lower PCI scores. Interestingly, we find that green products tend to be more complex than average – suggesting that part of the challenge in addressing climate change may relate to the fact that many clean energy technologies are fairly sophisticated and require substantial investment and expertise to scale for production.

To estimate which countries are currently best placed to become leaders in the green economy, we develop a new measure, called the Green Complexity Index (GCI), which is increasing in the number and complexity of green products that a country is competitive in. It is important to distinguish the GCI from the Economic Complexity Index (ECI) (Hidalgo and Hausmann, 2009; Hausmann et al., 2014). The ECI estimates the complexity of countries' production capabilities on the basis of the similarity in country export baskets (Kemp-Benedict, 2014; Mealy et al., 2017). The measure is calculated using a clustering algorithm (a dimension reduction method) that sorts countries into an ordering that places countries with similar exports near each other. What makes this ordering interesting is that it can explain more variation in income per capita and economic growth than other variables traditionally employed in growth equations.

The GCI differs from the ECI in two important ways. First, while the ECI is estimated on the basis of all traded products, the GCI is estimated on the basis of a *subset* of *green* traded products. Second while the ECI represents the *average* PCI of all products a country is competitive in, the GCI represents the *sum* of the PCI of all green products a country is competitive in. Note that while we have applied the GCI to a specific subset of green traded products, the measure is

[2] We say that a country is *competitive* in a product if its revealed comparative advantage (RCA) for this product is greater than 1 (Balassa, 1965). See Equation 2 below.

completely general and can be applied to any subset of products (such as biotech).

We rank countries according to the GCI and show that while it is positively correlated with the ECI, the GCI is able to explain more variation in environmentally-relevant variables. In particular, we find that controlling for countries' per capita GDP and ECI, countries with higher GCI tend to have significantly higher environmental patenting rates, lower CO_2 emissions and more stringent environmental policies.

We investigate country GCI rankings over the 1995-2014 period, and find relatively little variance in the highest rankings – top ranked countries such as Germany, Italy, US and Denmark have managed to remain leaders over the 20 year period. Some countries such as China, Vietnam and Uganda have made significant gains in their GCI scores, while other countries such as Australia show notable declines.

Turning to the second question of how countries may re-orient their industrial structure to become more competitive in green products, we exploit the fact that industrial development tends to be path-dependent. Countries or regions are more likely to diversify into products or industries that require production capabilities similar to what they currently possess (Patel and Pavitt, 1997; Weitzman, 1998; Hidalgo et al., 2007; Neffke et al., 2011; Boschma et al., 2013).

Drawing on measures developed in Hidalgo et al. (2007), which estimate the similarity in production capabilities between two products *(proximity)* and between a country and a product *(proximity density)* by considering countries' conditional probability of being competitive in one product given competitiveness in another, we construct each country's *Green Adjacent Possible (GAP)*. The GAP shows the set of green products that are proximate to a country's current production capabilities – i.e. the new green industrial opportunities that are likely to be the easiest to transition into, given what a country already knows how to do.

We then aggregate the information contained in each country's GAP into a single, comparable metric, which we call Green Complexity Potential (GCP). GCP measures each country's average proximity to complex green products that it is not yet competitive in. We show that GCP is able to significantly predict future increases in a country's GCI, green export share and the number of green products that a country is competitive in, even after controlling for each country's GDP per capita and ECI. We also find a strong positive correlation between GCP and GCI suggesting that countries that currently export a significant number of green complex products are generally well placed to diversify into other green complex products in the future.

Our results offer several contributions to policy discussions. First, we establish an extensive set of products relevant to the green economy and identify which countries currently have the capabilities to produce them competitively. Our findings complement Fankhauser et al. (2013)'s related efforts to analyse "who will win the green race", but provides a broader coverage of countries and an alternative analytical lens based on the economic complexity methodology. Second, our GCI measure allows policy makers to assess a country's green production capabilities relative to other countries and also consider how its green competitiveness has been changing over time. The path dependence in green diversification suggests that earlier and more aggressive action to establish green production capabilities is required in order to succeed in the future green economy (Aghion et al., 2014, 2016). Third, by identifying the GAPs we show clearly which products countries are best placed to gain a competitive edge in, informing policymakers about the optimal direction of government interventions and green industrial policy (Aghion et al., 2011; Huberty and Zachmann, 2011; Hallegatte et al., 2013; Rodrik, 2014). We also present some preliminary results on the effect of recent green stimulus policies on green exports and green complexity for a selection of countries.

This paper is organised as follows. Section 2 describes the data sources and presents some key empirical patterns associated with trade in green products. Section 3 examines the complexity of green products and develops the GCI. Section 4 looks at future green diversification opportunities and discusses product proximity, proximity density, GAP, and GCP. Section 5 briefly discusses some tentative policy implications and Section 6 concludes. The Appendix contains more information about the data (A.1), selected green products (A.2), countries (A.3), gives further regression robustness checks (A.4), reviews how various measures used in the paper are derived (A.5 and A.6), and provides a brief summary of terms relating to the economic complexity methodology (A.7).

2 Green Trade Data and Empirical Patterns

At the opening of the Doha Development Round of negotiations in 2001, the World Trade Organization received a mandate aimed at the "reduction or as appropriate, elimination of tariff and non-tariff barriers to environmental goods and services" (WTO, 2001, 33(iii)). We refer to these "environmental goods" as "green products" in this paper.

A number of international organisations have proposed lists of green products, but a universally accepted classification of green products is still not available. This is largely due to the difficulty of conceptually determining what products should be considered "green" and the practical challenges of classifying products within the existing trade classification system (Bucher et al., 2014).[3]

To construct a dataset of green products used in this paper, we draw on existing lists and classifications developed by the World Trade Organization (WTO, 2010, 2011), the Organisation for Economic Cooperation and Development (OECD, 1999; Sauvage, 2014), and Asia-Pacific Economic Cooperation (APEC, 2012) (see Table 5 in Appendix A.1). We combine all available lists to construct a dataset totalling 543 products classified at the 6-digit level in HS1992. We then combine this dataset with COMTRADE data to analyse environmental trade across countries for the period 1995-2014.[4]

While our dataset of 543 products represents a useful benchmark of *potentially* green products, the environmental status of a number of products included the broad-reaching WTO Reference List may be questionable.[5] In order to arrive at a robust set of products that share wide expert endorsement—and are useful to policymakers—we develop two main product lists. The first is a list of 293 green products, which we obtain by taking the union of the WTO Core list, OECD list,

[3]The latest round of talks on WTO Environmental Goods Agreement which promised to deliver a list of green products stalled in December 2016.

[4]Huberty and Zachmann (2011) undertook a detailed study of six green products within the context of the European Union. Hamwey et al. (2013) identified 11 green products in the product space, focusing on the case of Brazil. Fraccascia et al. (2018) studied the complexity of 41 green products in 141 countries between 2005 and 2013.

[5]For example 848210 (ball bearings) submitted by Saudi Arabia with the rationale that they are used in carbon capture and storage applications.

and the APEC list.[6] This refined list of green products has the advantage that each product has either been endorsed by a large number of WTO or APEC member countries, or its environmental benefits have been determined by the (rather selective) OECD. This list represents a wide range of environmental categories, such as air pollution, waste water management, and recycling. We use this green product list for our empirical analysis throughout the paper.[7]

We also develop a smaller list of 57 renewable energy products (a subset of the products on the green product list). This list includes all products falling under the WTO Renewable Energy Products category, under the OECD's Renewable Energy Plant categories, as well as two additional APEC renewable energy products (solar heliostats and parts for solar heliostats) that were not included on either the WTO or OECD lists. The renewable energy product list focuses on low-carbon technologies that are key for addressing climate change.

2.1 Data Advantages and Limitations

The green product classifications we use to construct our two product lists offer a number of advantages. First, for each proposed product in the WTO and OECD lists, it is possible to identify one (or more) environmental category that the product falls under. Although the WTO and OECD differ in the structure of their environmental categories, they are still broadly consistent and helpful for identifying a product's environmental purpose (such as renewable energy, waste water management, energy efficiency etc.) Second, the APEC and WTO lists also include specific information about each product's environmental benefits. This information was provided by member countries of the respective organisations as rationale for a proposed product's environmental endorsement. Thirdly, the APEC and WTO lists also indicate the set of member countries endorsing a given product as green. This information is useful for helping gauge the level of consensus associated with each product's environmental status.

[6] While the original set of green products included 295 goods, we had to remove Profile Projectors (903110) and Exposure meters (902740) due to data quality issues.

[7] All our data are available upon request.

A number of limitations are also important to keep in mind. First, the HS system (which classifies products for the purpose of trade and tariffs) was not set up to account for the environmental benefits of products. This can sometime result in poor alignment between a recognised environmental product (such as a wind turbine) and its most relevant HS code.[8] Second, many products are dual use, which means they can have both environmental and non-environmental purposes. Although WTO and APEC classifications provide "ex-outs" (a further description to identify relevant environmental products classified under the HS code), it can be very challenging to identify the precise environmental trade flow associated with a particular ex-out for a given HS category. As such, our analysis (which is based trade volumes for entire HS-6 commodity codes) will tend to somewhat over-estimate environmental trade volumes. Finally, our dataset does not provide information about the production process of a given product, only its use-oriented benefits. Consequently, our data do not allow us to examine the environmental impact of product production and use (e.g. lifecycle emissions of a product).

2.2 Empirical patterns

We now present a few empirical patterns associated with trade in green and renewable energy products. Figure 1 illustrates the change in trade volumes of green and renewable energy products between 1995 and 2014. Panel A shows that green and renewable energy products have exhibited steady growth in trade volumes–particularly over the 2000-2011 period–with a levelling off before 2014. However, when examining green trade as a proportion of total trade, we see relatively flat trajectories over the 20-year period.

[8]For example, a key relevant HS code for identifying wind turbine towers is a very broad HS category - 730820 - which relates to "Towers and lattice masts, iron or steel".

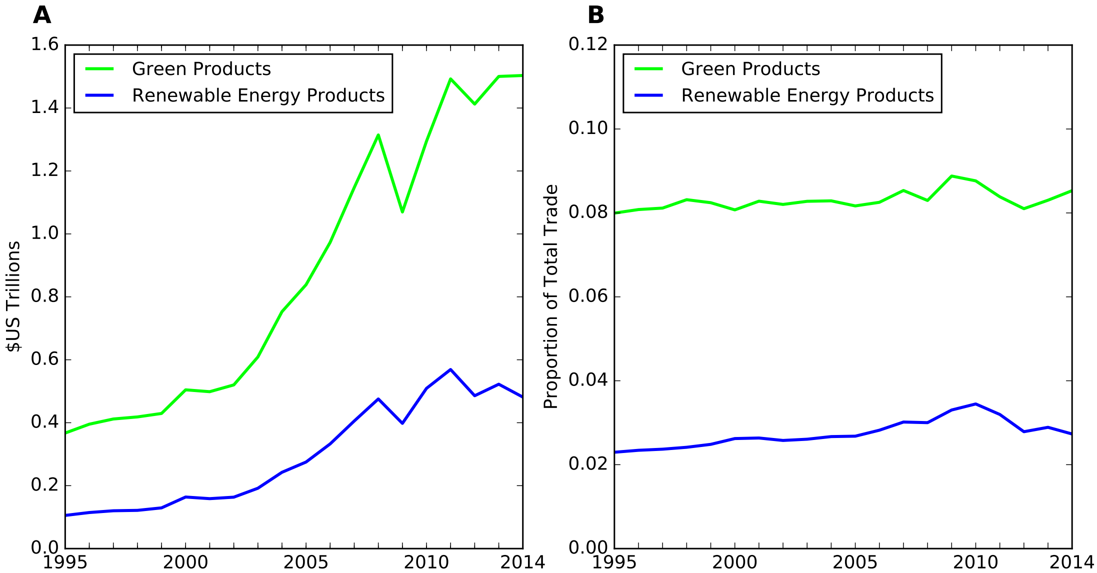

Figure 1: Growth in Green and Renewable Energy Products

Figure 2 shows the top exporters of all green products (by trade volume). Panel A presents leaders in absolute terms. While the US was the largest green exporter from 1995-2003, Germany took over in 2004 but was in turn displaced by China in 2010. Panel B shows the green exports of these same countries, but instead as a proportion of each country's total exports. Denmark has had the highest relative share of green exports – peaking over the financial crisis period at around 14 per cent. Of all these countries, South Korea has seen the largest "greening" of its export basket – its green exports increased as a percentage of total exports from around 6 percent in 2002 to around 12 percent in 2010.

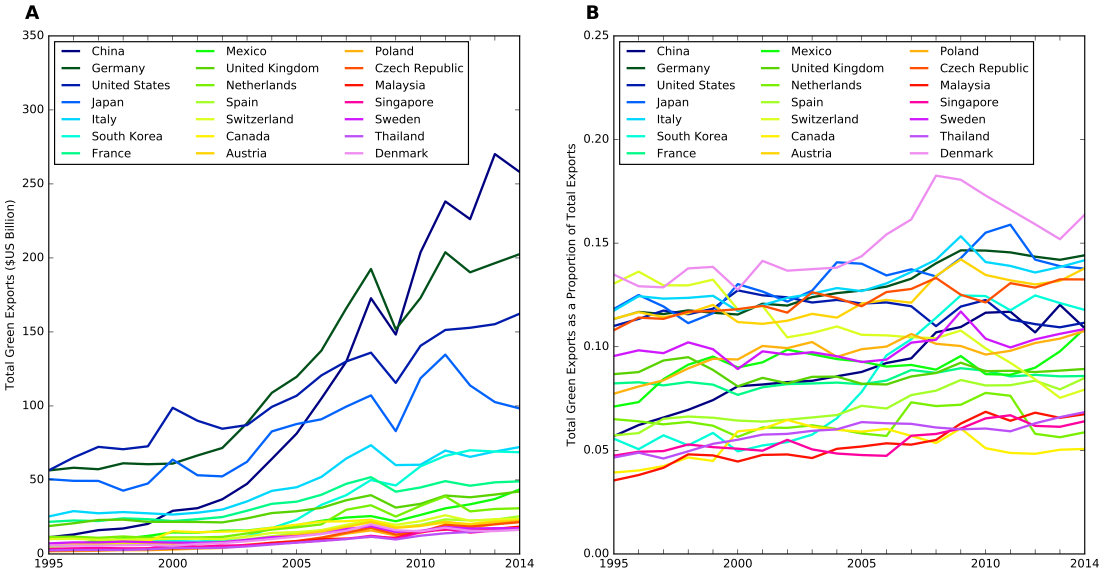

Figure 2: Top 20 Exporters of Green Products

Figure 3 shows the top exporters of renewable energy products. Again, Panel A presents the leading countries in absolute terms. As before, China has become the largest exporter of renewable energy products and its export dominance in renewable energy products (in some years exceeding $20 billion) is even greater than its dominance in all green products. In Panel B, we show the same countries' renewable energy exports relative to each nation's total exports. Here, South Korea's and Denmark's rapid patterns of green export growth become even more prominent.

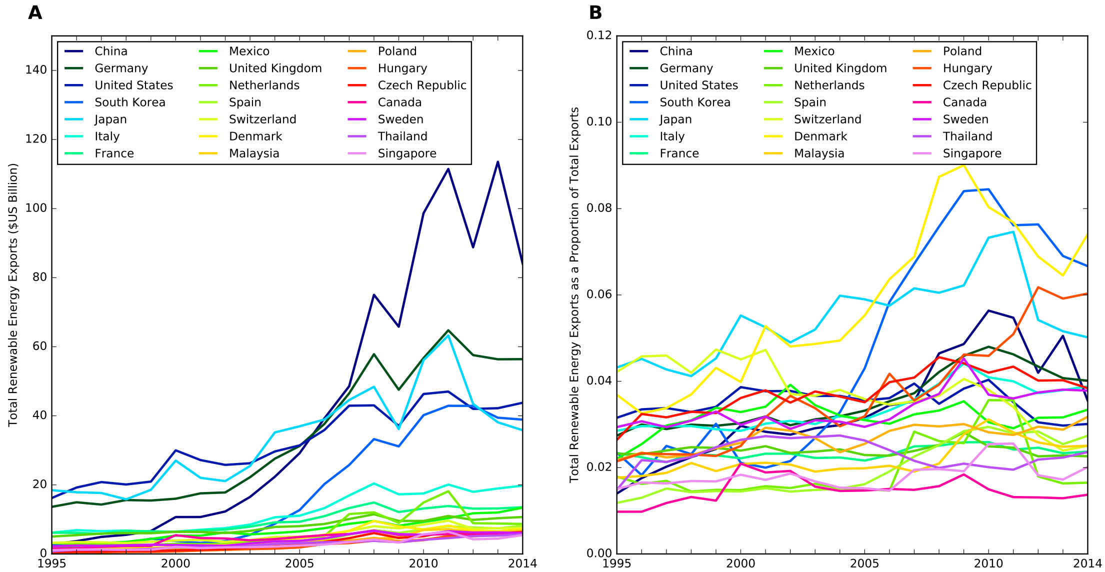

Figure 3: Top 20 Exporters of Renewable Energy Products

Next, we examine the typical income level of countries that export and import green and renewable energy products. Here we use *trade-adjusted GDP per capita* (denoted Y_X) that calculates the weighted average of GDP per capita using countries' trade shares:

$$\mathrm{Y}_X = \frac{\sum_i \frac{X_c}{\sum_c X_c} GDP_c}{\sum_i \frac{X_c}{\sum_c X_c} POP_c} \tag{1}$$

where
$X \in \{$green exports, green imports, RE exports, RE imports, total exports, total imports$\}$, X_c relates a particular trade measure to country c, GDP_c is country c's total GDP, and POP_c is country c's total population.[9]

Figure 4 shows that in 1995, green and renewable energy product exporters were much richer than an average exporter. By 2014, this was no longer the case. Figure 5 shows that the trade-adjusted GDP per capita of green and renewable

[9]If $\frac{X_c}{\sum_c X_c} = \frac{1}{N}$ (where N is the number of countries), we would simply calculate the world GDP per capita.

energy importers has increased slightly towards the income of an average importer throughout the period.

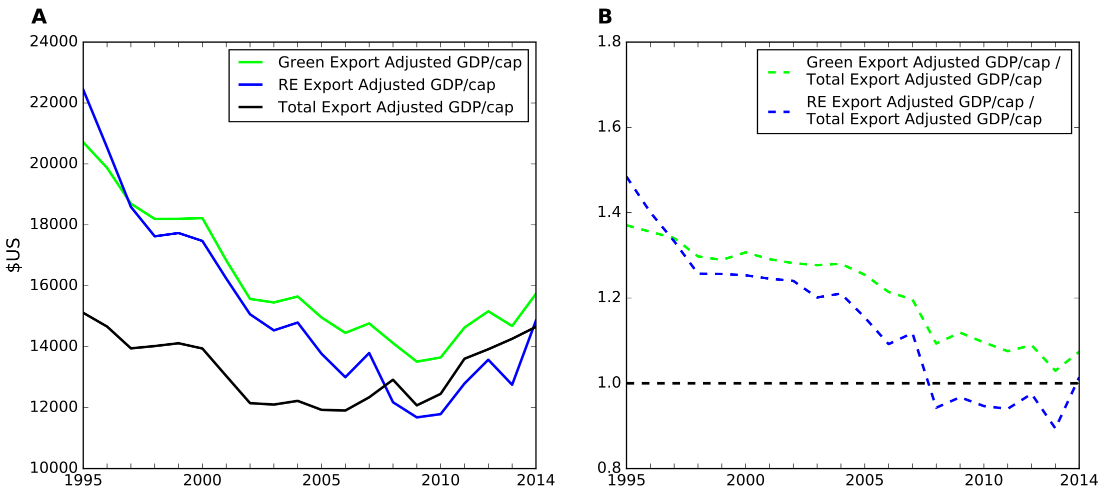

Figure 4: Green and Renewable Energy Export-Adjusted GDP/capita

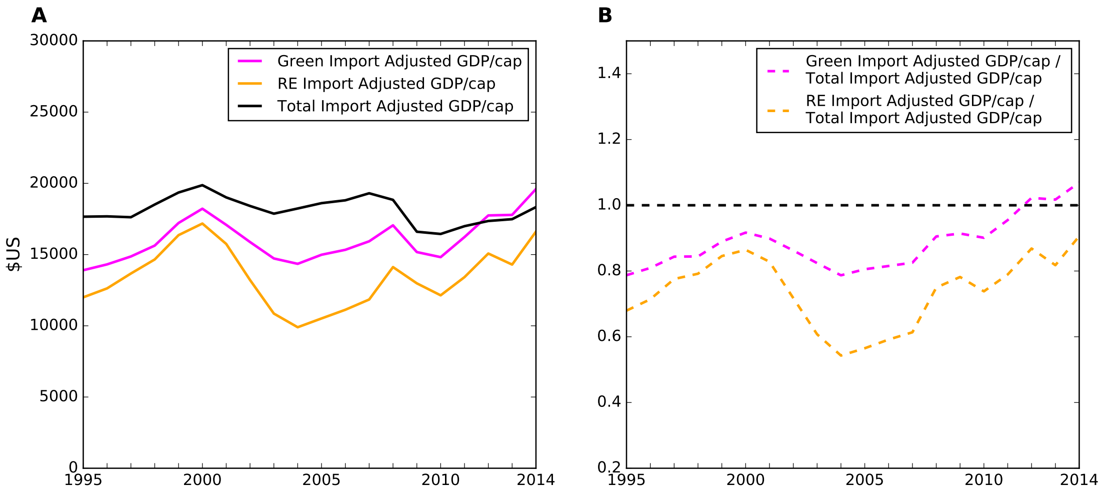

Figure 5: Green and Renewable Energy Import-Adjusted GDP/capita

An alternative way to look at the income associated with green products is to draw on a measure developed by (Hausmann et al., 2007) called *PRODY*. This measure estimates the income level associated with countries that can export a particular product *competitively*. *PRODY* for a given product p is calculated as the weighted average per capita income of countries exporting p. The weights are based on countries *revealed comparative advantage* (RCA) (Balassa, 1965). This ratio represents the size of a country c's export share in product p, relative to that product p's share of world trade, that is:

$$RCA_{cp} = \frac{x_{cp}/\sum_p x_{cp}}{\sum_c x_{cp}/\sum_c \sum_p x_{cp}} \tag{2}$$

where x_{cp} is country c's exports in product p.

Hence, the *competitiveness-adjusted GDP per capita* associated with a given product p is:

$$PRODY_p = \sum_c \frac{RCA_{cp}}{\sum_c RCA_{cp}} Y_c \tag{3}$$

where Y_c represents the per-capita GDP of country c.[10]

Figure 6 shows how the average $PRODY$ of green exports (green line) and $PRODY$ of renewable energy exports (blue dotted line) has changed over time relative to the average $PRODY$ of green imports (pink line) and renewable imports (dotted purple line). Competitive exporters of green and renewable energy products are much richer on average than countries that import disproportionate amounts of green products. The gap has narrowed somewhat since 1995, but remains substantial in 2014.

[10]To calculate $PRODY$ based on the per capita incomes of countries *importing* a product, we use the same formula, but let x_{cp} represent country c's imports of product p.

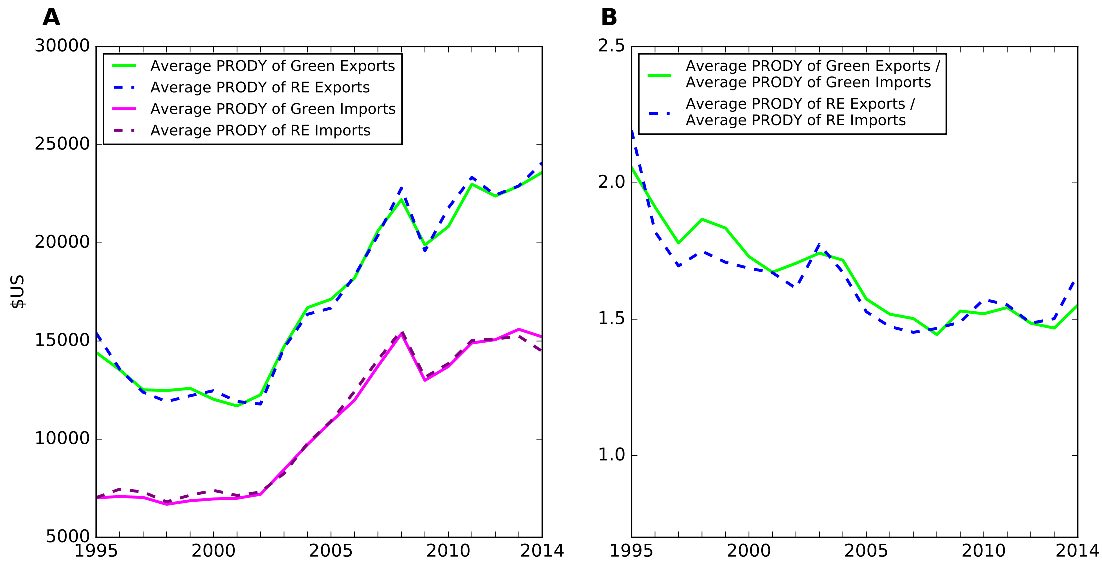

Figure 6: *PRODY* of Green and Renewable Exports and Imports

3 Economic Complexity and the Green Economy

Having looked briefly at some key empirical patterns associated with green trade, we now turn to considering the nature of green production capabilities. This section first reviews the literature on capabilities and existing measurement strategies, and then applies these analytical frameworks to capture information relevant to the green economy.

3.1 Capabilities and Complexity

The notion of capabilities has strong ties to the development and growth literature. In the development context, capabilities are often discussed with reference to the technologies, production knowhow, infrastructure and institutions that enable a country to improve its productivity and achieve higher growth rates (Lall, 1992; Bell et al., 1995; Sutton and Trefler, 2016). Here, we consider capabilities in a similar spirit – but with a distinct focus on the set of capabilities that are relevant to the green economy.

Despite its conceptual appeal, precisely defining and measuring capabilities has historically proved challenging. A number of efforts have aimed to infer information about countries' productive capabilities on the basis of their exports, with the key assumption that if a country is able to export a product, it must have the capabilities (i.e. productive knowhow, infrastructure, and institutional capacity) to produce it competitively (Lall, 2000; Lall et al., 2006; Hausmann et al., 2007; Hidalgo and Hausmann, 2009; Hausmann et al., 2014). Trade data is also advantageous in offering a rich source of detailed and comparable information on what countries are able to produce competitively.

While strategies to measure capabilities relevant for growth and development have taken various forms (see Verspagen et al. (2015) for a review), here we focus on the most recent analytical approaches, which operate on the network structure of trade data to arrive at measures of the relative complexity of capabilities associated with a given product or country (Hidalgo and Hausmann, 2009; Tacchella et al., 2012; Hausmann et al., 2014). While the term "complexity" is somewhat ambiguous, the measures are conceptually closely tied to more traditional notions of technological sophistication (Lall et al., 2006) and product quality (Sutton and Trefler, 2016).

The Economic Complexity Index (ECI) and the Product Complexity Index (ECI), which were proposed by Hidalgo and Hausmann (2009) and refined in Hausman et al. (2011) have attracted significant interest from researchers and policy makers as they are able to explain more variation in country income per capita and economic growth than other variables commonly employed in growth equations (such as governance, institutional quality, education, and competitiveness; see Sala-i-Martin, 1997). Although there has been some confusion as to what the measures capture and how they work, Mealy et al. (2017) recently showed that they,in fact, correspond to a standard clustering algorithm that partitions a similarity graph into two groups, such that entities in one group are similar to each other and dissimilar to the other group.

Viewed from this perspective, the ECI indirectly captures the "complexity" of countries' capabilities by exploiting the pattern of similarity in country export data. Countries receiving a high ECI have more similar export baskets to other countries with a high ECI, and these tend to be advanced economies that are able to export technologically sophisticated products. In contrast, countries assigned a low ECI have greater export similarity to other countries with low ECI, and these countries' export baskets tend to be characterised by less technologically sophisticated products. The PCI operates in exactly the same way, but instead provides an ordering over products in terms of the similarity in the countries that export them. That is, products receiving a higher PCI tend to be exported by a similar group of countries to other products receiving a high PCI, and tend to be more technologically sophisticated – and vice versa. More detail about the ECI and PCI can be found in Appendix A.5.

While this paper primarily focuses on the measures proposed by Hausmann et al. (2014), we note that alternative complexity measures have also been proposed by Tacchella et al. (2012). These measures are not related to a clustering algorithm, but calculated as the fixed-point solution of a non-linear mapping function, which instead exploits the pattern of export diversity (the number of products a country is able to export competitively). Tacchella et al. (2012)'s Country Fitness measure (an alternative to the ECI) can be thought of as a weighted-diversity measure, where each product that a country exports competitively is weighted by its complexity. Tacchella et al. (2012)'s corresponding Product Complexity measure is a non-linear function that is inversely related to the number of countries that can export the given product competitively. We have also performed the analysis in this paper using this alternative approach and find fairly consistent results (see Appendix A.4.5), suggesting that our findings are robust to the chosen complexity metric.

3.2 The Complexity of Green Products

Drawing on Hausmann et al. (2014)'s methodology, we first calculate the PCI for the entire set of HS1992 6-digit products. From the universal set of almost 5,000 products, we then identify products falling into our green and renewable energy product lists.

We present the key descriptive statistics for PCI of all products, green products, and renewable energy products in Table 1. The PCI values are normalised such that the set of all HS1992 6 digit products have a mean of 0 and standard deviation of 1. We find that green and renewable energy products have mean PCI value of 0.48 and 0.49 respectively. This suggests that, on average, green and renewable energy products require more complex capabilities for production than typical products.[11] In Figure 7, we present the distribution of the PCI values of all green and renewable energy products.

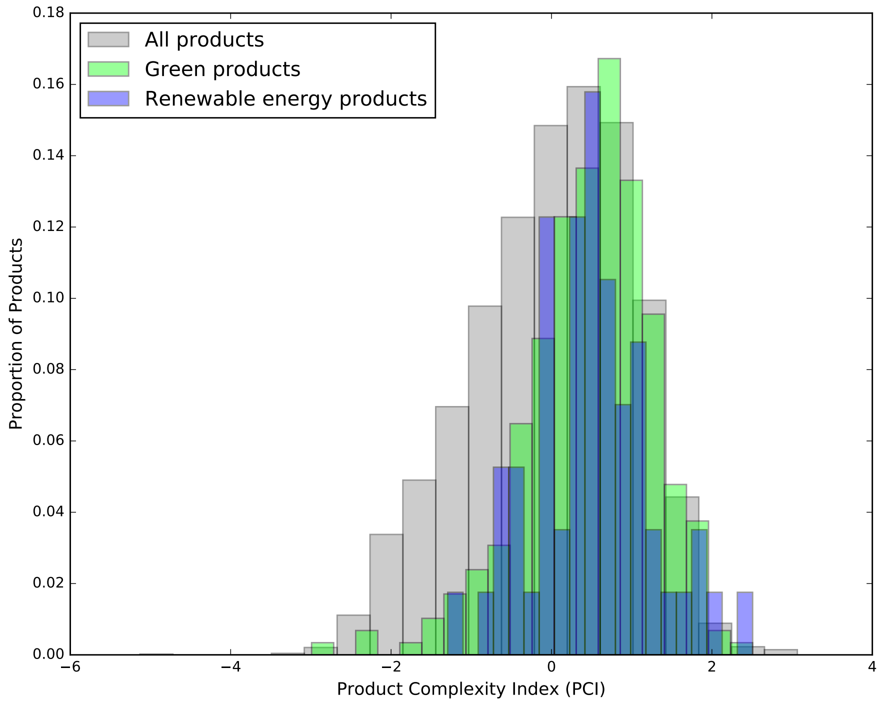

Figure 7: PCI distribution for all HS6 products, green products and renewable energy products

[11]The Kolmogorov-Smirnov 2-sample tests reject the null hypothesis that green product PCI distributions are different from all product PCI distributions (KS-Statistic for green products vs all products = 0.242, p-value = 1.11×10^{-14}). The Kolmogorov-Smirnov 2-sample test fails to reject the null hypothesis that the green and renewable energy products are drawn from the same distribution (KS-Statistic = 0.096, p-value = 0.747)

Table 1: Product PCI distribution descriptive statistics

Product Set	Number of Products	Mean PCI	Std PCI
All HS6 Products	4857	0	1
Green Products	293	0.48	0.79
Renewable Energy Products	57	0.49	0.72

In Appendix A.2, we present the top 10 and bottom 10 green products ranked according to their PCI values for the year 2014. We also present analogous PCI rankings for renewable energy products. We include the environmental benefit or category associated with each product as well as the environmental list each product is included in. The most complex green products relate to devices used for environmental monitoring and analysis, and concentrated solar technologies (Table 6), while the most complex renewable products represent a range of different mechanical devices and associated parts used in concentrated solar, wind and gas turbines (Table 8). Less complex green goods tend to relate to environmentally-friendly products – many of which are made from vegetable material (Table 7). Less complex renewable products represent a mixed bag of electrical components, biofuels, mirrors for solar PV and masts for wind turbine towers (Table 9).

3.3 The Green Complexity Index

Which countries have the most complex green production capabilities? To answer this question, we introduce the *Green Complexity Index (GCI)*, which is an increasing function of both the number and complexity of green products that a country is able to export competitively. Specifically, the GCI of country c is given by

$$GCI_c = \sum_g \rho_g \widetilde{PCI}_g \tag{4}$$

where ρ_g is a binary vector in which a 1 corresponds to a country having $RCA > 1$ in green product g and 0 otherwise, and $\widetilde{PCI}_g$ is the Product Complexity Index of g normalised to take a value between 0 and 1.

While existing measures such as Hausmann et al. (2014)'s ECI and Tacchella et al. (2012)'s Country Fitness measure operate on the entire set of traded products, the GCI is a function of the *subset* of green products. This definition is of course completely general, and could be applied to any product subset of interest.[12]

In Figure 8, we show how the GCI ranks of countries have changed between 1995 (left axis) and 2014 (right axis). Interestingly, there has been relatively little variance in the rankings of the top 10 countries. Impressively, Germany has managed to keep its top spot for the entire 20 year period. Some countries, such as China, Vietnam and Uganda have made significant gains in their green production capabilities, while other countries, such as Australia, have seen a substantial decline in their GCI rankings.

[12]We compare the GCI calculated using the Hausmann et al. (2014) PCI and Tacchella et al. (2012)'s Product Complexity measure. As shown in Appendix A.4.5, both formulations give very similar results, suggesting that the GCI is robust to the choice of product complexity measure. It is also important to note that for this particular set of traded products, the complexity scores are fairly homogenous (see Figure 7), particularly when normalised to take a value between 0 and 1. As such, the GCI score is very strongly correlated to a country's green diversity (the number of green products it is competitive in). However, this will not necessarily be the case for different product subsets, where there is greater variation in product complexity.

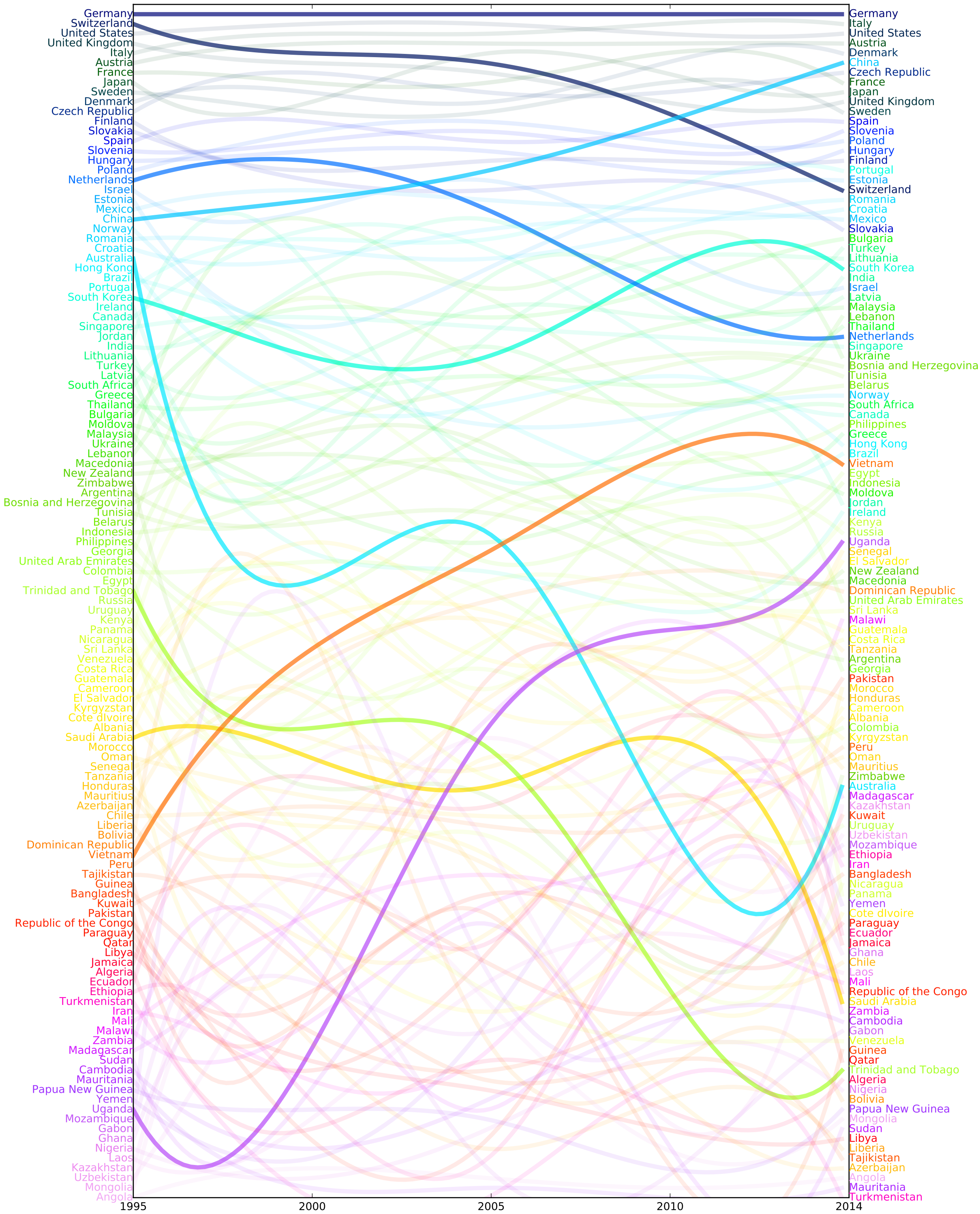

Figure 8: Green Complexity Index rankings over time

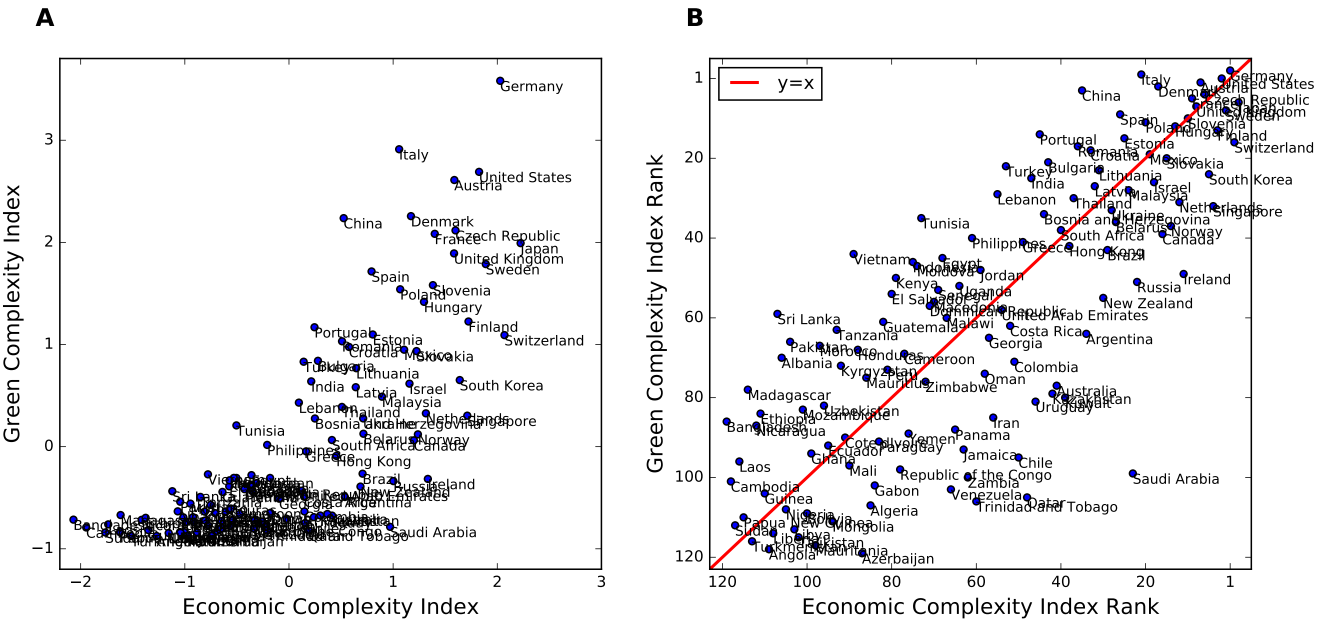

Figure 9: GCI and ECI comparisons for 2014

GCI is positively correlated with ECI, as shown in Figure 9. Panel A shows the correlation between GCI and ECI scores[13], while Panel B shows the relationship between country rankings.[14] The positive correlations are unsurprising given that richer countries have higher economic complexity and green products tend to be more complex on average.[15] However, the deviations in the ranks and values of ECI and GCI are informative about the differences in the orientation of countries' export baskets. For example, countries that are heavily focused on exporting oil and petroleum products, such as Saudi Arabia, Trinidad and Tobago, and Qatar, have lower GCI compared to ECI. In contrast, Tunisia, China, and Italy have much higher GCI scores relative to their ECI, suggesting that their production capabilities may be more aligned to green products. It may also suggest that if a green transition substantially increased demand for green goods, these countries could stand to benefit, relative to other countries having similar levels of economic complexity.

[13] Pearson correlation coefficient $= 0.766$, p-value$= 0.5 \times 10^{-25}$)

[14] Spearman's rank correlation coefficient $= 0.79$, p-value$= 5.2 \times 10^{-27}$.

[15] The correlation between ECI and GCI has remained relatively stable over the 1995-2014 period. These results are available upon request.

In Figure 10, we show the relationship between GCI and log GDP/capita for 2014. Again, the positive relationship is not surprising,[16] but the variance in the relationship provides additional insights into the current orientation of countries' economies. Consistent with Figure 9, a number of resource-rich countries have low GCI scores given their income. Germany, Italy, China, and India stand out as having much higher GCI scores given their income per capita, suggesting that their production capabilities are more oriented to the green economy than other countries with a similar standard of living.

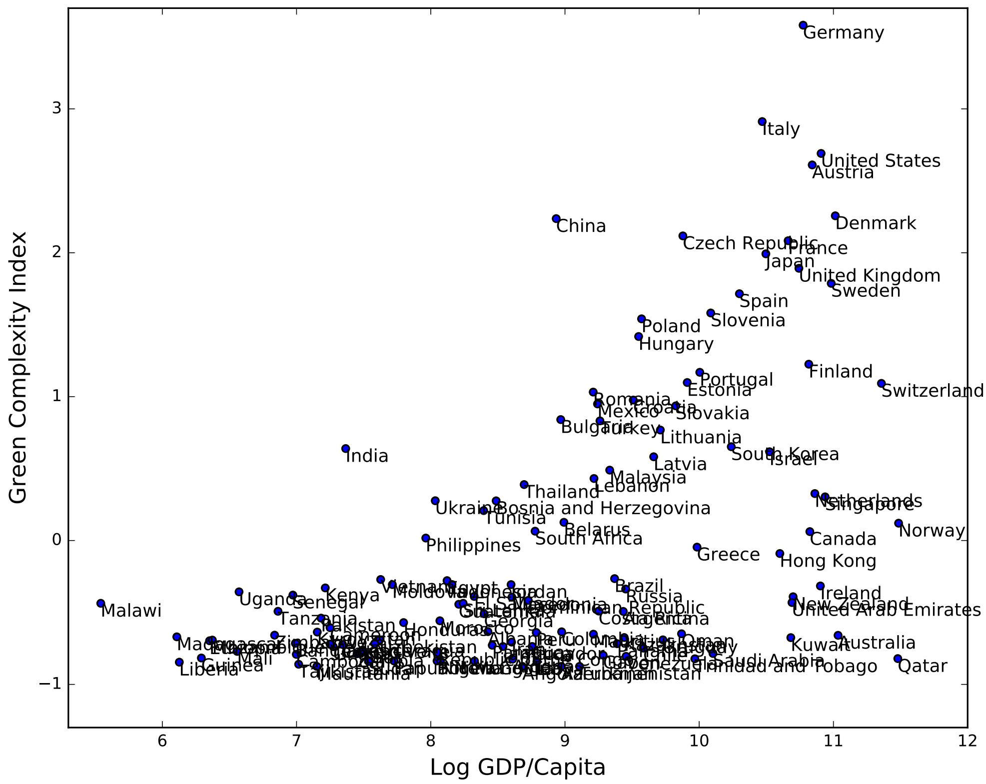

Figure 10: GCI vs log GDP per capita for 2014

Finally, if GCI really captures the green economy capabilities of countries, we should expect it to explain variation in environmentally-relevant country characteristics. We examine GCI's ability to explain cross-country variation in environmental patents, CO_2/capita emissions, and the OECD measure of stringency

[16] Pearson's correlation coefficient $= 0.55$, p-value $= 7.52 \times 10^{-11}$.

of environmental policy (EPS), after controlling for each country's ECI and per capita income.

Since GCI and ECI can fluctuate year on year due to variability in trade data, we use simple regressions on time-averaged explanatory variables as follows:

$$\bar{y}_i = \bar{x}_i\beta + \epsilon_i$$

where $y_i \in \{\text{Log Env. Patents, CO}_2\text{/capita, Log EPS}\}$, $\bar{y}_i = \frac{1}{N}\sum_{t=t_0}^{t=t_N} y_{it}$, $\bar{x}_i = \frac{1}{N}\sum_{t=t_0}^{t=T_N} x_{it}$ are time-averaged explanatory variables for N available periods, and ϵ_i is the error term.

Table 2 shows GCI's ability to explain variation in environmentally-relevant variables over the twenty year period covered by our data. We find that GCI is strongly positively correlated with the number of environmental patents across countries, even after controlling for GDP/capita and ECI. This provides further validation that the GCI captures green-economy relevant know-how across countries. We also find that countries with higher GCI tend to have lower CO_2 emissions. This relationship is particularly interesting, given our dataset does not account for the emissions intensity of each product's production process. Additionally, we find a positive relationship between GCI and the OECD's Environmental Policy Stringency Index, suggesting there is some association between the environmental policies in place in a country and its green production capabilities. While the results in Table 2 reflect GCI's explanatory power over the long run, we also run regressions for different years in Appendix A.4 and find consistent results.

Table 2: Green Complexity Index

	Log Env. Patents	Log CO_2/cap	Log EPS
GCI	1.009***	−0.307***	0.100***
	(0.215)	(0.102)	(0.029)
ECI	1.158***	0.290*	−0.115**
	(0.286)	(0.157)	(0.053)
Log GDP/Cap	0.116	0.850***	0.213***
	(0.128)	(0.086)	(0.034)
Intercept	1.593	−6.196***	−1.093***
	(1.125)	(0.734)	(0.315)
Observations	1220	2318	558
Adjusted R^2	0.766	0.765	0.7532

Robust standard errors in parenthesis.
Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Environmental patents data covers 2000 and 2005-2013, available from http://stats.oecd.org/. CO_2 (metric tons per capita) data covers 1995-2013, available from https://data.worldbank.org/indicator/EN.ATM.CO2E.PC. Environmental Policy Stringency (EPS) data covers 1995-2012, available from http://stats.oecd.org/. For all regressions, we take country averages over all available time periods.

4 The Green Product Space and Future Green Industrial Transitions

In providing an estimate of countries' capabilities to export green, complex products, the GCI gives us an idea of which countries are *currently* likely to be best placed to be leaders in the green economy. However, successfully transitioning to a greener economic growth model will no doubt require many countries to re-orientate their existing industrial structure and cultivate new green industries. To understand nature of the green transition, we now turn to investigating the question: How might countries re-orient their industrial structure to become more competitive in green products in the future?

To answer this question, we draw on a theory, advanced in both the economic complexity and economic geography literatures, which proposes that economic development is path-dependent due to the underpinning knowledge accumulation process. The underlying intuition is that if a country has the capabilities to produce T-shirts, it is relatively easy for the country to diversify into trousers because much of the requisite production capabilities (e.g. in sewing techniques, factory layout, textile supply chains, design of clothes) and factors of production are similar. However, it is much more difficult to diversify *directly* from T-shirts into automobiles because the country would have to acquire a large amount of new production knowhow and invest into completely new factors of production. By estimating the similarity of production knowhow underpinning different products, and combining this with information on the country's *current* production capabilities (from the export data), we identify the industries and products that countries would be more likely to be able to easily diversify into in the future.

We focus on two measures developed by Hidalgo et al. (2007), who applied these measures specifically to export data. They argued that if products share similar capabilities, they are more likely to be exported competitively together. On this basis, they suggested that the *proximity* (similarity in capabilities) between two exported products could be calculated by their pairwise conditional probability of being co-exported competitively. Further, to estimate how proximate a product is to a country (or, how easy a product might be to export competitively given what the country already exports competitively), Hidalgo et al. (2007) proposed a *proximity density* metric, which calculates the average proximity of a country's exports to the given product. Importantly, Hidalgo et al. (2007) were able to provide empirical support for the path-dependence of knowledge accumulation as measured by proximity density. They showed that over time, countries were much more likely to become competitive in products that were proximate to their existing capabilities.

In this section, we apply proximity and proximity density measures to the green product dataset. First, we explore green products in terms of the similarity of their requisite capabilities and visualise this by constructing a *green product space*. Second, we estimate how proximate countries are to green goods on the basis of their current export basket. Third, we develop a new metric to estimate countries' *potential* to become competitive in green products in the future.

4.1 The Green Product Space

Understanding what capabilities green products share helps us estimate how easy it is to export one green product (e.g. batteries) competitively if a country already has the capabilities to export another green product (e.g. solar panels) competitively.

Using Hidalgo et al.'s 2007 proximity measure given below we calculate the proximity between each green product i and green product j (denoted ϕ_{ij}) on the basis of their conditional probability of being co-exported competitively:

$$\phi_{ij} = \min(P(RCA_i > 1|RCA_j > 1), P(RCA_j > 1|RCA_i > 1)) \quad (5)$$

where $P(RCA_i > 1|RCA_j > 1)$ is the conditional probability of being competitive in green product i given you are competitive in green product j. Taking the minimum ensures that the proximity matrix is symmetrical ($\phi_{ij} = \phi_{ji}$)

To visualise the similarity in capabilities underpinning green products, we also follow Hidalgo et al. (2007) and construct a hierarchically clustered network where green products are linked to other green products if they have a high probability of being co-exported. To create this network, we construct a maximum spanning tree[17] from the weighted matrix ϕ and add additional edges with proximity greater than a given threshold (here we use a proximity threshold = 0.37).[18] This ensures we only connect green products that have a high probability of being co-exported. We show the resulting network – *the green product space* – in Figure 11.

[17]A spanning tree of a given graph is a tree (contains no cycles) that connects all vertices with the minimum possible number of edges. A *maximum* spanning tree is a spanning tree of a weighted graph that has the maximum weight. That is, it connects nodes by adding edges with the largest weight until the graph is fully connected.

[18]Alternative thresholds give similar results.

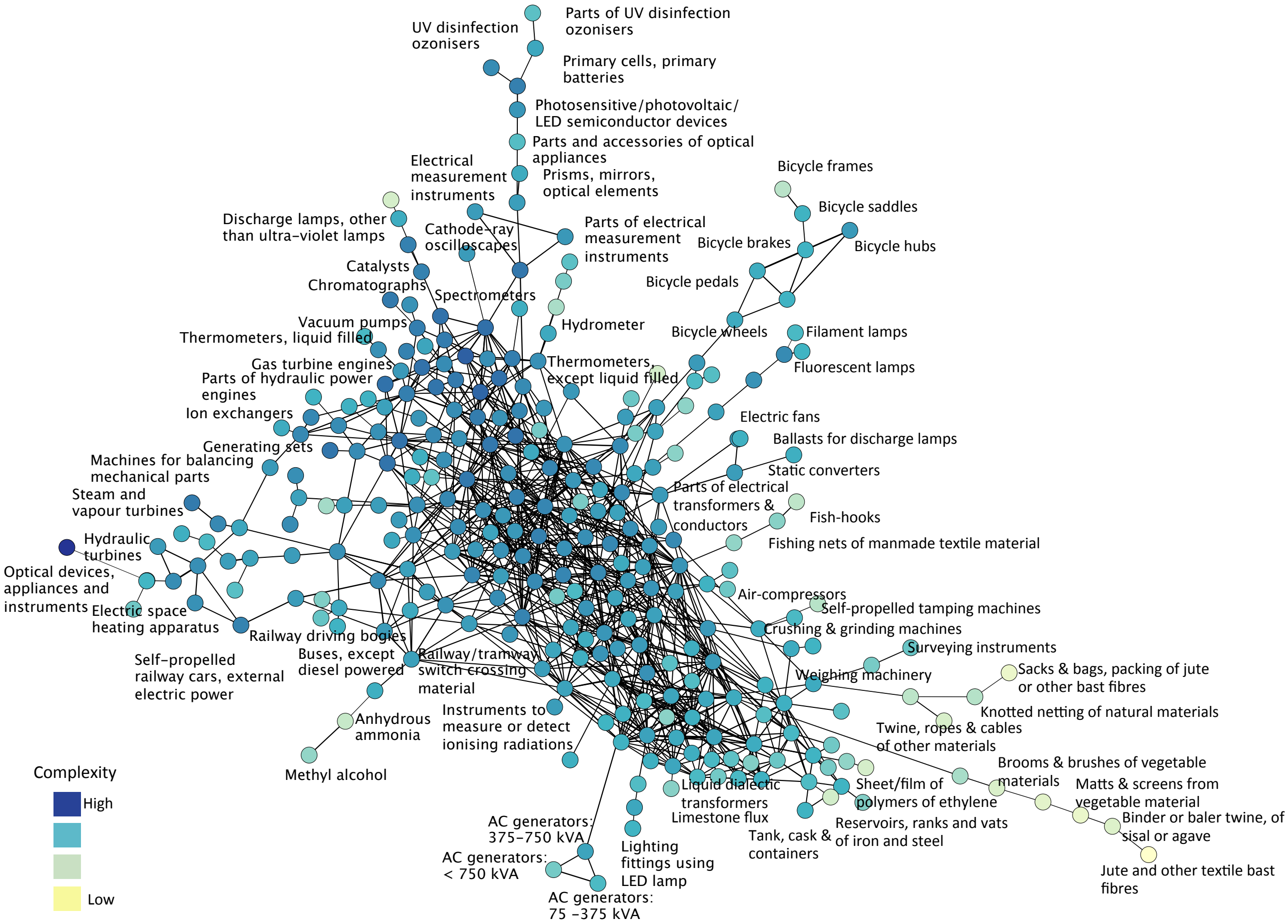

Figure 11: Proximity and the Green Product Space

Similar to Hidalgo et al.'s (2007) product space for the entire set of traded products, we find that less complex green products tend to be located in the periphery of the green product space, while more complex products are located in the core. This is interesting from a green diversification-oriented development perspective: while it may be relatively easy to export green products with lower complexity competitively, the accumulated capabilities may have limited spillover opportunities into other green products. However, as more complex products tend to be technologically linked to many other green products, gaining capabilities to export more complex green products could provide greater future green industrial development possibilities.

The green product space also provides a new way to visualise each country's competitive green exports. We show a selection of different countries in Figure 12. Holding the underlying network fixed, we colour (in green) products that a given country exports competitively. While the most striking aspect of Germany's export basket is the sheer abundance of competitive green products, it is interesting to note that the majority of these are located in the core of the green product space. South Korea also competitively exports a number of complex green products located in the green product space core, but specialises in a distinct branch of green products relating to solar photovoltaics and batteries. As a developing country, Uganda currently exports fewer green products - many of which are less complex and tending relate to vegetable materials. Finally and unsurprisingly, Saudi Arabia currently exports very few green products - all located around the periphery of the green product space. In line with the results above, this signals that countries with production capabilities too narrowly focused on resource extraction activities may find that their green production capabilities are underdeveloped and their competitive advantage is less aligned with the direction of the future green economy.

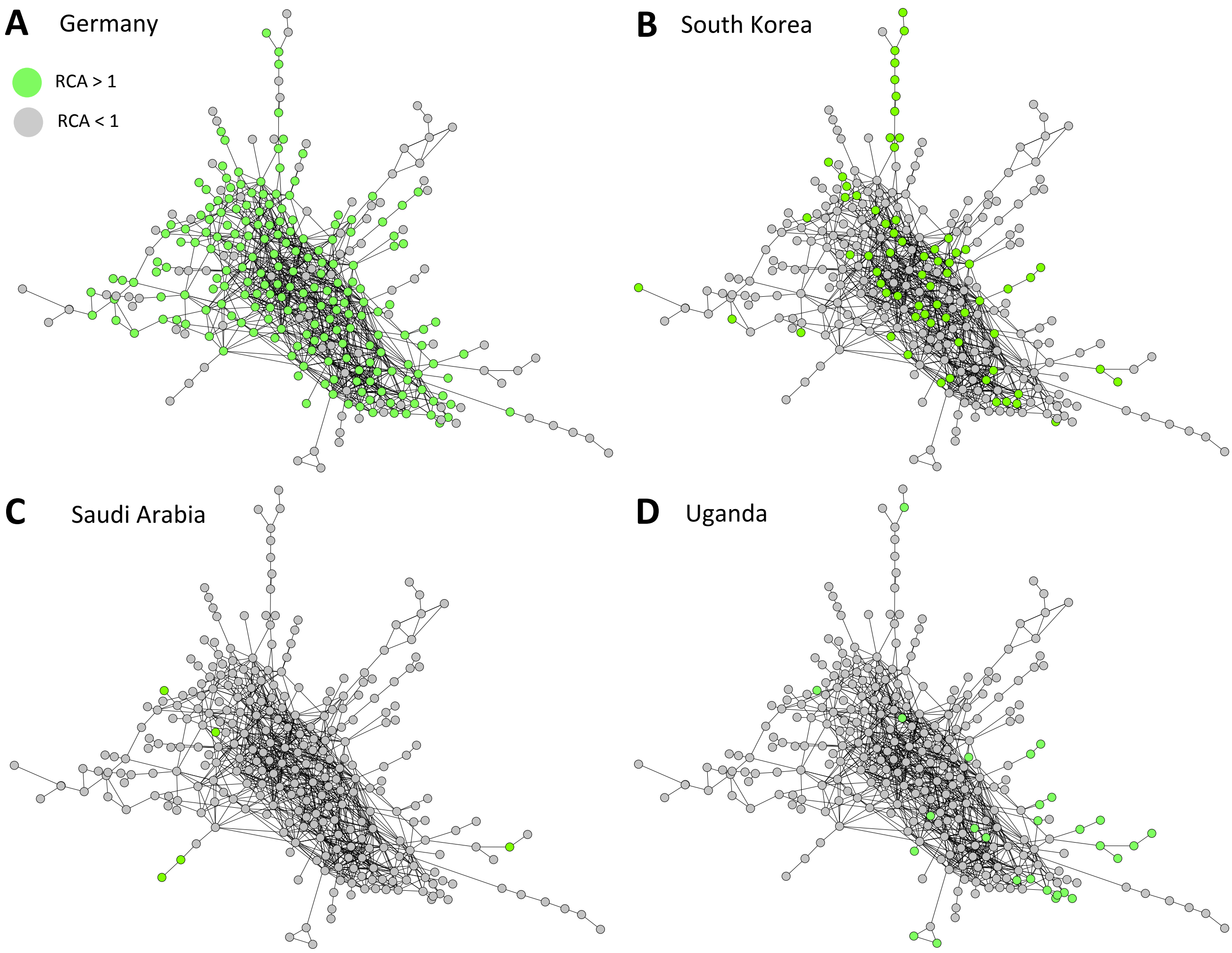

Figure 12: Competitive green product spaces for a selection of countries

4.2 Proximity Density and the Green Adjacent Possible

Visualising countries' positions in the green product space gives us an indication of countries' current and future green diversification potential. An alternative quantitative way to explore green transition possibilities is to draw on Hidalgo et al.'s second proximity measure: *proximity density*. While *proximity* (described in the previous section) estimates the similarity in green productive capabilities underpinning two products i and j, *proximity density* estimates the similarity between a country c's current set of green productive capabilities and the capabilities required to produce a given green product j. Put another way, *proximity density* estimates how easy it is to diversify into a new product j, given all the products country c can export already competitively.

Proximity density (given below) is a function of the *proximity* metric ϕ_{ij} defined above and is calculated as the average *proximity* between a given green product j and *all* the other products country c exports competitively:

$$\omega_j^c = \frac{\sum_i \rho_i \phi_{ij}}{\sum_i \phi_{ij}} \tag{6}$$

where ρ_i is a vector of i products for which country c has $RCA > 1$.

In Figure 13, we show the same selected countries depicted in Figure 12. These plots characterise each country's *Green Adjacent Possible* (GAP)–the set of green industrial opportunities that are proximate to a country's current production capabilities. In each panel, dots represent green products that countries do not currently export competitively. The x-axis shows the proximity density value for each green product for a given country and the y-axis measures each product's PCI.

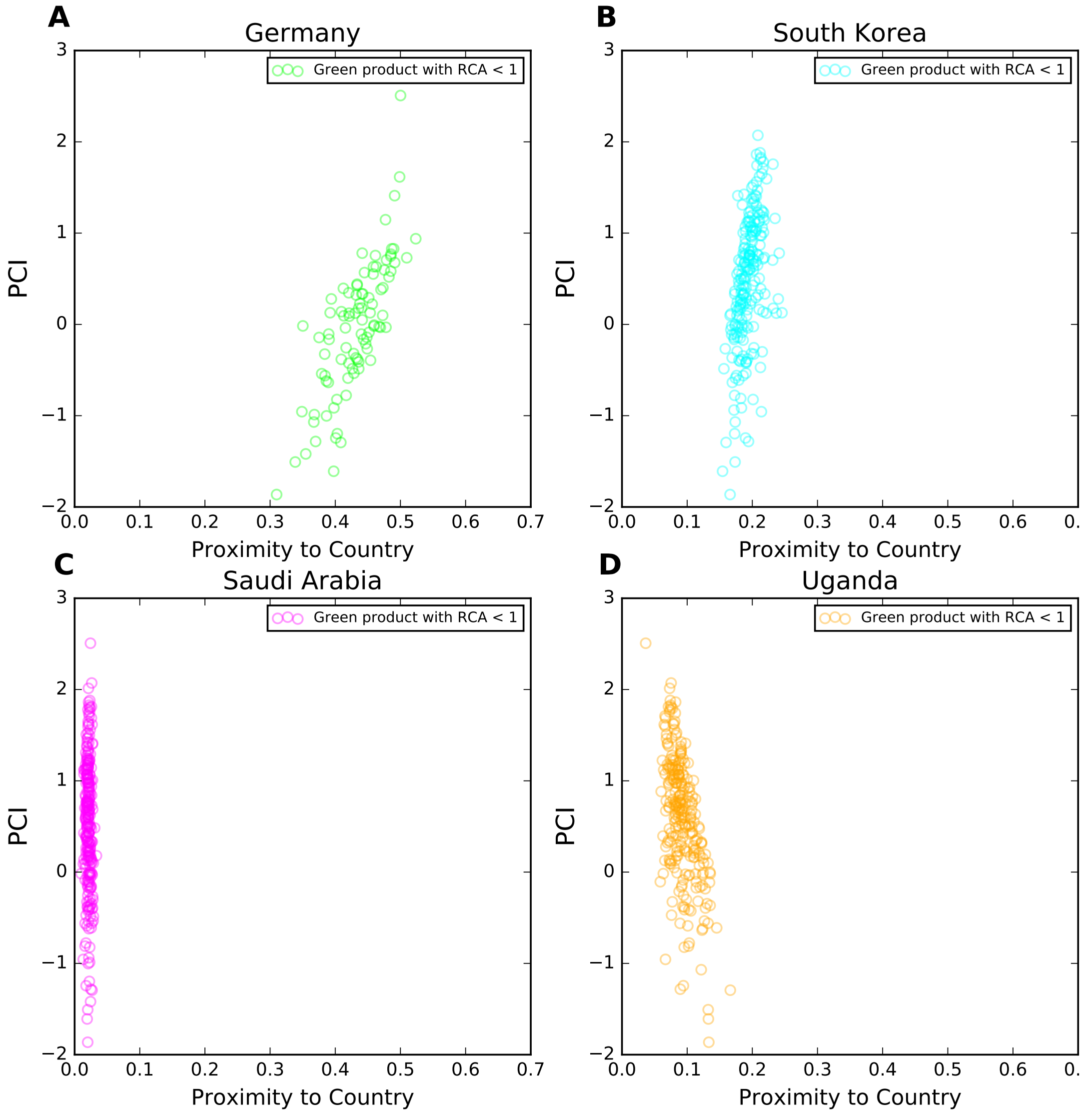

Figure 13: Characterising the Green Adjacent Possible for different countries. In each plot, the circles represent green products that the denoted country is not yet competitive in. The y-axis represents the complexity (as given by the PCI) of each product, and the x-axis represents that product's *proximity density* to a country (an estimate of how close it is to the country's current capabilities)

A number of things are interesting to note. As we would expect, Saudi Arabia is much less proximate to the set of green products because its productive knowhow is more closely focused on extracting fossil fuel resources. Uganda, a developing country, is also less proximate to more complex green products because it currently has fewer production capabilities overall. In contrast, being more economically advanced and specialising in a number of complex green products, South Korea's industrial structure is proximate to a number of green products. A slight positive slope is also evident, suggesting that South Korea's productive capabilities are more oriented towards complex green products than less complex green products. Finally, Germany's advanced manufacturing base and significant expertise in green products is reflected in its greater positive slope and high proximity to very complex green products.

4.3 Green Complexity Potential

Thus far our the GAP analysis has only been illustrative and focused on four countries. We now summarise the GAP of each country into a single aggregate number that can be compared across countries and over time. To this end, we develop the *Green Complexity Potential* metric, which which measures the *average* proximity to green complex products a country currently is not competitive in:

$$GCP_c = \frac{1}{|1-\rho_g|}\sum(1-\rho_g)\omega_g^c\widetilde{PCI}_g \tag{7}$$

where $1-\rho_g$ is the vector of green products a country currently does not have RCA > 1 in, ω_g^c is the proximity of product g to country c, and $\widetilde{PCI}_g$ is the PCI of product g, normalised to take a value between 0 and 1. GCP is similar to *Complexity Outlook Index* (Hausmann et al., 2014) and the *Complexity Potential* measure (O'Clery et al., 2016). However, while these measures are applied to the entire set of traded products (Hausmann et al., 2014) or industries (O'Clery et al., 2016), the GCP is specific to the subset of green products.

Figure 14 shows the relationship between GCP and GCI for 2014. Panel A shows the relationship between GCP and GCI scores, while Panel B shows the relationship between GCP and GCI ranks. In both cases, we find a strong correlation which indicates that the more green production capabilities a country has, the easier it is to diversify into additional new green products.[19]

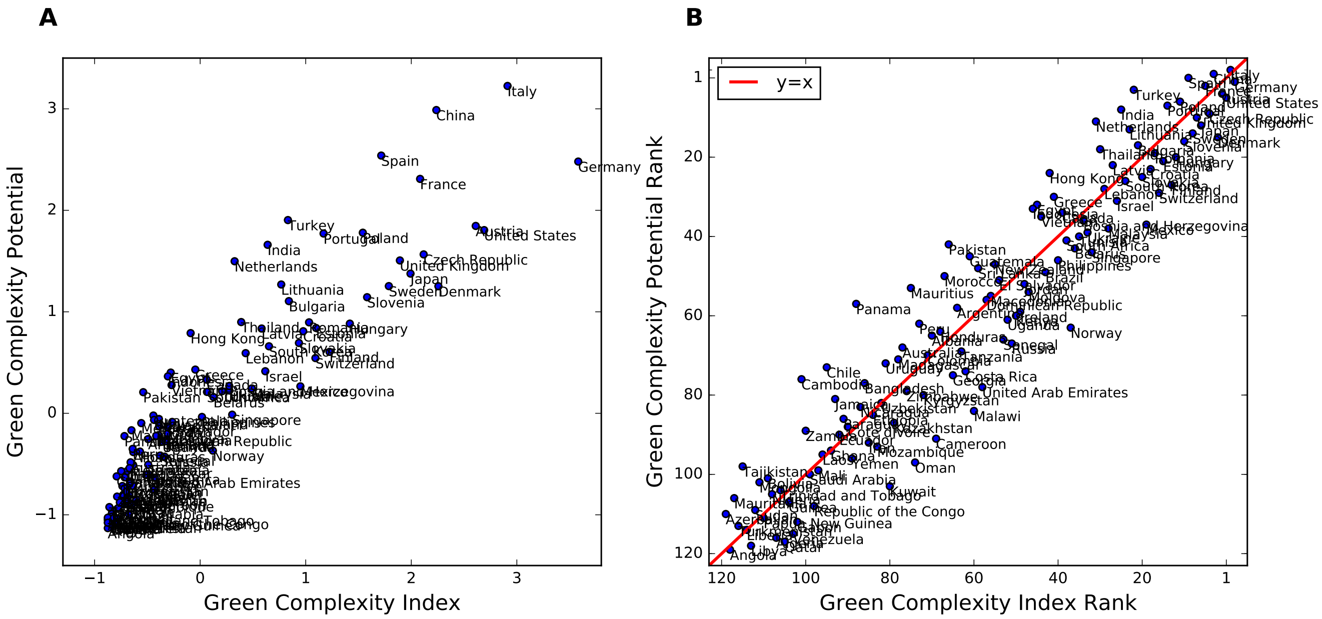

Figure 14: GCP and GCI comparison for 2014

However, the differences between GCI and GCP provide additional information about future growth: countries including China, Spain, Turkey, India and the Netherlands have higher significantly higher GCP than GCI, suggesting that these countries may be particularly well-positioned for fast development of future green capabilities. In contrast, while countries like the US, Japan and Denmark currently have very strong green production capabilities; their lower GCP score indicate that future expansion into new green product markets could be relatively slower.

In Table 3, we explore how predictive a country's GCP is for future increases in its green capabilities (as measured by GCI), the number of green products it is able to export competitively, and the share of green exports in its total export basket. Specifically, we regress the countries' GCP at the beginning of the period (averaged over 1995-2000) on the change in countries' GCI, number of competitively exported green products and green export trade ratio at the end of the period (averaged

[19]Panel A: Pearson correlation coefficient = 0.921, p-value= 3.49×10^{-51}, Panel B: Spearman correlation coefficient = 0.951, p-value= 2.11×10^{-63}.

over 2009-2014) i.e.

$$\Delta \bar{y}_i = \bar{x}_i \beta + \epsilon_i$$

where $y_i \in \{\text{GCI, \#Green exported products, Green exports}\}$, $\Delta \bar{y}_i = \frac{1}{5}\sum_{t=2009}^{t=2014} y_{it} - \frac{1}{5}\sum_{t=1995}^{t=2000} y_{it}$, $\bar{x}_i = \frac{1}{5}\sum_{t=1995}^{t=2000} x_{it}$ are explanatory variables averaged at the beginning of the sample, and ϵ_i is the error term. This specification is similar to the approach taken by O'Clery et al. (2016). However, to ensure our results are robust to year on year trade data fluctuations, we take 5-year averages.

Controlling for countries' current incomes and ECI, we find that countries with higher GCP scores are more likely to have greater future increases in their GCI, green export trade ratio and number of green products they are able to export competitively.

Table 3: Green Complexity Potential

	Δ GCI $(t+\delta)$	Δ #Green exported products $(t+\delta)$	Δ Green export trade ratio $(t+\delta)$
Log GCP(t)	0.172***	7.118***	0.012***
	(0.038)	(1.678)	(0.003)
Log GDP/Cap(t)	−0.005	−0.448	0.001
	(0.024)	(1.135)	(0.002)
ECI(t)	−0.143**	−7.450***	−0.006*
	(0.043)	(2.112)	(0.004)
GCI(t)	−0.060		
	(0.051)		
Green exported products(t)		0.084	
		(0.057)	
Green export trade ratio(t)			−0.075
			(0.158)
Intercept	0.577**	29.715***	0.039**
	(0.245)	(11.110)	(0.016)
Observations	1220	1220	1220
Adjusted R^2	0.203	0.212	0.169

Robust standard errors in parenthesis.
Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
t relates to country averaged values over years 1995-2000 and $t + \delta$ relates to country averaged values over years 2009-2014. #Green exported products refers to the number of green exports in which the country has $RCA > 1$ (i.e. diversity).

In Appendix A.4, we show that the predictive power of GCP is robust to different time-averaging specifications.

5 Policy Implications

Our results have a number of policy implications.

First, we are able to identify and measure the entire green export basket by drawing on a number of international agreements and independent policy sources. Our dataset is therefore a robust, consensus-driven definition of green products that can be used in research and policy. Our results in Section 3 also indicate that green and renewable energy products tend to be complex and are consequently likely to require substantial investment and expertise to scale for production.

Second, we estimate which countries are currently best positioned to thrive in the green economy - shedding light on increasingly important question for policy makers. Our work complements that of Fankhauser et al. (2013), who investigated a similar question by focusing on the trade competitiveness and patenting rates in 110 manufacturing sectors across 8 countries. We provide a more extensive coverage of countries and green products, and also advance an alternative analytical framework based on the economic complexity methodology.

Third, we show how a country's capabilities relevant to the green economy can evolve over time. A country that finds itself sliding down the GCI or GCP ranking may want to strengthen policies aimed at increasing its green capabilities. In fact, we can present some preliminary evidence that direct government intervention can improve green production capabilities. We use data on green stimulus packages in 19 countries over the early years of the global financial crisis (Barbier et al., 2010). Many countries embarked on stimulus programmes to boost their weak economies and green spending formed a significant part of the stimulus. Table 4 shows that even after controlling for GDP per capita, the size of the stimulus packages is positively associated with increases in GCI, in the number of green exports that the country is competitive in, and in the ratio of green exports to total exports between 2008 and 2011 (this holds both for stimulus and stimulus per capita, see Appendix A.4).

Finally, the path dependence of green capabilities tentatively indicates a role for industrial policy (see, for example, Aghion et al., 2011; Hallegatte et al., 2013; Rodrik, 2014). However, we cannot recommend a specific green industrial policy based on our results. By identifying the GAP, we can precisely indicate where the next competitive green opportunities for each country are likely to be. Stimulating competitiveness in some green industries – particularly in more complex green products – is likely to make it easier for countries to transition to other green industries in the future. But whether a transition to these technologies requires interventionist industrial policy or regulatory reform needs to be decided on a case by case basis. Our green stimulus results only provide some indication that government policy can have an effect on green capabilities. It is also important to stress that GCI, GCP, and GAP only reflect the particular orientation of countries' current export baskets and does not account for domestic or service-based green production capabilities that may exist within these countries. A proper green industrial policy should take all green capabilities and all relevant domestic policy objectives and constraints into account.

Table 4: Green Stimulus Analysis

	Δ GCI $(t+\delta)$	Δ #Green exported products $(t+\delta)$	Δ Green export trade ratio $(t+\delta)$
Green Stimulus	0.970***	41.565***	0.027*
	(0.205)	(9.699)	(0.015)
Log GDP/Cap(t)	0.000**	0.000**	0.0000
	(0.000)	(0.000)	(0.0000)
GCI(t)	0.054*		
	(0.027)		
#Green exported products(t)		0.076**	
		(0.029)	
Green export trade ratio(t)			0.082*
			(0.043)
Intercept	0.056	−0.337	−0.007*
	(0.047)	(2.204)	(0.003)
Observations	19	19	19
Adjusted R^2	0.495	0.495	0.265

Robust standard errors in parenthesis.
Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
t relates to the year 2008 and $(t+\delta)$ relates to the year 2011.
Green Stimulus units are US '000 per capita. Green Stimulus data are from Table 1 of Barbier et al. (2010), and relates to low carbon support for renewable energy, carbon capture and sequestration, energy efficiency, public transport and rail, and improving electrical grid transmission. #Green exported products refers to the number of green exports in which the country has $RCA > 1$ (i.e. diversity).

6 Conclusion

This paper has advanced an approach to systematically analyse countries' current capabilities and future potential to succeed in the green economy.

Our comprehensive new dataset revealed a number of important patterns. First, green and renewable products have not grown as a fraction of total trade in the last twenty years. Given the urgency of the transition towards a green economy, agreements to advantage trade in these products might play an important role. Second, using the economic complexity methodology, we showed that how countries' capabilities inferred from export data can explain a number of environmentally-relevant variables. Third, we identified particular green products that countries could gain a competitive edge in as they transition towards green-oriented growth models.

There are plenty of fruitful areas for further work. First, we have only considered capabilities based export data. While the GCI and GCP explain variation in environmentally-relevant measures across countries, we cannot account for capabilities embodied only in services (Stojkoski et al., 2016; OECD, 2017) or in goods sold only domestically. Second, we do not account for occupation-specific skills relevant for new green economy products (Neffke and Henning, 2013; Mealy et al., 2017). Third, we do not look at regional or city-level variation (Boschma et al., 2013; O'Clery et al., 2016). Fourth, we have not considered channels for green technology diffusion across neighbouring countries (Bahar et al., 2014). Fifth, we have not explored regional green industrial policy or regional specialisation (e.g. Pearl River Delta, Silicon Valley): government policy and research might want to focus directly on the competitiveness of regional production clusters (Delgado et al., 2014). Finally, it would be worth understanding what roles services, skills, and regional specialisation play in a more expanded definition of the green economy by looking closely at green patents, green research and development, carbon emissions and environmental protection.

A Appendix

A.1 Description of the data sources

Table 5: Green Product Data Sources

List	Description	Source
WTO Reference Universe	408 products that represent a universe of potentially green products proposed by different WTO Member States	• WTO Report by the Chairman to the Trade Negotiations Committee on the Committee and Trade and Environment in Special Session TN/TE/19 (22 March 2010) • WTO Report by the Chairman to the Trade Negotiations Committee on the Committee and Trade and Environment in Special Session TN/TE/20 (21 April 2011)
WTO Sample Core List	26 products with wide endorsement from WTO Member States	• WTO Report by the Chairman to the Trade Negotiations Committee on the Committee and Trade and Environment in Special Session TN/TE/20 (21 April 2011)
APEC List of Environmental Goods	54 green products for which APEC Member states agreed to reduce applied tariff rates to 5% or less by the end of 2015	• 2012 APEC Leaders Declaration Annex C
OECD (1999) Illustrative Product List of Environmental Goods	List of 121 illustrative environmental products developed by the OECD/Eurostat Informal Working Group	• OECD (1999), "Future Liberalisation of Trade in Environmental Goods and Services: Ensuring Environmental Protection as well as Economic Benefits" • A Comparison of the APEC and OECD Lists", *OECD Trade and Environment Working Paper No. 2005-04* Table A1.
List of 257 customised products developed by the OECD	List of 257 customised products developed by the OECD	• Sauvage (2014), "The Stringency of Environmental Regulations and Trade in Environmental Goods", *OECD Trade and Environment Working Papers*, 2014/03

A.2 Products

Table 6: Top 10 Green Products by PCI

Rank	PCI	HS6 Code	Product Description	Environmental Benefits	Environmental Lists
1	2.5073	901380	Optical devices, appliances and instruments, nes	Solar Heliostats (Heliostats orient mirrors in concentrated solar power systems to reflect sunlight on to a CSP receiver)	APEC, OECD (2014)
2	2.0716	902790	Microtomes, parts of scientific analysis equipment	Microtomes are devices that prepare slices of samples for analysis - used in environmental monitoring	APEC, OECD (1999), OECD (2014)
3	2.0134	847989	Machines and mechanical appliances, nes	Machines and appliances designed for a wide range of areas of environmental management including waste, waste water, drinking water production and soil remediation	WTO Sample, APEC, OECD (1999), OECD (2014)
4	1.8805	902730	Spectrometers, spectrophotometers, etc using light	Used in a wide range of environmental applications, including identification of unknown chemicals, toxins and trace contaminants, environmental control, water management, food processing, agriculture and weather monitoring	WTO Sample, APEC, OECD (1999), OECD (2014)
5	1.8625	902780	Equipment for physical or chemical analysis, nes	Used to measure, record, analyse and assess environmental samples or environmental influences	APEC, OECD (1999), OECD (2014)
6	1.8291	680690	Mineral heat or sound insulating materials and articles	Used for heat and energy management	OECD (2014)
7	1.8119	902720	Chromatographs, electrophoresis instruments	Used to monitor and analyse air pollution emissions, ambient air quality, water quality, etc.	APEC, OECD (1999), OECD (2014)
8	1.8077	902710	Gas/smoke analysis apparatus	Used for monitoring and analysing environmental pollution.	APEC, OECD (1999), OECD (2014)
9	1.7945	847990	Parts of machines and mechanical appliances nes	Parts for environmental management devices (Machines and appliances designed for a wide range of areas of environmental management including waste, waste water, drinking water production and soil remediation)	APEC, OECD (2014)
10	1.7795	848360	Clutches, shaft couplings, universal joints	Used for initial assembly, repair, and maintenance of wind energy systems	OECD (2014)

Table 7: Bottom 10 Green Products by PCI

Rank	PCI	HS6 Code	Product Description	Environmental Benefits	Environmental Lists
284	-1.2445	871200	Bicycles, other cycles, not motorized	Cleaner or more resource efficient technology or product	OECD (2014)
285	-1.2826	871411	Motorcycle Saddles	Cleaner or more resource efficient technology or product	OECD (2014)
286	-1.2935	220710	Undenatured ethyl alcohol $>$ 80% by volume	Renewable Energy Plant	OECD (1999)
287	-1.4189	560790	Twine, cordage, ropes and cables, of other materials	Environmentally preferrable product	OECD (2014)
288	-1.5074	960310	Brooms/brushes of vegetable material	Waste collection equipment (solid waste management)	OECD (1999)
289	-1.6088	560721	Binder or baler twine, of sisal or agave	Environmentally preferrable product	OECD (2014)
290	-1.864	460120	Mats, matting and screens, vegetable plaiting material	Environmentally preferrable product	WTO Sample
291	-2.1905	530599	Vegetable fibre nes, processed not spun, tow and waste	Environmentally preferrable product	OECD (2014)
292	-2.2365	630510	Sacks and bags, packing, of jute or other bast fibres	Environmentally preferrable product	OECD (2014)
293	-2.9908	530310	Jute and other textile bast fibres, raw or processed but not spun	Environmentally preferrable product	OECD (2014)

Table 8: Top 10 Renewable Energy Products by PCI

Rank	PCI	HS6 Code	Product Description	Environmental Benefits	Environmental Lists
1	2.5073	901380	Optical devices, appliances and instruments, nes	Solar Heliostats (Heliostats orient mirrors in concentrated solar power systems to reflect sunlight on to a CSP receiver)	APEC, OECD (2014)
2	2.0134	847989	Machines and mechanical appliances nes	Machines and appliances designed for a wide range of areas of environmental management including waste, waste water, drinking water production and soil remediation	WTO Sample, APEC, OECD (1999), OECD (2014)
3	1.7795	848360	Clutches, shaft couplings, universal joints	Used for initial assembly, repair, and maintenance of wind energy systems	OECD (2014)
4	1.7554	848340	Gearing, ball screws, speed changers, torque converte	Gearboxes transform the rotation of the blades of wind turbines into the speed required to produce renewable electricity	OECD (2014)
5	1.7419	841199	Parts of gas turbine engines except turbo-jet/prop	Parts for gas turbines, which generate electrical power from recovered landfill gas, coal mine vent gas, or biogas	APEC, OECD (2014)
6	1.4104	841181	Gas turbine engines nes of a power < 5000 kW	Gas turbines for electrical power generation from recovered landfill gas, coal mine vent gas, or biogas (clean energy system)	WTO Sample, OECD (2014)
7	1.2239	840619	Steam and vapour turbines nes	Turbines designed for the production of geothermal energy (renewable energy) and co-generation ((CHP) which allows for a more effective use of energy than conventional generation)	WTO Sample, OECD (2014)
8	1.216	903289	Automatic regulating/controlling equipment nes	Used in renewable energy and smart grid applications, as well as other process control instruments and apparatus for temperature, pressure, flow and level, and humidity	APEC, OECD (1999), OECD (2014)
9	1.1399	841950	Heat exchange units, non-domestic, non-electric	Provide cooling effect to heat exchangers in solar collector or solar system controllers to avoid overheating. Heat exchangers are also used in geothermal energy systems.	WTO Sample, OECD (1999), OECD (2014)
10	1.1216	840690	Parts of steam and vapour turbines	Parts for turbines designed for production of geothermal energy (renewable energy) and co- generation ((CHP) which allows for a more effective use of energy than conventional generation	APEC, OECD (2014)

Table 9: Bottom 10 Renewable Energy Products by PCI

Rank	PCI	HS6 Code	Product Description	Environmental Benefits	Environmental Lists
48	-0.14782	761100	Aluminium reservoirs,vats, tanks, etc, volume >300l	Containers for the production of biogas, waste water management, drinking water production and solar thermal energy purposes.	OECD (2014)
49	-0.31929	850432	Transformers electric, power capacity 1-16 KVA, nes	Renewable Energy Plant	OECD (2014)
50	-0.36528	850421	Liquid dielectric transformers $<$ 650 KVA	Used for initial assembly, repair, and maintenance of wind energy systems	OECD (2014)
51	-0.38168	850161	AC generators, of an output < 75 kVA	Used in conjunction with boiler and turbines to generate electricity in renewable energy plants	OECD (2014)
52	-0.41086	850720	Lead-acid electric accumulators except for vehicles	Provides for energy storage in off-grid PV system	OECD (2014)
53	-0.56155	700992	Glass mirrors, framed	Renewable Energy Plant	OECD (2014)
54	-0.61976	730820	Towers and lattice masts, iron or steel	Used to elevate and support a wind turbine for the generation of renewable energy	WTO Sample, OECD (2014)
55	-0.63559	290511	Methyl alcohol	Renewable Energy Plant	OECD (1999)
56	-0.81094	850431	Transformers electric, power capacity < 1 KVA, nes	Renewable Energy Plant	OECD (2014)
57	-1.2935	220710	Undenatured ethyl alcohol > 80		

A.3 Countries

In Table 10, we present each country's GCI, GCP and ECI ranks for 2014. We also identify each country's most proximate green product that they are not yet competitive in and show the proximaty density of that product to the given country.

Table 10: Country Rankings and most proximate green product for 2014

Country	GCI Rank	GCP Rank	ECI Rank	Most proximate green product	Proximity Density
Germany	1	4	3	Webs, mattresses, other nonwoven fibreglass products	0.523527
Italy	2	1	24	Multiple-walled insulating units of glass	0.551191
United States	3	8	5	Vacuum pumps	0.393836
Austria	4	7	10	Manostats	0.407972
Denmark	5	18	20	Mineral and aerated waters not sweetened or flavoured	0.338434
China	6	2	38	Jute and other textile bast fibres, raw or retted	0.547997
Czech Republic	7	12	9	Parts of wash, filling, closing, aerating machinery	0.357498
France	8	5	12	Valves, pressure reducing	0.4277
Japan	9	15	1	Railway maintenance-of-way service vehicles	0.355749
United Kingdom	10	13	11	Compression refrigeration equipment with heat exchange	0.335603
Sweden	11	17	4	Gas/smoke analysis apparatus	0.316329
Spain	12	3	29	Mineral and aerated waters not sweetened or flavoured	0.486129
Slovenia	13	19	13	Domestic iron/steel solid fuel appliances, not cooker	0.299162
Poland	14	9	23	Mineral and aerated waters not sweetened or flavoured	0.398532
Hungary	15	23	16	Manostats	0.267572
Finland	16	30	6	Mufflers and exhaust pipes for motor vehicles	0.228582
Portugal	17	10	48	Brooms/brushes of vegetable material	0.422045
Estonia	18	24	28	Mineral and aerated waters not sweetened or flavoured	0.284672
Switzerland	19	32	2	Clutches, shaft couplings, universal joints	0.230932
Romania	20	22	39	Liquid dielectric transformers < 650 KVA	0.282028
Croatia	21	26	36	Building blocks, bricks of cement, or artificial ston	0.307701
Mexico	22	40	22	Gas supply/production/calibration meters	0.170645
Slovakia	23	28	18	Prefabricated structural items of cement or concrete	0.241184
Bulgaria	24	20	46	Mineral and aerated waters not sweetened or flavoured	0.327624
Turkey	25	6	56	Brooms/brushes of vegetable material	0.462755
Lithuania	26	16	34	Cans, iron/steel, capacity <50l closed by crimp/solde	0.336749
South Korea	27	29	8	Bicycle brakes, parts thereof	0.245542
India	28	11	50	Brooms/brushes of vegetable material	0.388543
Israel	29	34	21	Surveying, etc instruments nes	0.1938
Latvia	30	25	35	Tank, cask or container, iron/steel, capacity 50-300l	0.280853
Malaysia	31	41	27	Parts and accessories of optical appliances nes	0.182011
Lebanon	32	31	58	Building blocks, bricks of cement, or artificial ston	0.262736
Thailand	33	21	40	Mats, matting and screens, vegetable plaiting material	0.268803
Netherlands	34	14	15	Surveying, etc instruments nes	0.344208
Singapore	35	47	7	Optical devices, appliances and instruments, nes	0.183491
Ukraine	36	42	31	Sheet etc, cellular of polymers of styrene	0.189066
Bosnia and Herzegovina	37	39	47	Liquid dielectric transformers < 650 KVA	0.216554
Tunisia	38	43	76	Sacks and bags, packing, of jute or other bast fibres	0.231006
Belarus	39	46	30	Mineral and aerated waters not sweetened or flavoured	0.186029
Norway	40	66	17	Anhydrous ammonia	0.112998
South Africa	41	44	43	Sacks and bags, packing, of jute or other bast fibres	0.205328
Canada	42	37	19	Railway cars nes, closed and covered	0.204049
Philippines	43	49	64	Brooms/brushes of vegetable material	0.167938
Greece	44	33	52	Sacks and bags, packing, of jute or other bast fibres	0.24185
Hong Kong	45	27	41	Bicycle hubs, free-wheel sprocket wheels	0.264135
Brazil	46	52	32	Railway cars nes, closed and covered	0.139184
Vietnam	47	38	92	Jute and other textile bast fibres, raw or retted	0.282421
Egypt	48	35	71	Sacks and bags, packing, of jute or other bast fibres	0.278484
Indonesia	49	36	78	Jute and other textile bast fibres, raw or retted	0.273387
Moldova	50	57	77	Mineral and aerated waters not sweetened or flavoured	0.159036
Jordan	51	55	62	Sacks and bags, packing, of jute or other bast fibres	0.181749
Ireland	52	62	14	Surveying, etc instruments nes	0.125117
Kenya	53	63	82	Sacks and bags, packing, of jute or other bast fibres	0.195668
Russia	54	70	25	Gas turbine engines nes of a power < 5000 kW	0.10655
Uganda	55	64	67	Undenatured ethyl alcohol > 80% by volume	0.166241

Continued on next page

Table 10 – continued from previous page

Country	GCI Rank	GCP Rank	ECI Rank	Most proximate green product	Proximity Density
Senegal	56	69	72	Surveying, etc instruments nes	0.134271
El Salvador	57	54	83	Brooms/brushes of vegetable material	0.183812
New Zealand	58	50	33	Surveying, etc instruments nes	0.164334
Macedonia	59	58	73	Brooms/brushes of vegetable material	0.169198
Dominican Republic	60	59	74	Sacks and bags, packing, of jute or other bast fibres	0.179649
United Arab Emirates	61	81	57	Anhydrous ammonia	0.098455
Sri Lanka	62	51	110	Sacks and bags, packing, of jute or other bast fibres	0.24724
Malawi	63	87	70	Surveying, etc instruments nes	0.072619
Guatemala	64	48	85	Sacks and bags, packing, of jute or other bast fibres	0.237824
Costa Rica	65	77	55	Chlorine	0.089105
Tanzania	66	72	96	Sacks and bags, packing, of jute or other bast fibres	0.169185
Argentina	67	61	37	Methyl alcohol	0.133796
Georgia	68	78	60	Undenatured ethyl alcohol $>$ 80% by volume	0.088708
Pakistan	69	45	107	Jute and other textile bast fibres, raw or retted	0.307798
Morocco	70	53	100	Brooms/brushes of vegetable material	0.2086
Honduras	71	67	91	Undenatured ethyl alcohol $>$ 80% by volume	0.14617
Cameroon	72	94	80	Undenatured ethyl alcohol $>$ 80% by volume	0.054028
Albania	73	68	109	Brooms/brushes of vegetable material	0.162402
Colombia	74	73	54	Undenatured ethyl alcohol $>$ 80% by volume	0.101699
Kyrgyzstan	75	83	95	Sacks and bags, packing, of jute or other bast fibres	0.083056
Peru	76	65	84	Sacks and bags, packing, of jute or other bast fibres	0.149909
Oman	77	100	61	Mineral and aerated waters not sweetened or flavoured	0.044163
Mauritius	78	56	89	Brooms/brushes of vegetable material	0.186092
Zimbabwe	79	82	75	Jute and other textile bast fibres, raw or retted	0.088834
Australia	80	71	44	Methyl alcohol	0.112851
Madagascar	81	74	117	Brooms/brushes of vegetable material	0.148984
Kazakhstan	82	90	45	Anhydrous ammonia	0.07086
Kuwait	83	106	42	Methyl alcohol	0.032296
Uruguay	84	75	49	Undenatured ethyl alcohol $>$ 80% by volume	0.0896
Uzbekistan	85	85	99	Sacks and bags, packing, of jute or other bast fibres	0.08202
Mozambique	86	96	104	Jute and other textile bast fibres, raw or retted	0.072479
Ethiopia	87	88	114	Sacks and bags, packing, of jute or other bast fibres	0.10837
Iran	88	95	59	Liquid dielectric transformers $<$ 650 KVA	0.042025
Bangladesh	89	80	122	Brooms/brushes of vegetable material	0.14754
Nicaragua	90	86	115	Sacks and bags, packing, of jute or other bast fibres	0.111789
Panama	91	60	68	Sacks and bags, packing, of jute or other bast fibres	0.169703
Yemen	92	99	79	Sacks and bags, packing, of jute or other bast fibres	0.056184
Cote dIvoire	93	91	94	Surveying, etc instruments nes	0.066838
Paraguay	94	89	86	Sacks and bags, packing, of jute or other bast fibres	0.069216
Ecuador	95	93	98	Sacks and bags, packing, of jute or other bast fibres	0.067348
Jamaica	96	84	66	Mineral and aerated waters not sweetened or flavoured	0.082543
Ghana	97	97	102	Undenatured ethyl alcohol $>$ 80% by volume	0.059005
Chile	98	76	53	Anhydrous ammonia	0.091139
Laos	99	98	119	Sacks and bags, packing, of jute or other bast fibres	0.070638
Mali	100	102	93	Sacks and bags, packing, of jute or other bast fibres	0.056515
Republic of the Congo	101	111	81	Sacks and bags, packing, of jute or other bast fibres	0.023712
Saudi Arabia	102	103	26	Manganese oxides other than manganese dioxide	0.033556
Zambia	103	92	65	Sacks and bags, packing, of jute or other bast fibres	0.066985
Cambodia	104	79	121	Jute and other textile bast fibres, raw or retted	0.153735
Gabon	105	115	87	Surveying, etc instruments nes	0.017623
Venezuela	106	118	69	Surveying, etc instruments nes	0.011949
Guinea	107	110	113	Sacks and bags, packing, of jute or other bast fibres	0.03639
Qatar	108	120	51	Buoys, beacons, coffer-dams, pontoons, floats nes	0.009239
Trinidad and Tobago	109	107	63	Mineral and aerated waters not sweetened or flavoured	0.029218
Algeria	110	119	88	Sodium hydroxide (caustic soda) solid	0.009689
Nigeria	111	108	108	Jute and other textile bast fibres, raw or retted	0.029281
Bolivia	112	104	103	Jute and other textile bast fibres, raw or retted	0.042712
Papua New Guinea	113	114	118	Sacks and bags, packing, of jute or other bast fibres	0.02736
Mongolia	114	105	97	Sacks and bags, packing, of jute or other bast fibres	0.032406
Sudan	115	112	120	Sacks and bags, packing, of jute or other bast fibres	0.033396
Libya	116	121	106	Sacks and bags, packing, of jute or other bast fibres	0.010857
Liberia	117	117	111	Surveying, etc instruments nes	0.016883
Tajikistan	118	101	105	Jute and other textile bast fibres, raw or retted	0.046313
Azerbaijan	119	113	90	Methyl alcohol	0.020978
Angola	120	122	112	Methyl alcohol	0.003356
Mauritania	121	109	101	Sacks and bags, packing, of jute or other bast fibres	0.027647
Turkmenistan	122	116	116	Sacks and bags, packing, of jute or other bast fibres	0.018702

A.4 Robustness checks for regression results

There is not enough within country variation in GCI and GCP for the relatively short period covered by our dataset to run a country-fixed-effect panel regression. Instead, we present additional regression analyses for different years covered by our dataset.

A.4.1 GCI and Environmental Patents

Table 11: Robustness tests for the relationship between GCI and Log Env. Patents over different years

	2010	2005	2000
GCI	1.144***	1.034***	1.205***
	(0.201)	(0.213)	(0.177)
ECI	0.956***	1.147***	0.782***
	(0.307)	(0.273)	(0.189)
Log GDP/Cap	0.208	0.003	0.111
	(0.150)	(0.127)	(0.102)
Intercept	0.632	2.338**	1.089
	(1.237)	(1.067)	(0.798)
Observations	122	122	122
Adjusted R^2	0.752	0.741	0.755

Robust standard errors in parenthesis.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01
The Env. Patent variable can be found in the OECD Statistics database under Environment – Innovation in environment-related tech – Technology Development (Family Size: one or greater; Technology Domain: Selected Environment-Related Technologies). Available at: http://stats.oecd.org/

A.4.2 GCI and CO_2 Emissions

Table 12: Robustness tests for the relationship between GCI and Log CO2/cap emissions over different years

	2010	2005	2000
GCI	−0.171*	−0.333***	−0.2765***
	(0.097)	(0.100)	(0.103)
ECI	0.048	0.377**	0.398**
	(0.158)	(0.152)	(0.153)
Log GDP/Cap	0.923***	0.767***	0.746***
	(0.091)	(0.080)	(0.087)
Intercept	−7.086***	−5.432***	−5.017***
	(0.807)	(0.679)	(0.708)
Observations	122	122	122
Adjusted R^2	0.756	0.755	0.715

Robust standard errors in parenthesis.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01
CO_2/cap (metric tons per capita) is sourced from https://data.worldbank.org/indicator/EN.ATM.CO2E.PC

A.4.3 GCI and Environmental Policy Stringency

Table 13: Robustness tests for the relationship between GCI and Environmental Policy Stringency over different years

	2010	2005	2000
GCI	0.085*	0.100**	0.099***
	(0.049)	(0.047)	(0.028)
ECI	−0.079	−0.096	−0.091
	(0.085)	(0.083)	(0.057)
Log GDP/Cap	0.236***	0.218***	0.155***
	(0.055)	(0.038)	(0.031)
Intercept	−1.154**	−1.122***	−0.704***
	(0.538)	(0.331)	(0.242)
Observations	31	31	31
Adjusted R^2	0.527	0.556	0.647

Robust standard errors in parenthesis.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01
Environmental Policy Stringency (EPS) data is sourced from http://stats.oecd.org/

A.4.4 GCP - 10 year average predictions

Table 14: Green Complexity Potential Regression Analysis (10 year averages)

	Δ GCI $(t+\delta)$	Δ #Green exported products $(t+\delta)$	Δ Green export trade ratio $(t+\delta)$
Log GCP(t)	0.132***	5.223***	0.009***
	(0.028)	(1.194)	(0.003)
Log GDP/Cap(t)	0.004	0.018	0.001
	(0.017)	(0.757)	(0.001)
ECI(t)	−0.124***	−6.374***	−0.005*
	(0.032)	(1.508)	(0.003)
GCI(t)	−0.032		
	(0.037)		
#Green exported products(t)		0.086**	
		(0.040)	
Green export trade ratio(t)			−0.012
			(0.130)
Intercept	0.381*	17.989**	0.025*
	(0.170)	(7.449)	(0.013)
Observations	2440	2440	2440
Adjusted R^2	0.211	0.251	0.152

Robust standard errors in parenthesis.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01
t relates to country averaged values over years 1995-2004 and $t+\delta$ relates to country averaged values over years 2005-2014.

A.4.5 GCI robustness tests using alternative complexity measures

Since there are currently two alternative approaches for calculating the complexity of products, we compare the GCI regression results using different product complexity formulations. Here we use *GCI(HH)* to denote GCI calculated on the basis of the Hausmann et al. (2014) Product Complexity Index (as specified in equation 4) and GCI(Tacch) to denote GCI calculated on the basis of the alternative Product Complexity measure proposed by Tacchella et al. (2012).

In Table 15 we show that the relationship between environmental patents, carbon emissions and environmental policy stringency are very similar for both GCI(HH) and GCI(Tacch). This suggests that the GCI is robust to the choice of product complexity measure.

Table 15: Comparison of GCI regression results using alternative complexity measures

	Log Env. Patents		Log CO_2/cap		Log EPS	
GCI(HH)	1.551***		−0.168**		0.070***	
	(0.174)		(0.080)		(0.022)	
GCI(Tacch)		1.584***		−0.180**		0.056**
		(0.169)		(0.077)		(0.021)
Log GDP/Cap	0.524***	0.532***	0.946***	0.948***	0.168***	0.175***
	(0.109)	(0.104)	(0.060)	(0.059)	(0.021)	(0.022)
Intercept	−1.913***	−1.975**	−6.990***	−7.010***	−0.757***	−0.805***
	(0.908)	(0.864)	(0.521)	(0.510)	(0.204)	(0.215)
Observations	1220	1220	2318	2318	558	558
Adjusted R^2	0.727	0.747	0.760	0.761	0.726	0.708

Robust standard errors in parenthesis.
Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
GCI (HH) refers to GCI calculated using the Hausmann et al. (2014) Product Complexity Index and GCI (Tacch) refers to GCI calculated using the Tacchella et al. (2012) Product Complexity measure Environmental patents data covers 2000 and 2005-2013, available from http://stats.oecd.org/. CO_2 (metric tons per capita) data covers 1995-2013, available from https://data.worldbank.org/indicator/EN.ATM.CO2E.PC. Environmental Policy Stringency (EPS) data covers 1995-2012, available from http://stats.oecd.org/. For all regressions, we take country averages over all available time periods.

A.4.6 Green Stimulus - Total Spend

Table 16: Green Stimulus Total Spend

	Δ GCI $(t+\delta)$	Δ #Green exported products $(t+\delta)$	Δ Green export trade ratio $(t+\delta)$
Green Stimulus ($US Bn)	0.0028***	0.1276***	0.0001***
	(0.0004)	(0.0179)	(0.0000)
Log GDP/Cap(t)	0.0000	0.0000	0.0000
	(0.0000)	(0.0001)	(0.0000)
GCI(t)	-0.0042		
	(0.0153)		
Green exported products(t)		0.0171	
		(0.0184)	
Green export trade ratio(t)			0.0605
			(0.0479)
Intercept	-0.0054	-0.3881	-0.0080*
	(0.0368)	(1.7720)	(0.002)
Observations	19	19	19
Adjusted R^2	0.586	0.628	0.236

Robust standard errors in parenthesis.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01
t relates to the year 2008 and $(t+\delta)$ relates to the year 2011.
Green Stimulus Data is from Table 1 in Barbier et al. (2010), and relates to low carbon support for renewable energy, carbon capture and sequestration, energy efficiency, public transport and rail, and improving electrical grid transmission.
#Green exported products refers to the number of green exports in which the country has $RCA > 1$.

A.5 Calculation of Hausmann et al. (2014) Economic Complexity Index and Product Complexity Index

The ECI and PCI are calculated simultaneously according to the following three steps.

Hidalgo and Hausmann (2009) firstly define M_{cp} as a binary matrix based on each country's RCA. $M_{cp} = 1$ if country c's Revealed Comparative Advantage (RCA) is greater than 1 and 0 otherwise. RCA is calculated as follows:

$$RCA_{c,p} = \frac{x(c,p)/\sum_{p} x(c,p)}{\sum_{c} x(c,p)/\sum_{c,p} x(c,p)} \tag{8}$$

where $x(c,p)$ is the value of country c's exports of product p. A country is considered to be *competitive* in product p if its RCA value is > 1).

Second, Hidalgo and Hausmann (2009) define two measures: country diversity ($k_{c,0}$), which represents the total number of products for which a country has RCA > 1 and product ubiquity ($k_{p,0}$), which represents the total number of countries exporting a product (with RCA > 1). These are given in Equations 9 and 10.

$$k_{c,0} = \sum_{p} M_{cp} \tag{9}$$

$$k_{p,0} = \sum_{p} M_{cp} \tag{10}$$

In the original *Method of Reflections*, Hidalgo and Hausmann (2009) take the country diversity and product ubiquity vectors as a starting point and use one to recursively 'correct' the other, as follows:

$$k_{c,N} = \frac{1}{k_{c,0}} \sum_{p} M_{c,p} k_{pN-1} \tag{11}$$

$$k_{p,N} = \frac{1}{k_{cp,0}} \sum_{c} M_{c,p} k_{cN-1} \tag{12}$$

They show that by inserting Equation 12 into 11 and rewriting gives

$$\begin{aligned} k_{c,N} &= \frac{1}{k_{c,0}} \sum_p M_{c,p} \frac{1}{k_{p,0}} \sum_{c'} M_{c',p} k_{c',N-2} \\ &= \sum_{c'} k_{c',N-2} \sum_p \frac{M_{c,p} M_{c',p}}{k_{c,0}, k_{p,0}} \\ &= \sum_{c'} \widetilde{M_{c,c'}} k_{c',N-2} \end{aligned} \tag{13}$$

where

$$\widetilde{M_{c,c'}} \equiv \sum_p \frac{M_{c,p} M_{c',p}}{k_{c,0}, k_{p,0}} \tag{14}$$

As shown by Caldarelli et al. (2012), if $\vec{k_N}$ is the vector whose c'th element is $k_{c,N}$, then

$$\vec{k_N} = \widetilde{M} \times \vec{k_{N-2}} \tag{15}$$

where $\widetilde{M}$ is the matrix whose (c, c')th element is $\widetilde{M_{c,c'}}$. Taking N to infinity gives a distribution which remains fixed up to a scalar factor:

$$\widetilde{M} \times \vec{k_{N-2}} = \lambda \vec{k} \tag{16}$$

Therefore $\vec{k}$ is an eigenvector of $\widetilde{M}$. Since the eigenvector associated with the largest eigenvalue (which is 1 since $\widetilde{M}$ is row stochastic is constant, Hausmann et al. (2014) instead look for the eigenvector associated with the second largest eigenvalue. This vector, which is normalised by subtracting the average and dividing by the standard deviation as follows, is chosen to define the Economic Complexity Index

$$ECI = \frac{\vec{K} - < \vec{K} >}{\text{stdev}(\vec{K})} \tag{17}$$

The Product Complexity Index (PCI) is calculated symmetrically by exchanging the index of countries (c) with products (p) in the equations outlined above.

Although there has been some confusion about what this measure captures and how it works, Mealy et al. (2017) showed that the algorithm corresponds to a standard clustering algorithm used to partition a similarity graph into two parts as to minimise the links between the parts. Viewed through this lens, one can interpret the ECI as collapsing the high dimensional space of countries and their export baskets onto a single dimension)where countries with similar exports are clustered together.

A.6 Calculation of Tacchella et al. (2012) Country Fitness and Product Complexity

An alternative approach for estimating the complexity of productive capabilities associated with countries and exported products has also being proposed by Tacchella et al. (2012). This methodology uses the same binary M_{cp} matrix constructed on the basis of countries' RCA's, as defined in section A.5. However, Tacchella et al. (2012) introduce a different formulation for arriving at a country-specific estimate (called *Fitness*) and a product-specific estimate (called *Complexity*).

The measures are calculated as the fixed-point solution of the non-linear iterative mapping given by

$$\begin{cases} \tilde{F}_c^{(N)} = \sum_p M_{cp} Q_p^{(N-1)} \\ \\ \tilde{Q}_p^{(N)} = \dfrac{1}{\sum_c M_{cp} \dfrac{1}{F_c^{(N-1)}}} \end{cases} \rightarrow \begin{cases} F_c^{(N)} = \dfrac{\tilde{F}_c^{(N)}}{\frac{1}{C} \sum_c \tilde{F}_c^{(N)}} \\ \\ Q_p^{(N)} = \dfrac{\tilde{Q}_p^{(N)}}{\frac{1}{P} \sum_p \tilde{Q}_p^{(N)}} \end{cases}, \tag{18}$$

where $\tilde{F}_c^{(N)}$ and $\tilde{Q}_p^{(N)}$ are the N^{th} iterations for the Fitness of country c and Complexity of the product p respectively, and P is the number of products. The initial conditions are given by vectors of 1's (i.e. $\tilde{F}_c^{(0)} = 1 \forall p$ and $\tilde{Q}_p^{(0)} = 1 \forall c$), and at each iteration, the intermediate variables $\tilde{F}_c^{(N)}$ and $\tilde{Q}_p^{(N)}$ are calculated and then normalised by the average values.

As shown in Cristelli et al. (2015, 2017), the Fitness measure appears useful for predicting the growth of countries falling into a particular region in the Fitness $\times$ GDP per capita plane.

A.7 Glossary of terms

Adjacent possible: set of nearby competitive technological opportunities.

Capability: the knowhow required to export a product competitively.

Complexity: the sophistication of the knowhow required to export a product competitively.

Competitive in a product: country has $RCA > 1$ in this product.

Diversity: total number of products which a country exports competitively.

Proximity: conditional pairwise probability of two products being competitively exported together.

Proximity density: average proximity from a country's set of competitive exports to a particular product.

Ubiquity/scarcity: total number of countries that export a product competitively.

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