Path dependence in national systems of production and "self discovery" of environmental technologies in the EU 28 countries

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Contribution to the Project

The research report addresses the question how innovation policy should be designed to support new development paths towards social and ecological targets. This means that innovation policy should on the one hand provide framework conditions that ensure that companies are able to generate new sources of value, and that this creation of new sources of value ensures that all participants in an enterprise (employees, creditors, shareholders, government, firm, consumers) gain. On the other hand, innovation policy should also be able to direct technical change on to paths that ensure the development of business models, technologies and innovative products that support sustainable economic development while safeguarding and strengthening the competitiveness of firms.

The paper examines whether and how innovation activities can be shifted to less labour saving and more resource using technologies given that technological development is highly pastdependent. It develops a conceptual framework to examine the potential of innovation policies to shift technological trajectories deemed to be better aligned with a "high road" goal. The paper studies empirically existing path- or pastdependencies in the productive structures of the EU Member States. Finally, it examines the general characteristics of the innovation policies the EU and its Member States have in place and assess potential avenues for policy design to shift technological trajectories on to a "high road" path.

Path dependence in national systems of production and "self discovery" of environmental technologies in the EU 28 countries

Andreas Reinstaller and Peter Reschenhofer

August 3, 2015

Abstract

The development of "green" industries is commonly seen as a necessary even though not sufficient condition for the transition towards ecologically sustainable paths of economic development. It is also a recurrent view that pro-active and successful policy action in this domain will not only promote sustainable development but also secure competitive advantage of successful countries in these industries. However, a complex constellation of path-dependencies in systems of production and (negative) externalities constrain the emergence and expansion of environmental technologies.

This paper presents evidence that path-dependencies in systems of production have a dual role in the development of new industries. They are not only a source of structural lock-in, but also a potential starting point for new developments. The paper shows that factors causing path dependence in systems of production are also an important source of competitiveness both for all traded commodities and for environmental technology industries. Hence, policies supporting the emergence of industries producing environmental technologies should try to exploit this mechanism.

Drawing on this evidence a counterfactual analysis is carried out to investigate potential trajectories of development of the EU28 countries in the environmental technologies. The results indicate that some countries that up to recent times have been pioneers in environmental technologies may lose their strong position in these technologies. In other countries instead new strengths in environmental technologies have the potential to emerge, as some environmental technologies can draw on untraded interdependencies that have not been brought to full fruition so far.

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1 Introduction

There is a long-standing impression among policymakers that the development of "green" industries is a necessary even though not sufficient condition for the transition towards sustainable economic and social development. It is also a recurrent view that successful action in this domain will not only promote sustainable development but also secure a competitive advantage in international markets of successful countries in the related industries.[1]

However, investments in environmental technologies typically face a so-called *double externality problem*: Innovation investments in general suffer from the problem that the limited appropriability of knowledge causes the private returns to R&D to be lower than social returns leading to a private underinvestment in R&D. In addition, innovations in environmental technologies, eco-innovations or more generally innovations supporting social and ecological sustainability suffer from the problem that prices for competing non-sustainable products or production processes typically do not internalise negative environmental, social or ecological externalities in their prices such that firms have even lower incentives to invest into the development of new environmental technologies (for a discussion see del Río Gonzáles, 2009; Faber and Frenken, 2009).

Recent contributions argue that this type of double failure requires the combined and coordinated use of policies to ensure that technologies to mitigate climate change and other critical unsustainable developments are available, when they are needed (cf. Jaffe, 2012). Aghion, Veugelers, and Hemous (2009) and Acemoglu, Aghion, Hemous, and Bursztyn (2012) propose to solve this problem by changing the relative costs structure to bias technical change in directions that are socially and ecologically more sustainable. This policy would involve both general carbon taxes and research subsidies to the clean technology sector in order to internalise external costs and foster innovation in environmental technologies.

[1] See for instance the European Commission's Eco-Innovation Action Plan `http://ec.europa.eu/environment/ecoap/about-action-plan/objectives-methodology/index_en.htm`

However, Unruh (2000, 2002) and others have argued that even such policies may not be enough to overcome the constraints environmental technology industries face as the presence of dynamically increasing returns and positive feedback effects in techno-institutional systems can seriously limit the substitutability of production techniques and make transitions difficult even if the double-externality problem did not exist. Hence, only massive internationally coordinated government intervention would be needed to internalise double-externalities, overcome path-dependencies in the national systems of production and create markets for environmental technologies and in particular climate change mitigating goods.

However, the presence of spillovers across countries related to demand led technology pull policies create negative incentives for policy makers to pursue them (Peters, Schneider, Griesshaber, and Hoffmann, 2012), which may negatively affect the stability of international coordination efforts for policies to promote environmental technologies. Hence, the overall constellation of path-dependencies in the productive system and (negative) externalities at the company level for the development of environmental technologies as well as on the country level in the deployment of policies severely constrain the emergence and expansion of environmental technology industries.

Nevertheless, a closer look at path-dependencies in systems of production reveals that they may not be that negative for the development of environmental technology industries after all. A number of authors have stressed that economic actors such as companies rely on their past experiences to shape the future (Garud and Karnøe, 2001; Garud, Kumaraswamy, and Karnøe, 2010). It is the embedding of these actors in a specific context that that cause path dependence or more generally high persistency in economic structures. The embedding factors can be strategic variables to create new paths of development. Similarly, other authors have argued that new (technological) combinations enabling to leave existing seemingly irreversible situations emerge from the combination of existing and new knowledge in small market niches (cf. Kemp, Rip, and Schot, 2001).

This highlights that path dependence in systems of production is the outcome of a process of exploration of the cost structure of an economy given specific institutional and technological interdependencies that predetermine the direction of technological search. Therefore, path dependent structures can also be the starting point for the development of new trajectories, as the underlying cumulated competencies and embedding factors can be a source of competitive advantage and can therefore be used to support transitions. This paper explores the conjecture whether embedding factors play a major role both in the discovery of goods and the exploitation of economic opportunities empirically in general and for in environmental technologies in particular.

The factors causing a high persistence and their relationship to the competitiveness of firms in specific markets will be discussed in detail in the next section of this paper. Relying on recent developments in the analysis of trade networks (Hidalgo, Klinger, Barabasi, and Hausmann, 2007) the paper will then use trade data to examine empirically the aforementioned exploration process along the lines set out in Hausmann and Rodrik (2003). It will analyse to what extent current embedding factors are also the source of competitive strengths in environmental technologies across the European countries. The paper will then apply the framework worked out in the earlier sections of the paper to establish to what extent European countries have advantageous or feasible cost structures to engage into and hence enforce or create new paths in the production of environmental technology. A final discussion of policy implications closes the paper.

2 The conceptual framework

2.1 Technological relatedness and local capabilities as embedding factors

It is well documented that firms have an incentive to improve and diversify their products and services relying upon their existing technological base. Idiosyncratic competencies, put them even further apart from their competitors (cf. Nelson and Winter, 1982; Nelson, 1991). The economic literature refers to this phenomenon as "local (technological) search" and "localised technical change".

The economic explanations for local search focus on the importance of sunk costs and irreversibility in the choice of production techniques. Antonelli (1998), for instance, argues that "all existing capital stocks, both tangible, such as fixed assets, and intangible, such as reputation, experience and competence, have high levels of durability ... Hence it is costly to change both the amount of capital stock as well as the proportions in which it is used with other complementary inputs due to changing market conditions". Specific combinations of tangible and intangible assets linked to one another through complementarities therefore become quasi-fixed factors of production.

The technical explanations for local (technological) search gravitate around the nature of learning processes at the company level and untraded interdependencies. Technical knowledge is localised in the production techniques currently used by a firm, in the markets in which it operates, in existing information channels among firms, customers, suppliers and external sources of knowledge generation such as research institutes or universities. This knowledge accumulates over time through learning (e.g. learning by doing) and is embodied in individuals, company routines or technological blueprints (e.g. Dosi, 1988). These routines are perpetuated and developed further to improve the established products. This product specific localised knowledge accumulation is important to achieve high levels of productivity. It enables firms to exploit existing economic opportunities related to their own idiosyncratic technological or organisational capabilities. In order to explore new opportunities, however, companies need to constantly tap into external knowledge sources. Hence, firms have to strike a balance between on the one hand deepening their knowledge related to specific product or services, and on the other hand broadening their knowledge base in order to be able to diversify into new products.

Cohen and Levinthal (1989) have argued that firms can understand, absorb and implement external knowledge when it is close to their own knowledge base. In other words, effective knowledge transfer between firms and external sources of knowledge (such as other firms, research institutes etc.) requires absorptive capacity and cognitive proximity to enable effective communication and hence to ensure that knowledge can spill over

(Nooteboom, 2000). This implies however, that even when firm absorb external knowledge this amounts to a diversification process in which existing cumulated capabilities are constantly broadened and developed further. In this way firms leverage intertemporal economies of scope (cf. Breschi, Lissoni, and Malerba, 2003) when they diversify into products that are technologically related to their current products. The process of product development and innovation is thus highly cumulative and dependent on the sequence of past choices, and innovative search outcomes at the firm level are likely to be serially correlated in time. This makes firms different from their competitors in international markets and is therefore an important determinant of their international competitiveness.

Firm specific learning processes are generally quite idiosyncratic. However, the nature of knowledge absorption ensures that next to completely idiosyncratic elements the knowledge base of companies consists also of capabilities that are locally shared with other companies and institutions. Over time their very specific competencies, co-evolve with the local pool of capabilities and this process puts them even further apart from their international competitors. The presence of such untraded interdependencies in the productive system of a country causes persistency and the path dependent development observed at the firm level carries over to entire industries.

These untraded interdependencies can be related to technological complementarities, untraded technological linkages and information flows, common infrastructures as well as economic, technical or educational institutions, various sorts of dynamic economies of scale, and so forth (Dosi, Soete, and Pavitt, 1990). They do not necessarily correspond to the flows of commodities, and represent a truly collective asset of groups of firms or industries in a country. These interdependencies are instrumental in generating common experiences and skills embodied in people and organisations, and capabilities overflowing from on economic activity to another. Companies or sectors that are better embedded in this flow of information and coordination externalities will also be able to benefit more from and translate them into higher productivity and hence competitive advantages. As a consequence under the presence of cumulative local learning and untraded interdependencies one should observe clusters of firms with similar techniques that will however differ in their individual efficiencies due to idiosyncratic learning Cantner and Westermann (1998).

The circumstance that untraded interdependencies are potentially and important source of competitiveness, can be used to examine the path dependence of productive structures across countries relying on disaggregated trade data. Typically, more productive firms select themselves into exports (cf. Melitz, 2003) and therefore, also those firms that benefit most from local externalities are also more likely to export. Observed clusters in comparative advantages at highly disaggregated levels of trade data in a country therefore reflect the aforementioned exploration process of the cost structure of the economy given its peculiar embedding factors. This does not only allow to identify potential path dependencies in the productive structure of an economy, but also to identify potentials to successfully diversify it into specific types of products, such as environmental technologies, that can benefit from the embedding factors of the economy and therefore create new paths of development. In the next subsection the paper works out the relationship between intensive margins and extensive margins in trade more formally.

2.2 Local capabilities and competitiveness

The development of intensive margins in trade is essentially related to processes of market selection and competition on international markets. The model by Metcalfe (1994) provides a consistent theoretical framework to examine the relationship between market selection and local capabilities empirically. One can reformulate the model assuming that all variables reflect country averages across exporting companies in a specific product class and that changes take place in discrete time. The market share $s_{p,c,t}$ a country c obtains in a specific product class p at time t is then given by

$$s_{p,c,t} = s_{p,c,t-1} + \Delta s_{p,c,t}, \tag{1}$$

, where

$$\Delta s_{p,c,t} = s_{p,c,t-1}(g_{p,c,t} - \overline{g}_{p,t}), \tag{2}$$

which represents the basic replicator process driving the share dynamics in the world market for a specific product p. Variable $g_{p,c,t} = f_{p,c,t}(pr_{p,c,t} - h_{p,c,t})$ is the growth rate of exports of country c in product class p and $\overline{g}_{p,t} = \sum_c s_{p,c,t} g_{p,c,t}$ is the weighted average of this growth rate across countries. Variable $f_{p,c,t}$ reflects accumulation heuristics used in the production of a product in country c and $h_{p,c,t}$ is the average unit costs producers in country c incur for product p. The export growth rate $g_{p,c,t}$ can therefore be interpreted as being determined by the propensity $f_{p,c,t}$ to reinvest the unit profit margin $pr_{p,c,t} - h_{p,c,t}$ into production capacities.

The growth of international demand for domestic products of type p depends on the difference of avg. domestic prices $pr_{p,c,t}$ from the average price $\overline{pr}_{p,t} = \sum_c s_{p,c,t} pr_{p,c,t}$ for which these products are traded on the world market and the strengths of competitive pressure $\delta_{p,c,t}$ that captures how much customers penalise deviations from the world market price, $g_{Dp,c,t} = \overline{g}_{p,t} + \delta_{p,c,t}(\overline{pr}_{p,t} - pr_{p,c,t})$. It is an indicator for the degree of market imperfection. If it is high then barriers to switching are low on the customer side. In a perfect market with uniform prices $\delta_{p,c,t} = \infty$, whereas in a perfectly monopolistic structure $\delta_{p,c,t} = 0$ implying that customers are essentially locked into their existing supplier.

The normal price $pr^*_{p,c,t}$ ensures that the growth of capacity to export product p is in line with the growth of international demand for the output of country c of that product. It is obtained by equating the two growth rates $g_{p,c,t}$ and $g_{Dp,c,t}$ and solving for the price. Plugging the result back into $g_{p,c,t}$ one obtains the balanced export growth rate for product class p,

$$g^*_{p,c,t} = \frac{f_{p,c,t}}{f_{p,c,t} + \delta_{p,c,t}} \overline{g}_{p,t} + \frac{f_{p,c,t}\delta_{p,c,t}}{f_{p,c,t} + \delta_{p,c,t}} \overline{pr}_{p,t} - \left[f_{p,c,t} + \frac{f^2_{p,c,t}}{f_{p,c,t} + \delta_{p,c,t}} \right] h_{p,c,t}, \tag{3}$$

which depends on the capability of producers in country c to capture a share of world demand (first term), on their relative price performance (second term), and their avg. unit costs (third term). The share dynamics in equation (2) is governed by the difference

$\Delta g_{p,c,t} = g_{p,c,t} - \overline{g}_{p,t}$. Plugging in equation (3) for $g_{p,c,t}$ one gets

$$\Delta g_{p,c,t} = -\frac{\delta_{p,c,t}}{f_{p,c,t} + \delta_{p,c,t}} \overline{g}_{p,t} + \frac{f_{p,c,t}\delta_{p,c,t}}{f_{p,c,t} + \delta_{p,c,t}} \overline{pr}_{p,t} - \left[f_{p,c,t} + \frac{f_{p,c,t}^2}{f_{p,c,t} + \delta_{p,c,t}} \right] h_{p,c,t}. \tag{4}$$

The development of world market shares in a specific product class in country c is therefore driven by general demand conditions, relative prices, market structure and costs. In line with Metcalfe's baseline extension of his model unit costs $h_{p,c,t}$ can be modelled as a function of a number of factors reflecting different processes that go along with (locally) increasing returns, i.e. $h_{p,c,t} = f(v_{p,c,t}, L_{p,c,t}, E_{p,c,t})$. Variable $v_{p,c,t}$ stands for current output and reflects (increasing) returns to scale on unit cost. Unit costs will fall in $v_{p,c,t}$ if the production of product p is scale elastic. Function $L_{p,c,t} = \Phi(V_{p,c,t})$ captures the effects of product specific learning on average unit costs accumulated through the past production experience $V_{p,c,t} = \sum_{t0}^{t} v_{p,c,t}$, for product p in country c, with $\frac{dL_{p,c,t}}{dV_{p,c,t}} > 0$ and $\frac{\partial h_{p,c,t}}{\partial L_{p,c,t}} < 0$. Function $E_{p,c,t} = \Psi(\omega_{pq,c})$, finally, maps the impact of external economies on average unit cost for product p in country c, with $\frac{dE_{p,c,t}}{d\omega_{pq,c,t}} > 0$ and $\frac{\partial h_{p,c,t}}{\partial E_{p,c,t}} < 0$.

This last factor is of particular interest for our analysis. Variable $\omega_{pq,c,t}$ captures the relatedness of product p to all other products q country c produces. The assumption is that companies can absorb knowledge spillovers and benefit from factor mobility across companies with greater ease the more their product i is technologically related to other products q country c produces. Hence, external economies for product p, $E_{p,c,t}$, increase in the degree of its relatedness $\omega_{pq,c,t}$. As the focus of our empirical analysis is on international competition and in order to reduce potential noise and capture only the most relevant products I redefine $\omega_{pq,c,t}$ more narrowly as the relatedness of product p to products q the country exports with comparative advantage. It is straightforward to show that if the world market share is determined by the process specified in equation (1) and all other assumptions apply the following relationship must hold:

$$\frac{\partial s_{i,c,t}}{\partial \omega_{pq,c,t}} > 0, \tag{5}$$

as $\omega_{pq,c,t}$ is positively related to changes in world market shares, $\frac{\partial \Delta g_{p,c,t}}{\partial h_{p,c,t}} \frac{\partial h_{p,c,t}}{\partial \omega_{pq,c,t}} > 0$, and by implication from (2) follows that $\frac{\partial \Delta s_{p,c,t}}{\partial \omega_{pq,c,t}} > 0$. Hence, an increase in product relatedness leads to an increases of world market shares. As a consequence the world market share a country achieves in a product class increases in its relatedness to other products the country exports with comparative advantage.

2.3 Local capabilities and market discovery

The previous section has shown how local capabilities and technological relatedness are a source of competitiveness and contribute to achieve high market shares in international trade. However, if companies search locally for opportunities, these factors have also an impact on the entry into new international markets (extensive margin in trade) which amounts to a discovery that a certain good can be produced and exported at home at low cost or high quality compared to the international competitors. Indeed, entry into new markets at the firm level depends essentially on expected average costs of an entrant relative of that of incumbents. Such discrete choice situations are difficult to model in evolutionary models. The literature on market entry and the extensive margin in trade however suggests that sunk costs play an important role in this context. These can be related to tangible or intangible sunk costs related either to capital investments or investments to build up technological or market specific capabilities (cf. Sutton, 1991, 1998; Martin, 2002), or other trade related fixed costs to exporting (cf. Roberts and Tybout, 1997). Entry cost rise also in market size (cf. Eaton, Kortum, and Kramarz, 2011). These factors reduce the likelihood of entry of a country's producers in new markets. On the other hand, access to external economies tend to increase the likelihood of entry (cf. Gort and Klepper, 1982). Whereas the competition in a market and its growth potential have an important impact on the decision of a firm to export as well (cf. Grossman and Rossi-Hansberg, 2010). Hence, the probability of entry $P_{i,c,t}$ of a country c in product i at time t can be specified as

$$P_{p,c,t} = f(E_{p,c,t}, sc_{p,t}, ms_{p,t}, comp_{p,t}, gr_{p,t}), \tag{6}$$

with $sc_{p,t}$ standing for sunk costs in the international market for product i, $ms_{p,t}$ for its size, $comp_{p,t}$ for the intensity of competition producers face in market p and $gr_{p,t}$ for the growth potential of that market:

$$\frac{\partial P_{p,c,t}}{\partial \omega_{pq,c,t}} > 0. \tag{7}$$

From this follows the conjecture, that the probability of entry in a new international market increases in the relatedness of that product to the other products the country exports with comparative advantage. If it is to hold, then diversification processes in international trade should be viewed as processes of related diversification.

3 Embedding factors in the exploration and discovery of productive capabilities

3.1 Identifying interdependencies and embedding factors in a productive system

It has been argued earlier that untraded interdependencies between sectors, technologies and firms are of primary importance in the process of technical change and hence in the organisation of production and innovation in a country. They are an important determinant of international competitiveness. Given the highly intangible and complex nature of these interdependencies it is a challenge for the empirical analysis of international competitiveness to develop indicators that are able to adequately proxy them.

Recent developments in the analysis of trade patterns that have led to the establishment of the so-called product space approach (Hausmann and Klinger, 2007; Hidalgo, Klinger, Barabasi, and Hausmann, 2007) make it possible to empirically assess the importance of these untraded interdependencies. The product space is constructed from the conditional probability of countries having a comparative advantage in any two pairs of commodities

p and q at the same time. This conditional probability is a measure for the proximity of any pair of commodities in terms of relying on common factors of production, capabilities and so forth. It is calculated as follows:

$$\phi_{pq,t} = \min\left[P(RCA_{p,t} \mid RCA_{q,t}), P(RCA_{q,t} \mid RCA_{p,t})\right],$$

where RCA corresponds to the Balassa index for comparative advantage (Balassa, 1965). As the conditional probability is not symmetric between any pair of products, and because the conditional probability for a good p is one for every other good q when a particular country is the sole exporter of p, the minimum is taken.

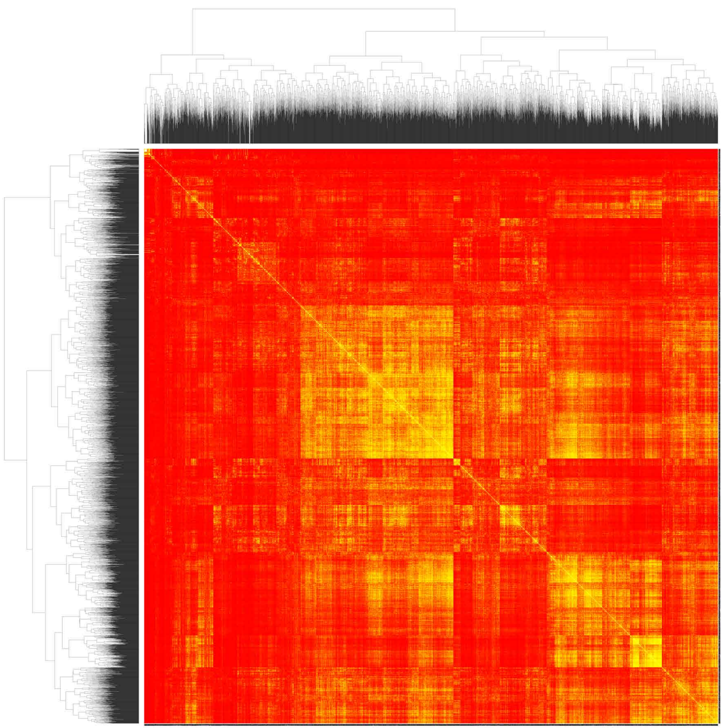

Figure 1: The product space in 2013: Plot of $\phi_{pq,t}$. BACI dataset (Gaulier and Zignago, 2010).

Figure 1 plots the proximity $\phi_{pq,2013}$ for all pairs of commodities traded in 2013. The values have been clustered using hierarchical cluster methods. The related dendrograms are shown on top and the sides of the figure. Light colors indicate high conditional probabilities of being jointly exported with comparative advantage across countries, whereas darker areas point to the contrary. It is apparent that comparative advantages across countries tend to cluster for specific product pairs as is evident from the light coloured areas, while there are also regions of unrelated product pairs.

The products space can be represented alternatively as a network. Denser parts of the network indicate as the lighter areas in Figure 1 clusters of closely related productive activities. Figure 2 shows such a representation with the position of the principal aggregates in international trade in environmental technologies chiefly related to renewable energies indicated by the coloured bubbles in the figure. The size of the bubbles indicates the share in world trade of the aggregate of products of which these technologies are part of. It is apparent from the figure that the environmental technologies related to renewable energy scatter relatively widely across the product space indicating a wide variation in the capabilities needed to successfully produce and export these technologies. Another aspect of these technolgies is that some of them are generally weakly related to other products countries export and therefore seem to require very specific capabilities. Also those product that are situated in denser areas of the network are rather placed in the peripheral parts of these clusters.

Using the proximity measure it is possible to calculate a country-product level indicator that measures how close a product is to the other products for which a country is a significant exporter, i.e. an indicator that captures how well embedded a product is in the productive system of a country. Following Hausmann and Klinger (2007) the measure for product relatedness is calculated as follows:

$$ProdRel_q^c = \sum_p x_{c,p,t}\phi_{pq,t} / \sum_p \phi_{pq,t} \quad x_{c,p,t} = 1 \quad \text{if } i \text{ exported by } c \text{ with RCA at time } t. \tag{8}$$

To avoid endogeneity issues in the econometric analysis the sum runs over all products p and excludes changes in export status by product q. As the discussion in Section 2

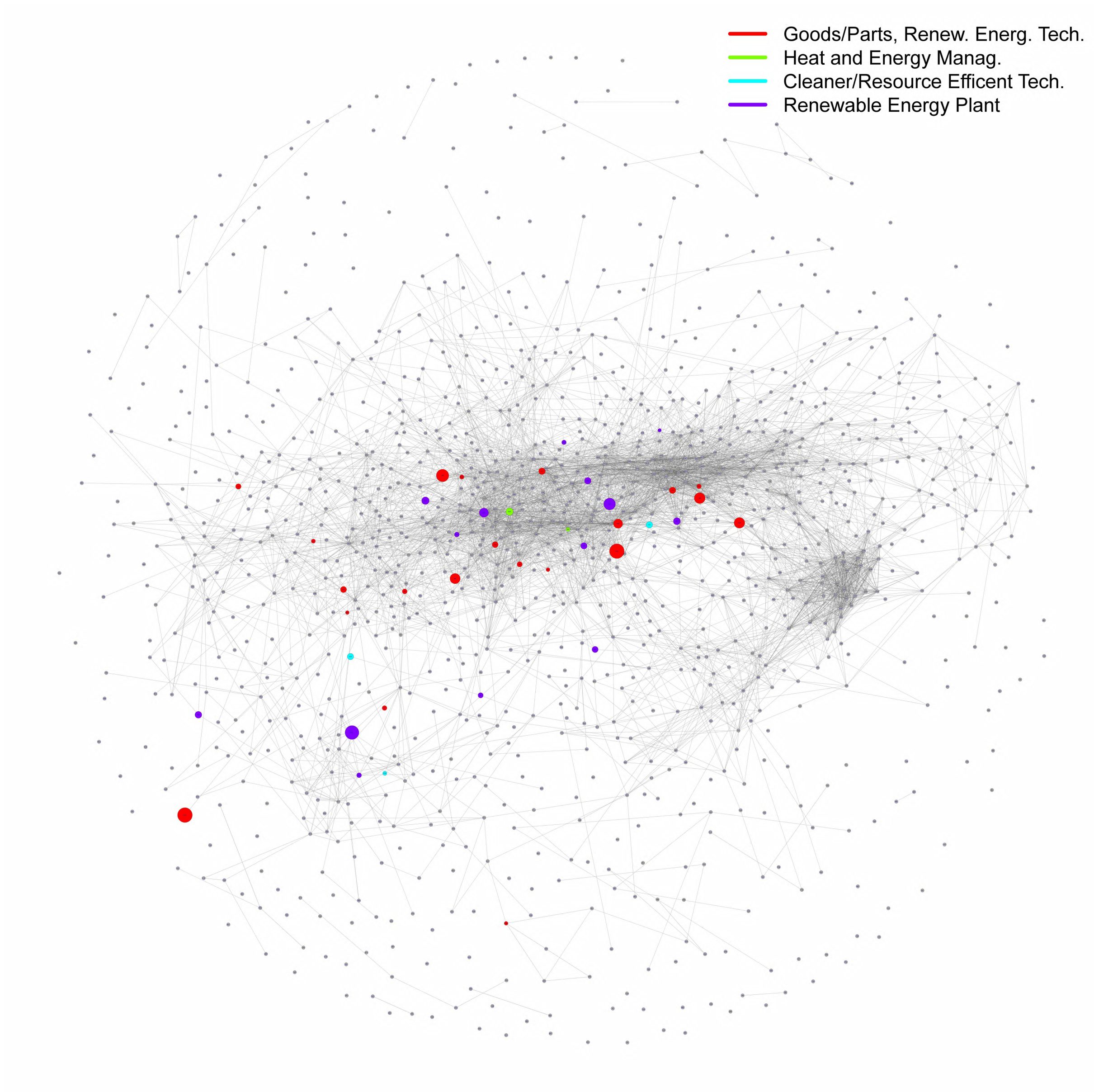

Figure 2: Environmental technologies related to renewable energies in the product space, network representation. BACI dataset (Gaulier and Zignago, 2010).

suggests, the absorption of external economies and their translation into lower costs or higher quality products is directly linked to the relatedness of one product in terms of the underlying technological and operative capabilities to the other products a country produces. If the proxmity in product spaces captures the presence of such interdependencies and if they translate into higher productivity then in every country the likelihood of observing competitive advantages in international markets for a good should increase with its closeness in product space to the other products a country exports.

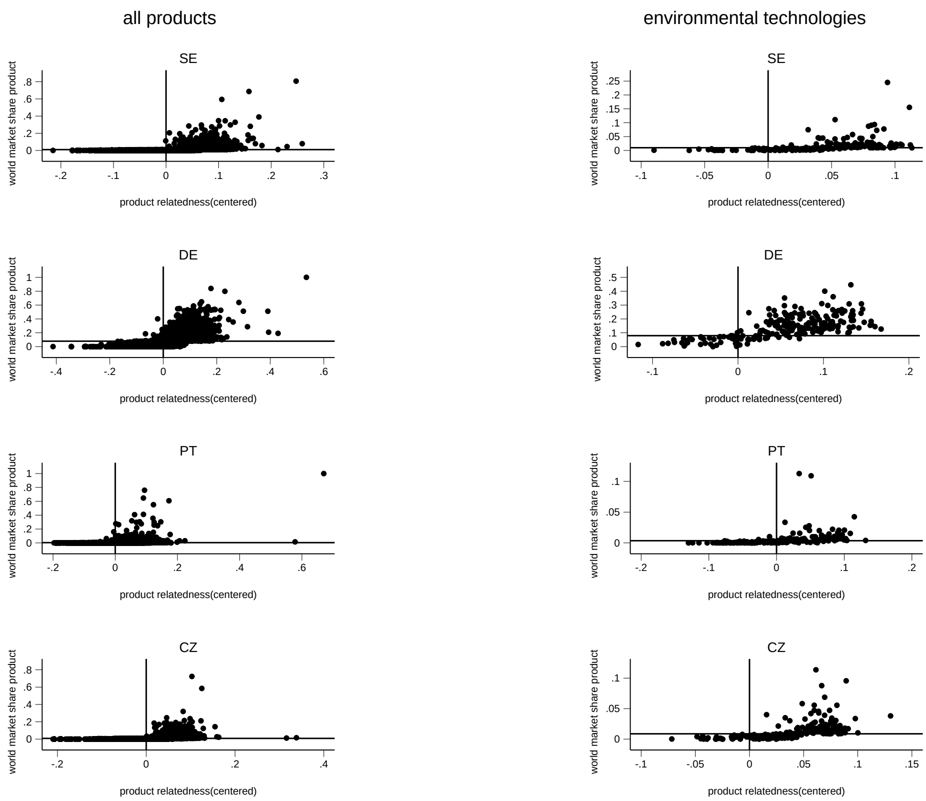

Figure 3: The relationship between world market shares and product relatedness for all products and environmental technologies in selected EU countries. BACI dataset (Gaulier and Zignago, 2010).

Figure 3 give a first impression on the relationship between the absolute competitiveness of a product and its relatedness to the other products a country exports. It plots the world market shares products from a selected number of European countries were able to obtain in the year 2013 against their product relatedness score (ProdRel) measured for that year. The horizontal line in the figure presents the world market share of each country in 2013. If the world market share of a product is above this threshold it is exported with revealed comparative advantage (RCA). The vertical line instead presents the average product relatedness in each country. The left panel of the figure shows the relationship for all products, whereas the right panel shows it for environmental technologies only.

The evidence presented in these figures clearly shows that there is a strong positive relationship between the world market share of a product which is also a measure for the intensive margin in trade and its relatedness to other products exported by the country with comparative advantage. Products with below average product relatedness have with a very few exceptions world market shares that are lower than the world market share of the country. Identical patterns can be observed for all countries (cf. Reinstaller, Hölzl, Kutsam, and Schmid, 2012) and are independent of the observation period. The relationship holds also for environmental technologies.

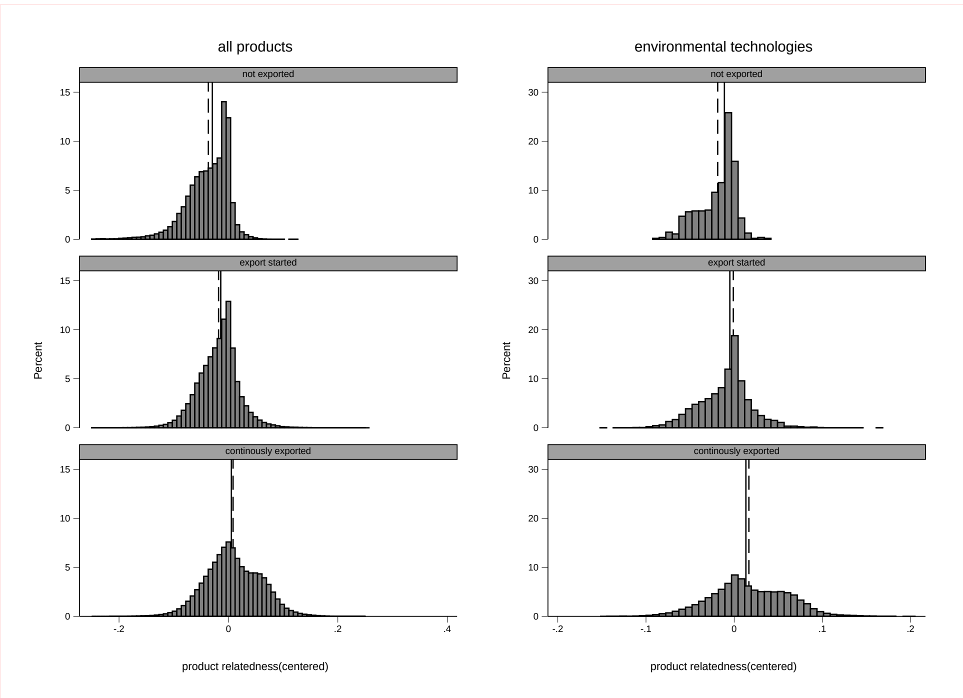

Figure 4: Distribution of product relatedness scores for non-exported and exported products over the period 1995-2013 (right) for all products and environmental technologies across all EU countries. BACI dataset (Gaulier and Zignago, 2010).

The world market shares in Figure 3 capture the intensive margin in trade. Figure 4 instead shows evidence for the extensive margin, i.e. entry into new markets. The figure shows the distribution of product relatedness scores for products according to their export status over the period of observation. The figure presents again data for all products and environmental technologies across all European countries. The upper panels show the distribution of product relatedness scores for products that have not been exported over the entire period. The middle panels show the distribution for products a country has started to export over that period, and the lower panels finally show the distribution for products the countries have exported throughout the observation period. The dotted and solid vertical lines indicate the mean and the median of the distributions. T-tests show that the observed means between the observed groups differ in a statistically significant from one another. They reject the null of no difference in means at the 1 percent level in each case. Similarly tests comparing the means of the products the European countries have started to export and those they have exported over the entire period of observation reject again the null at the 1 percent level of significance. This evidence therefore indicates that changes in the extensive margin in exports are closely associated with product relatedness. It indicates that the exploration of opportunities is closely associated with untraded interdependencies in a productive system. These relationships will be examined econometrically later in the paper.

3.2 Additional variables used in the econometric analysis

In order to test the conjecture whether embedding factors play a major role in the discovery of goods that can be exported and the development of competitive advantage in a country the econometric specification of the model draws on theoretical framework outlined in Section 2. The dependent variable will be world market shares at the level of disaggregated six digit product classes. Next to the indicator for product relatedness capturing the embeddedness of a product in local productive structures, the econometric model will include other covariates to control for additional factors that have an impact on market entry and market share dynamics in trade. More specifically, the model will control for product characteristics, market structure, the intensity of competition, the price level of competitors on the domestic product market, market size, country characteristics, as well as unobserved time and sector variation.

World market shares (wms) : World market shares are a measure for intensive margins in trade and for the absolute competitiveness of a country (cf. Dosi, Soete, and Pavitt, 1990). World market share are therefore the principal dependent variable in this analysis. The world market share $wms_{c,p,t}$ is the export value $x_{c,p,t}$ a country c obtains in product p in year t relative to the total value $X_{p,t} = \sum_c x_{c,p,t}$ traded in a product class the same year across countries,

$$wms_{c,p,t} = \frac{x_{c,p,t}}{X_{p,t}}.$$

Chained Fisher import price index (cFPI) : As can be inferred from equation (3) relative price levels play an important role in the dynamics of world market shares. Problems of endogeneity however arise if one would regress a price index containing domestic price levels on world market shares. The econometric estimations therefore rely on a chained Fisher price index of imports as a proxy for relative price developments. The Fisher price index is a geometric mean of a Paasche and Laspeyers index calculated on the basis of unit values. Feenstra (1997) has shown that the Laspeyres and Paasche indices are upper and lower bounds of the real price evolution hence Fisher price indices are a good approximation of real prices. Chained indices are used to eliminate the danger of potential Gershenkron effects in the series. The Fisher price index for both imports in product class p and country c is given by

$$cFPI_{p,c,t} = (cPPI_{p,c,t} \times cLPI_{p,c,t})^{\frac{1}{2}}$$

with $cPPI_{p,c,t}$ being a chained Paasche price index and $cLPI_{p,c,t}$ being a chained Laspeyeres price index. Ceteris paribus – following a strict market logic – an increase of import prices should be positively related to world market shares in exports obtained by domestic producers. It is however possible to think of situations where the indicator can turn negative: if for instance imported goods are complementary assets to exports in an industry, or if the quality of imports (proxied by high prices) is very superior to domestic products such that import substitution drives local producers out of the market.

Herfindahl Index (HERF) : In order to control for the market structure in each product class p, the econometric model relies on a Herfindahl-Index,

$$HERF_{p,t} = \sum_{c} (wms_{c,p,t})^2,$$

to measure market concentration and therefore proxy factors affecting the market structure in a product class such as different types of sunk costs. This indicator accounts also for product specific learning effects that act as barriers to entry and thus increase market concentration (cf. Sutton, 1998). For this reason noother indicator capturing product specific learning economies is included in the analysis. Higher market concentration will make it more difficult to increase market shares without response by competitors. Hence, higher market concentration should be negatively related to market entry and changes in market shares. High concentration implies high market shares for the few dominating exporters but low market shares for the big lot of them. Hence, on should expect also a negative relationship for intensive margins.

Grubel-Lloyd Index (GLI) : The Grubel-Lloyd index is a measure for inter-industry trade. It is defined as follows:

$$GLI_{c,p,t} = 1 - \frac{|x_{c,p,t} - m_{c,p,t}|}{x_{c,p,t} + m_{c,p,t}},$$

where variable $m_{c,p,t}$ corresponds to the total value of imports of country c in product class c. At values close to 1 the index reflects very intense intra-industry trade as the country imports almost as much of product class p as it exports products of this class. This implies that the traded commodities are more heterogeneous. Conversely, if the index takes on values close to zero inter-industry trade prevails and the country either just imports or exports products of class p and the traded commodities tend to be more homogeneous. High GLI values reflect monopolistic competition in a specific product class and the likelihood of exporters gaining some positive market share in some market niches increases. Hence, ceteris paribus, one should expect a positive relationship between the GLI and the world market shares for non-homogeneous goods. For homogenous goods instead high GLI values reflect higher competition and hence more atomistic markets and lower market shares for exporters. The sign of the GLI indicators will therefore depend on which types of commodities dominate the data set. By definition with exports jumping from zero to some positive value, also the GLI jumps from zero to some positive value. As a consequence, the indicator cannot be used in the analysis of the development in extensive margins.

Log market size world (logMS): In order to capture potential scale effects the econometric models include an indicator for global market size,

$$logMS_{p,t} = ln\left(\sum_c x_{c,p,t}\right).$$

Under the assumption of decreasing returns to scale market size should be negatively related to world market shares, whereas a positive sign should indicate the presence of constant or increasing returns to scale.

Time, country and sector dummies The regressions include time, country and sector dummies to control for unobserved variation over time or across countries and sectors affecting export behaviour not taken into account by other variables. Sector dummies have been specified on the basis of NACE 4-digit sectors that have been matched to the HS classification on the basis of available HS-CPC concordance tables.

3.3 Data and methodological issues

3.3.1 Dataset

The principal data source used in the current analysis is the Base pour l'Analyse du Commerce International (BACI) dataset from the Centre d'Études Prospectives et d'Informations Internationales (CEPII). It contains data for 232 countries and 5109 product categories classified using the Harmonized System at the 6-digit level in its 2002 covering the period 2003 till 2013. This dataset covers 5025 products.

Gaulier and Zignago (2010) provide a detailed description of the BACI database that has a number of advantages over the COMTRADE database provided by the United Nations on which it builds. It reconciles bilateral trade flows reported by the exporting and the importing country. It uses mirror flows to complete missing reportings and estimates and corrects for freight costs. It provides also harmonises the data on traded quantities such that unit values that are comparable across countries can be calculated for almost every product. This implies that price indices can be constructed covering a much larger number of commodities than would be possible with the COMTRADE data.

In the original version the BACI data base is highly unbalanced. For each country it reports only products that are either imported or exported in a specific year resulting in highly unbalanced panels. In order to analyse the development of extensive margins a balanced panel data set has been constructed by imputing product specific indicators to unfilled country-product combinations and calculating country specific indicators such as product relatedness for these products. Export values, quantities and variables derived from these indicators were either set to zero or marked as missing (e.g. unit value based price indices). Variables with missing values resulting from this imputation were not used in the analysis of market entry. The resulting panel is highly balanced. The results reported in this paper concerning the development of market shares and market share dynamics are robust with respect to the use of the balanced or the unbalanced panel data set.

The data have been filtered in order to reduce the noise. Following the filtering procedures outlined in Hallak and Schott (2008) observations where dropped if they met the following conditions:

- the country-product-year observations have quantity smaller than 50 and the annual export value is less than $ 50,000 in constant terms, and
- the country-product observations do appear in fewer than two years in the sample.

In addition a number of country-like entities like 'Areas not elsewhere specified' that are included in COMTRADE and BACI to have consistent accounts for data with insufficient information on the trading partners have been dropped.

The entire data set covering all countries is needed to calculate most of the indicators included in the following analysis. The econometric analysis itself however focuses on the EU28 countries.

For the estimations and data on environmental technologies the paper relies on a classification of traded goods originally developed by the World Bank (cf. World Bank, 2008). This classification has been considerably extended and reviewed by the Austrian Institute of Economic Research (WIFO) and is used in this paper.[2]

3.3.2 Descriptive statistics: general data and environmental technologies

Table (1) shows the descriptive statistics for the variables presented in the previous section for the entire data set and the set of products classified as environmental technologies. As can be seen from the data the panel for the EU28 countries used in this analysis is balanced and consists of about 1.5mio observations with more than 5000 cross sectional units (products) spanning over 11 years. The inclusion of the import price index reduces the number of cross sectional units to 3800. Occasionally also single observations in the time series are missing. Hence, the inclusion of import prices leads to a weakly balanced panel. The environmental technologies are only a small subset of the dataset.

[2] The correspondence tables are available from the authors upon request.

Only 208 products are classified as environmental technologies amounting to a total of 64.000 observations for 11 years and 28 countries. A striking difference between the entire population of products and the environmental technologies is that they the average market size in terms of the traded volume is larger. Unreported indicators also indicate that environmental technologies tend to be more sophsticated than the average commodity.

all products						
Variable		Mean	Std. Dev.	Min	Max	Observations
market share	overall	0.015	0.043	0.000	1.000	N = 1547775
	between		0.040	0.000	0.862	n = 140913
	within		0.016	-0.505	0.924	T = 10.98
product relatedness	overall	0.257	0.115	0.014	1.000	N = 1547721
	between		0.112	0.034	0.728	n = 140913
	within		0.025	-0.122	0.966	T = 10.98
Grubel-Lloyd Index	overall	0.375	0.322	0.000	1.000	N = 1547775
	between		0.264	0.000	0.985	n = 140913
	within		0.186	-0.488	1.284	T = 10.98
Herfindahl Index	overall	0.181	0.136	0.000	1.000	N = 1547775
	between		0.116	0.039	0.815	n = 140913
	within		0.072	-0.405	0.971	T = 10.98
log world value product	overall	12.917	2.120	0.047	21.361	N = 1547721
	between		2.005	5.152	20.817	n = 140913
	within		0.721	4.704	20.252	T = 10.98
import price index product (chained)	overall	1.436	1.093	0.014	242.775	N = 1064670
	between		0.761	0.147	76.358	n = 108993
	within		0.779	-73.922	191.947	T = 9.76
environmental technologies						
market share	overall	0.017	0.039	0.000	0.968	N = 64152
	between		0.038	0.000	0.437	n = 5832
	within		0.011	-0.170	0.868	T = 11
product relatedness	overall	0.270	0.119	0.028	0.898	N = 64152
	between		0.117	0.041	0.600	n = 5832
	within		0.023	0.125	0.671	T = 11
Grubel-Lloyd Index	overall	0.493	0.310	0.000	1.000	N = 64152
	between		0.256	0.000	0.985	n = 5832
	within		0.175	-0.224	1.402	T = 11
Herfindahl Index	overall	0.120	0.064	0.037	0.938	N = 64152
	between		0.056	0.044	0.441	n = 5832
	within		0.030	-0.054	0.821	T = 11
log world value product	overall	14.295	1.496	4.033	18.238	N = 64152
	between		1.450	8.728	17.586	n = 5832
	within		0.370	9.600	16.361	T = 11
import price index product (chained)	overall	1.424	0.995	0.026	48.355	N = 53986
	between		0.704	0.153	15.957	n = 5240
	within		0.706	-13.533	35.697	T = 10.30

Table 1: Descriptive statistics.

In the entire sample about 7 percent of observations for the world market share (wms) take on a share of zero. This corresponds to about 108.000 observations and an average of 350 products that are not exported each year in each country. The world market shares show also a high persistence over time. The simple correlation coefficient between of world market shares at time t and $t-1$ is .98 across units. It also turns out that for almost all variables the variation across products (between variation) is higher compared to that within a product over time.

Table (2) shows the correlation matrix for the indicators used in the analysis. Relatively high positive correlation can be observed between the world market shares at the product level and product relatedness. This strong positive correlation between the dependent and principal independent variable is expected. The GLI is in turn negatively related to market concentration (Herfindahl index). Higher intra-industry trade therefore seems to go along with lower market concentration as would be expected. Larger markets seem also to go along with higher intra-industry trade. Hence, market segmentation seems also to be more likely in larger markets. These patterns are largely consistent for all products and environmental technologies only.

	market share	product relatedness	import price product	Grubel-Lloyd Index	Herfindahl Index	log world value product	VIF VIF VIF
all products							
market share	1.00						1.45
product relatedness	0.52	1.00					1.64
import price product	-0.01	0.00	1.00				1.00
Grubel-Lloyd Index	0.13	0.42	-0.02	1.00			1.19
Herfindahl Index	-0.06	-0.14	0.01	-0.22	1.00		1.06
log world value product	0.02	0.10	0.06	0.27	-0.36	1.00	1.04
Mean VIF							1.21
environmental technologies							
market share	1						1.7
product relatedness	0.6116	1					1.94
import price product	-0.0274	-0.0184	1				1.01
Grubel-Lloyd Index	0.1032	0.3847	-0.0527	1			1.25
Herfindahl Index	-0.0326	-0.1057	-0.0249	-0.1076	1		1.02
log world value product	-0.0054	0.0453	-0.0196	0.2521	-0.1145	1	1.14
Mean VIF							1.31

Table 2: Correlation matrix for principal variables and test for multicollinearity (VIF).

Overall, some of the observed correlations may give rise to concerns on potential multicollinearity between the involved indicators. However, test statistics shown in the last column of the table based on variance inflation factors (VIF) clearly indicate that this is not an issue for any of the indicators included in our analysis. The correlation patterns are very similar for environmental technologies. As a consequence also the mulitcollinearity test does not deviate from what has been found for the entire sample.

3.3.3 Econometric issues

The principal dependent variable – the world market share in a product class p, $wms_{p,t}$ – is a fraction with $0 \leq wms_{p,t} \leq 1$.[3] For this type of data Papke and Wooldridge (1996) have suggested to model the share equation using a fractional logit model. In Papke and Wooldridge (2008) they have extended this approach to panel data,

$$E(y_{p,t} \mid \mathbf{x}_{p,t}, c_p) = G(\mathbf{x}_{p,t}\beta + c_p), \tag{9}$$

where $y_{p,t}$ is a share variable, $\mathbf{x}_{p,t}$ and β are the vectors of strictly exogenous explanatory variables and coefficients, and p and t are the relevant panel dimensions. Function $G(\cdot)$ is non-linear satisfying that the predicted variables will lie in the interval $[0, 1]$. Variable c_p stands for unobserved individual heterogeneity. If these unit effects are random then the individual heterogeneity c_p depends on the explanatory variables as follows:

$$c_p \mid (\mathbf{x}_{p,1}, \mathbf{x}_{p,2}, ..., \mathbf{x}_{p,T}) = \psi + \bar{\mathbf{x}}_p\xi + a_p, a_p \sim N(0, \sigma_a^2), \tag{10}$$

where $\bar{\mathbf{x}}_p$ is the vector of time averages, and a_p is the normally distributed error with zero mean. From this specification of individual heterogeneity the fractional response function in equation (9) can be re-written as

$$\begin{aligned} E(y_{p,t} \mid \mathbf{x}_{p,t}, a_p) &= G(\psi + \mathbf{x}_{p,t}\beta + \bar{\mathbf{x}}_p\xi + a_p), \quad \text{or} \\ E(y_{p,t} \mid \mathbf{x}_{p,t}) &= G(\psi_a + \mathbf{x}_{p,t}\beta_a + \bar{\mathbf{x}}_p\xi_a), \end{aligned} \tag{11}$$

where the subscripts a indicate that the original coefficients have been divided by the scaling factor $(1 + \sigma_a^2)^{1/2}$. The analysis in Section 2 (see equation 1) points to the persistence of world market shares, hence, a dynamic panel model with a lagged dependent variable should be estimated. Under the assumption of strict exogeneity of $\mathbf{x}_{p,t}$, Wooldridge (2005) has proposed to specify the distribution of c_p conditional on $\mathbf{x}_{p,t}$ and the initial values

[3] For ease of reading country subscripts c are dropped in this presentation.

y_{p0} of the dependent variable in order to solve the initial condition problem in dynamic, nonlinear unobserved effects models as those used here. The individual heterogeneity specified in equation (10) thus transforms into

$$c_p \mid (\mathbf{x}_{p,1}, \mathbf{x}_{p,2}, ..., \mathbf{x}_{p,T}; y_{p0}) = \psi + y_{p0}\xi_0 + \bar{\mathbf{x}}_p\xi + a_p, a_p \sim N(0, \sigma_a^2). \tag{12}$$

Integrating out a_p as before equation (11) transforms into

$$E(y_{p,t} \mid \mathbf{x}_{p,t}\mathbf{y}_{p,t-1}; \mathbf{y}_{p0}) = G(\psi_a + y_{p,t-1}\gamma_a + \mathbf{x}_{p,t}\beta_a + \bar{\mathbf{x}}_p\xi_a + \mathbf{y}_{p0}\xi_{0,a}), \tag{13}$$

The most popular link function for $G(\cdot)$ ensuring that the predicted variables lie in the interval $[0, 1]$ is the logistic function, $G(\mathbf{x}_{p,t}\beta) \equiv \frac{\exp(\mathbf{x}_{p,t}\beta)}{1+\exp(\mathbf{x}_{p,t}\beta)}$. Papke and Wooldridge (2008) propose to estimate the fractional response function (11) using a pooled quasi-maximum (Bernoulli)log-likelihood function to obtain a consistent and heteroscedasticity robust estimator.

The specifications in equations (11) or (13) model the relationship between world market shares and product relatedness, but they do not capture the development of both extensive and intensive margins. For this purpose a two-part model (cf. Ramalho and Ramalho, 2011) will be estimated. Ignoring for the moment the panel specification necessary for the analysis in this paper two-part models are generally specified as follows: Define

$$y^*_{p,t} = \begin{cases} 0 & \text{for} \quad y_{p,t} = 0 \\ 1 & \text{for} \quad y_{p,t} \in (0,1), \end{cases}$$

then the probability of observing a positive outcome can be specified as

$$Pr(y^*_{p,t} = 1 \mid \mathbf{x}_{p,t}) = E(y^*_{p,t} \mid \mathbf{x}_{p,t}) = \Phi(\mathbf{x}_{p,t}\beta_{1P}), \tag{14}$$

where $\Phi(\cdot)$ is a probit function, and β_{1P} is the coefficient vector of the first part model that is estimated using the entire sample. The second part of the model is identical to the fractional response models presented earlier,

$$E(y_{p,t} \mid \mathbf{x}_{p,t}) = G(\mathbf{x}_{p,t}\beta_{2P}), \tag{15}$$

but is estimated for the observations with positive outcomes $y_{p,t}$ only, hence β_{2P} is the coefficient vector for the second part of the model. The first part reflects a binary choice model governing market entry and hence changes in the extensive margin. The second part models intensive margins. The regressors $\mathbf{x}_p$ in equation (14) and (15) can but need not be identical in the first and second part of the model. In the analysis in this paper the two equations will both draw on the dynamic panel specification outlined in equation (13).

3.4 Econometric analysis

Table 3 presents results on the relationship between product relatedness and world market shares at the product level. To allow comparison of the relative importance of the different parameters it reports average partial effects (APEs). The individual heterogeneity as outlined in equations (10) and (12) is specified through the overlined variables representing time averages for each cross-sectional unit. These variables capture long-run or between effects as opposed to the time varying covariates that capture short run or within effects. The initial condition $wms_{p,t=0}$ is an additional indicator for individual heterogeneity. The table is split in two parts. On its left part it reports the results for the full sample, whereas in its right part it reports the results for the subset of environmental technologies.

One limitation of the estimators outlined in Section 3.3.3 is the fact that strict exogeneity of the explanatory variables is assumed. In order to assess the impact of including variables that potentially fail this assumption on the estimated effects of the explanatory variables a step-wise approach is pursued starting with a base line specification that includes only the indicators for product relatedness as well as time, sector and country dummies in a dynamic panel setting. The tables include statistics for likelihood ratio tests. These test the validity of the dynamic panel specification against a static one (see LR_γ with $H_0 : \gamma_a = 0$ in equation 13), and the validity of a static panel model against a pooled cross-section specification without time averages of the independent variables (see LR_{ξ} with $H_0 : \xi_a = 0$ in equation 11). The table reports also Wald tests for the joint significance of the different dummies included in the regressions(with H_0 postulating no joint significance).

As argued in Section 3.3, the product relatedness indicator represents the proximity of a product to other products the economy exports with comparative advantage. It is a proxy for untraded interdependencies in the productive system. By construction it is determined by the characteristics of the production system only and can therefore safely be considered as being exogenous to the world market share of any product class p. One result worked out in Section 2 maintains that the world market share a country achieves in a product class increases in its relatedness to other products the country exports with comparative advantage. Hence, one should expect the APEs for variables $ProdRel$ and $\overline{ProdRel}$ to be significant and positive.

The first model in data columns (1) and (1e) shows that both indicators are highly significant and positive supporting the conjecture that embedding factors or untraded interdependencies play a major role in the exploitation of economic opportunitues. The average partial effects for product relatedness are very similar for the full data set and the subset of environmental technologies. The coefficient for the lagged dependent variable is however much larger for the environmental technologies indicating that the competitiveness (or the lack thereof) is considerably more persistent in environmental technologies than for all products. Wald tests for the joint significance of the sector and the time dummies, W_{sector} and W_{sector}, reject the null of no significance at the 1 percent level for both data sets. Hence, the inclusion of these dummies is warranted. The reported likelihood ratio test L_{ξ} rejects the null of insignificance of individual heterogeneity at the 1 percent level for both data sets. Similarly the likelihood ratio test L_{γ} rejects the null of insignificance of persistency at the 1 percent level of both data sets. Taking into account individual heterogeneity and persistency therefore improves model quality. Finally, the results for the $PseudoR^2$ statistic indicate that this parsimonious model explains 78 percent of the total variation for the full data set and even 85 percent of total variation for environmental technologies, which are very high values. Unreported tests indicate that the lagged dependent variable and the initial condition account for about three fifths of the variation and product relatedness for about two fifths.

The second model in data columns (2) and (2e) of Table 3 presents a full model controlling for market structure, the intensity of competition, the price level of competitors on the domestic product market, market size, country characteristics, as well as unobserved time and sector variation. The average partial effect for both $ProdRel$ and $\overline{ProdRel}$ is again highly significant and positive. The coefficient of the time-varying variable capturing short-run effects is slightly smaller than in the first model, whereas the time invariant variable reflecting long run changes increases relative to the parsimonious model. The total effect remains approximately the same. The average partial effects of product relatedness again are also considerably higher than those of the other control variables. This is true for both the entire data set and the subset of environmental technologies. Hence, an important conclusion from these results is that they support the conjecture that embedding factors play a major role both in the development of competitive advantage in environmental technologies.

Looking at the results for the control variables for all products the import price (cFPI) indicators, and the long-run effect of the Herfindahl-Index are not significant. All other variables are and with the expected sign. For environmental technologies the import prices, the Herfindahl indices and the market size indicators are not or only weakly significant. Indicating that market concentration seems not to be a factor that significantly impacts the exploitation of economic opportunity in environmental technologies. Different types of scale economies captured by the market size indicators seem also not to have a significant impact on the competitiveness of exporters across EU 28 countries on average.

The model diagnostic tests and statistics for the second model indicate that it is preferred to the parsimonious model. However, the added control variables improve the $PseudoR^2$ statistics only by little. This confirms that product relatedness is a powerful explanatory variable for world market shares, and that persistency in general plays a major role for the competitiveness of EU countries in environmental technologies.

	QML Flogit Estimator							
	all products				environmental technologies			
Model	(1)		(2)		(1e)		(2e)	
Dep. var: world market share	APE (SE)		APE (SE)		APE (SE)		APE (SE)	
world market share (t-1)	0.0870	***	0.1484	***	0.1226	***	0.1446	***
	0.0013		0.0014		0.0077		0.0099	
world market share (t=0)	0.0231	***	0.0161		0.0225	***	0.0250	***
	0.0011		0.0012		0.0057		0.0069	
product relatedness	0.1176	***	0.0918	***	0.1104	***	0.0953	***
	0.0015		0.0013		0.0104		0.0052	
product relatedness (LR)	0.0170	***	0.0464	***	0.0334	***	0.0577	***
	0.0015		0.0014		0.0104		0.0053	
Import price index			0.0000				0.0000	
			0.0000				0.0001	
Import price index (LR)			0.0001				-0.0001	
			0.0000				0.0002	
Grubel-Lloyd Index			0.0006	***			-0.0049	***
			0.0002				0.0008	
Grubel-Lloyd Index (LR)			0.0055	***			0.0053	***
			0.0002				0.0009	
Herfindahl Index			-0.0250	***			-0.0155	+
			0.0009				0.0095	
Herfindahl Index (LR)			0.0005				-0.0041	
			0.0010				0.0095	
log world value product			0.0002	***			0.0001	
			0.0001				0.0005	
log world value product (LR)			-0.0007	**			-0.0005	
			0.0001				0.0005	
Time dummies	Y		Y		Y		Y	
Country dummies	Y		Y		Y		Y	
Sector dummies	Y		Y		Y		Y	
N	1303533		886168		52110		43592	
log likelihood	-58014.52		-50228.39		-2743.28		-2606.47	
Pseudo R^2	0.78		0.85		0.85		0.87	
Deviance	10324.54		6259.68		279.25		221.88	
W_{time}	0.000		0.000		0.000		0.000	
$W_{country}$	0.000		0.000		0.000		0.000	
W_{sector}	0.000		0.000		0.000		0.000	
LR_{ξ}	0.000		0.000		0.000		0.000	
LR_{γ}	0.000		0.000		0.000		0.004	

+ p<0.15, * p<0.10, ** p<0.05, *** p<0.01
APE: coefficients represent average partial effects.

Table 3: Fractional response panel models.

As has been argued in Section 3.3.3 the dependent variable *wms* is a share variable bounded between zero and a potential maximum of one. For many observations the share is zero but the country may start to export the related product classes at some point in time. It is therefore important to distinguish between changes in the extensive margin of exports as a country enters or leaves export markets, and changes in the intensive margins implying changes in the world market share once is has already entered a market. The former reflects an search process in which producers of a country explore the product space for market opportunities given their (local) capabilities. The latter is a process of exploitation of opportunities relying on the competitive strengths rooted in local capabilities.

For this reason the relationship modelled in Table 3 should be further refined. Table 4 presents the results of a two part model (see equations 14/15) for the full dynamic panel model specified in Table 3. Regressions (2a) and (2ae) present the result for the binary part of the model where the dependent variable is a dummy which is one if a product is exported and zero otherwise for all products and environmental technologies respectively. Regressions (2b) and (2be) instead present the second part of the model that is identical to model (2) and (2e) in Table 3 with the exception that it is run for non zero world market shares only. The coefficients presented in the table are, as before, APEs.

Looking at the binary part of the model first the results point to a very high persistence in the export status of a product as indicated by the very high value of the lagged dependent variable. The lagged world market share is highly significant and positive and has also the largest APE of all explanatory variables for both models.

The product relatedness coefficients are both significant for all products. For the environmental technologies only the short run effect is significant which indicates that as product relatedness induced by changes in export status by related product changes also the likelihood of discovering the export potential and entering international markets in an environmental technology increases. This evidence therefore lends support to the conjecture that untraded interdependencies increase the likelihood of discovery of potential productive capabilities and related export markets. Indeed, the results show that the probability of entry in a new international market increases in the relatedness of that product to the other products the country exports with comparative advantage.

The other coefficients indicate that short run increases in high market concentration negatively affect the likelihood of entry into new international markets for all products. For environmental technologies the short run effect of market concentration is not significant. However, across environmental technologies entry seems to take place in more concentrated markets, as the long run effect of the Herfindahl index is significant and positive for model (2ae). This may indicate that markets for environmental technologies are concentrated possibly due to very specific capabilities and that this acts as an incentive for entry across countries. Import prices that were not significant a in the generic fractional logit model (see Table 3) now are significant with a negative sign. High import prices may indicate high quality of imports which may contribute to deter local companies of entering these markets. The short run effect of market size has a very high and positive impact, indicating that exporters react to perceived opportunities in international markets.

	(2a)		(2b)		(2ae)		(2be)	
	Two part model (MQL Fisher scoring)							
	all products				environmental technologies			
Model	binary part		fractional part		binary part		fractional part	
Dep. var: world market share	APE (SE)		APE (SE)		APE (SE)		APE (SE)	
world market share (t-1)	4.1592	**	0.1529	***	24.3531		0.1465	***
	2.0009		0.0015		18.1815		0.0103	
world market share (t=0)	0.1583		0.0165	***	0.6966		0.0252	***
	0.1995		0.0013		1.4013		0.0072	
product relatedness	0.2156	***	0.0942	***	0.1833	***	0.0964	***
	0.0118		0.0014		0.0453		0.0055	
product relatedness (LR)	0.2339	***	0.0477	***	0.0588		0.0584	***
	0.0167		0.0014		0.0654		0.0055	
Import price index	-0.0007		0.0000		0.0001		0.0000	
	0.0005		0.0000		0.0005		0.0001	
Import price index (LR)	-0.0016	***	0.0001		-0.0020	**	-0.0001	
	0.0004		0.0000		0.0009		0.0003	
Grubel-Lloyd Index			0.0002				-0.0051	***
			0.0002				0.0008	
Grubel-Lloyd Index (LR)			0.0057	***			0.0054	***
			0.0002				0.0010	
Herfindahl Index	-0.0427	***	-0.0257	***	-0.0451		-0.0157	+
	0.0041		0.0010		0.0439		0.0102	
Herfindahl Index (LR)	0.0061		0.0008		0.1558	***	-0.0043	
	0.0043		0.0010		0.0443		0.0101	
log world value product	0.0160	***	0.0002	**	0.0228	***	0.0000	
	0.0005		0.0001		0.0062		0.0005	
log world value product (LR)	0.0002		-0.0007	***	-0.0094	+	-0.0005	
	0.0004		0.0001		0.0061		0.0005	
Time dummies	Y		Y		Y		Y	
Country dummies	Y		Y		Y		Y	
Sector dummies	Y		Y		Y		Y	
Pseudo R^2	0.25		0.85		0.30		0.87	
Deviance	142823		6179.53		2999.20		220.38	
N	886168		858614		28780		42974	

+ p<0.15, * p<0.10, ** p<0.05, *** p<0.01
APE: coefficients represent average partial effects.

Table 4: Dynamic two-part model.

The fractional part of the two part model leads to very similar results as models (2) and (2e) in Table 3. The significance of some coefficients has changed while the magnitude of all coefficients has remained largely unaltered. The model fit has even slightly increased. The most important change for environmental technologies is that the long run effect of product relatedness is now again highly significant and positive. The other two changes regard the market size effects that now no longer significant for environmental technologies, indicating that global market size and changes thereof are important incentives for market entry but do no affect the exploitation of market opportunities. Hence, also the more differentiated two part model estimation confirms that untraded interdependencies captured by the product relatedness indicator have a positive and significant impact on both the discovery of productive capabilities and related export markets as well as the exploitation of economic opportunities.

4 Counterfactual analysis of diversification potentials in environmental technologies

The previous sections have shown that the embeddedness of a product in a production system is closely associated with the potential to explore and exploit economic opportunities in international markets. The circumstance that product relatedness has considerable power to predict both world market shares and entry into international markets of a country can be used to construct counterfactual evidence on where the EU28 countries are likely to deepen or develop new specialisations in environmental technologies or loose them. While this analysis cannot replace more focused in-depths analyses relying on more specific data, it can be used as a device focusing attention on particularly well or badly embedded product classes and as a consequence develop better targetted diversification policies in the domain of environmental technologies.

If the covariates in the previous regression models adequately ensure that product relatedness is independent of outcomes, then predictions of world market shares on the basis of the regression model in Table 3 deliver potential outcomes which can be used as counterfactual (Angrist and Pischke, 2009, chpt. 3). The econometric model is thus used to predict the world market shares each product class should obtain given its relatedness to other products in the economy and its competitive environment. Under the assumption that in the last year in the sample the global trade volume in each industry is constant and that whatever market share the EU countries gain or lose in a product class will translate into equivalent market losses or gains in the rest of the world this prediction is used to estimate trade changes in the trade volumes in each sector or technology field. These estimated gains or losses are then translated into changes in the export shares of each country for each broad category of environmental technologies.

A further restriction to keep in mind is that the process of discovery and exploitation analysed so far deals with exploration processes of specific goods and technologies already available in world markets that can however be produced at low cost or superior quality. These are however in line with aspects of recent policy oriented literature concerned with the governance of (smart) diversification processes mainly in the regional context (cf. Foray, David, and Hall, 2011; McCann and Ortega-Argilés, 2013). This discussion gives major attention to the diversification of a given set of economic activities into new activities into technologically related fields (cf. Reinstaller, Hölzl, Kutsam, and Schmid, 2012; Boschma and Gianelle, 2014).

Figure 5 compares the average product relatedness with the revealed comparative advantage each environmental technology-country combination scores by means of heat maps across EU28 countries. In these plots shades of green indicate high indicator values and shades of red low indicator realisations. The left panel shows a heat map of the product relatedness indicator. The observations have been clustered by means of a hierarchical cluster algorithm as shown by the dendrograms on top and the side of each figure. The base value for the product relatedness heat map is the percent deviation of environmental technology specific product relatedness to the average country product relatedness. The right panel instead shows a heat map for the average values for the revealed comparative advantages each EU28 country has achieved over the period 2011-2013 normalised (variance one, mean zero) in each environmental technology field. For better comparison in this heat map the ordering of countries and technologies of the left panel has been maintained.

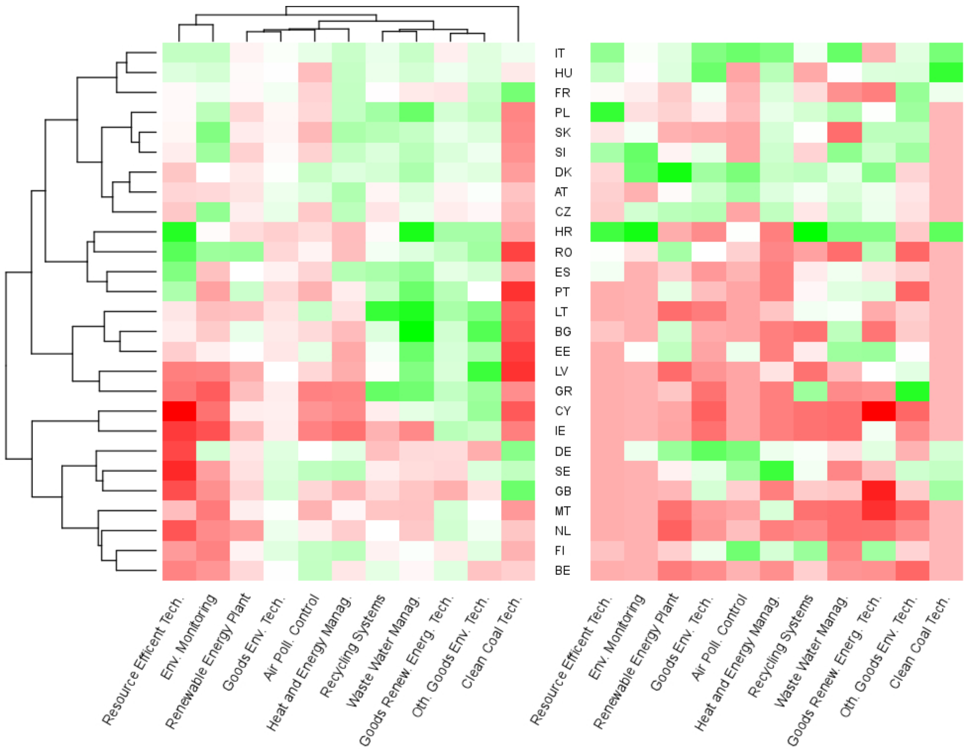

Figure 5: Product relatedness (left) and comparative advantages (right) in environmental technologies across the EU28. BACI dataset (Gaulier and Zignago, 2010).

As the revealed comparative advantage (RCA) is a competitiveness measure normalising the world market share a country has obtained in an environmental technology field by its world market share across all product classes, from the earlier analysis one should expect a high correspondence of the patterns of the two heat maps. Indeed, by and large the patterns match. However, in some instances one can observe significant deviations. For instance, Denmark has a high revealed comparative advantage in renewable energy plant technologies which is in line with the fact that the world's largest manufacturer of wind turbines operates from Denmark. However, the product relatedness indicator shows that in the aggregate these technologies are not very strongly embedded in the country's productive structure which could potentially go along with competitive disadvantages if the local producers cannot draw on untraded interdependencies that support competitiveness, and other indicators also show that this particular technology has suffered from competitive pressure in the recent past. In other countries instead the reverse pattern can be observed.

Figure 6 presents the counterfactual evidence for the potential export values from the model estimations again by means of a heat map that shows the the potential export value growth in each technology field and country calculated from the difference of the predicted and the actual export value for each environmental technology field relative to the total export value of a country. In the heat map the value has been scaled (variance is set to one) for each sector to allow for a visualisation independent of sector size. As before green shades indicate an increase of potential export values and red shades a potential decrease.

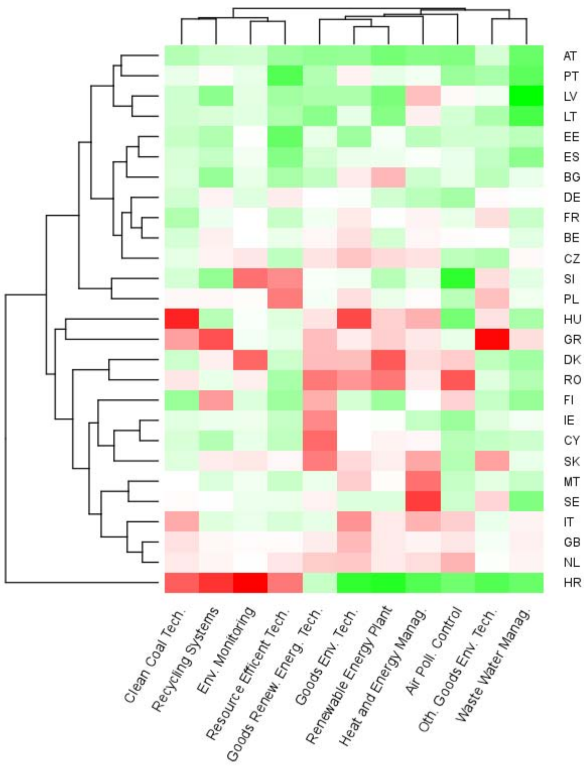

Figure 6: Potential export values across environmental technology fields and the EU28 countries. BACI dataset (Gaulier and Zignago, 2010).

The heat map for the potential export values indicates for which environmental technologies potential market outcomes could be higher or lower relative to the current position given their embeddedness in a national production system and the international competitive situation in related markets. The heat map pattern indicates that a number of European countries could potentially increase their export shares in some product classes despite them not being strongly embedded in domestic productive structures. Indeed, a weak embeddedness as shown in Figure 5 does not necessarily imply losses of market shares. It rather tells that relative to other better embedded products the market shares the country will be able to obtain will be on average lower.

Hence, some countries like Portugal (PT), Spain (ES) or Austria (AT) have the potential to deepen their presence in international markets despite some environmental technologies being embedded relatively weekly in the local production system. Most environmental technologies can potentially draw on untraded interdependencies that have not been brought to full fruition so far. The cluster of countries on top of the figure consist of many countries of this type. They have the potential to generally deepen their specialisation in environmental technologies. This is in line with the figures presented in Table 5 that show that these countries could increase their international market presence relative to the level obtained in 2013. Table 5 summarises the data by presenting the environmental technology fields with the highest and lowest gains or losses and the potential aggregate gain or loss over all environmental technology field for each country.

The middle part of the heat map shows a relatively large group of countries for which the estimations point at a scenario of potential shifting of trajectories in the production of environmental technologies that go along with a restructuring of their productive portfolio of environmental technologies leading to reductions in export values for some countries and increases in others. Table 5 shows that these potential shifts could have a different impact on the overall specialisation of these economies in environmental technologies. Some countries would potentially benefit while others could potentially lose from these restructuring processes. The case of Denmark is again very prominent, as it is the country in the sample with the highest overall export share in environmental technologies and especially in renewable energy plant technologies, but it would lose market shares due to the relatively weak embedding and the competitive situation in most environmental technologies, such that the counterfactual analysis would predict a shift away from the established specisation trajectory. The results of this counterfactual analysis therefore suggest that some countries that up to recent times have been pioneers in environmental technologies may lose their strong competitive position in these technologies due to a weak embedding of the related economic activities in the overall productive structure of their economies.

	Minimum predicted change		Maximum predicted change		All environm. technologies	
country	percent gain/loss	category	percent gain/loss	category	Export share country†	Potential percentage change‡
AT	0.01%	Oth. Goods Env. Tech.	1.42%	Goods Env. Tech.	9.40%	3.07%
BE	-0.64%	Goods Env. Tech.	0.18%	Renewable Energy Plant	5.34%	-0.52%
BG	-0.44%	Renewable Energy Plant	0.39%	Goods Renew. Energ. Tech.	6.30%	-0.17%
CY	-1.39%	Goods Renew. Energ. Tech.	0.12%	Recycling Systems	5.10%	-1.22%
CZ	-1.23%	Goods Env. Tech.	0.03%	Resource Efficent Tech.	10.98%	-1.70%
DE	-0.03%	Recycling Systems	0.18%	Renewable Energy Plant	12.78%	0.35%
DK	-1.35%	Goods Env. Tech.	0.06%	Clean Coal Tech.	14.21%	-3.07%
EE	0.00%	Env. Monitoring	1.36%	Goods Env. Tech.	8.59%	1.88%
ES	0.00%	Heat and Energy Manag.	0.27%	Goods Env. Tech.	6.60%	0.87%
FI	-0.76%	Goods Renew. Energ. Tech.	0.60%	Goods Env. Tech.	9.81%	0.23%
FR	-0.44%	Goods Env. Tech.	0.10%	Clean Coal Tech.	7.48%	-0.18%
GB	-1.45%	Goods Env. Tech.	0.00%	Oth. Goods Env. Tech.	7.92%	-1.87%
GR	-0.61%	Goods Renew. Energ. Tech.	0.01%	Resource Efficent Tech.	4.33%	-1.96%
HR	-0.47%	Recycling Systems	2.87%	Goods Env. Tech.	9.69%	3.21%
HU	-3.76%	Goods Env. Tech.	0.11%	Recycling Systems	12.94%	-4.58%
IE	-1.10%	Goods Renew. Energ. Tech.	0.04%	Clean Coal Tech.	4.53%	-0.92%
IT	-2.23%	Goods Env. Tech.	0.15%	Goods Renew. Energ. Tech.	11.81%	-2.36%
LT	-0.01%	Heat and Energy Manag.	0.72%	Goods Renew. Energ. Tech.	5.31%	1.80%
LV	-0.04%	Heat and Energy Manag.	1.14%	Goods Env. Tech.	5.29%	2.54%
MT	-1.04%	Goods Env. Tech.	0.12%	Goods Renew. Energ. Tech.	3.28%	-0.91%
NL	-1.13%	Goods Env. Tech.	0.00%	Oth. Goods Env. Tech.	5.44%	-1.88%
PL	-0.67%	Goods Env. Tech.	0.08%	Renewable Energy Plant	8.42%	-0.66%
PT	-0.27%	Goods Env. Tech.	0.48%	Goods Renew. Energ. Tech.	7.75%	0.52%
RO	-2.21%	Goods Env. Tech.	0.04%	Resource Efficent Tech.	9.55%	-4.30%
SE	-0.13%	Heat and Energy Manag.	0.49%	Goods Env. Tech.	9.36%	0.42%
SI	-0.14%	Env. Monitoring	0.30%	Renewable Energy Plant	10.17%	0.54%
SK	-1.22%	Goods Renew. Energ. Tech.	0.04%	Clean Coal Tech.	7.35%	-2.24%

† in 2013, all environmental technologies
‡ relative to realisation in 2013

Table 5: Summary table on potential diversification outcomes in environmental technologies across EU 28 countries.

5 Summary and policy implications

5.1 Summary of the empirical results

This paper has shown that in an evolutionary market selection environment product embeddedness is a source for increasing returns and as a consequence a determinant of competitive advantages. This has been tested empirically analysing both the development of intensive and extensive margins in trade. The first set of results has shown that there is a clear cut empirical relationship between embedding factors proxied by product relatedness and the world market shares a country achieves in international trade at the level of highly disaggregated product classes. The results hold both for all traded commodities and environmental technologies and are thus fairly general.

The second set of results shows that the probability that a country enters international markets in a specific product class markedly increases in its relatedness to other products the country exports with comparative advantage. At the same time, local capabilities contribute also to deepen the presence of exporters of a country in international markets in which they are already active. Hence, local capabilities drive both the export specialisation and export diversification of a country. Again the results are fairly general and hold both for all traded commodities as well as the subset of environmental technologies. They show that the development of competitiveness in international markets is a process of related diversification. Indeed, the composition of the export portfolio of a country evolves through related diversification.

The results highlight also the "dialectic" nature of embedding factors. On the one hand, they offer opportunities for diversification and drive export competitiveness. On the other hand, they may also be a source of a structural lock-in. While some contributors to the economic development literature have highlighted especially this latter effect (cf. Hidalgo, Klinger, Barabasi, and Hausmann, 2007; Jankowska, Nagengast, and Perea, 2012; Metha and Felipe, 2014), our results suggest that path dependencies should be overcome by relying on path dependencies. Hence, policies to promote the development of environmental industries should capitalise on related capabilities. Such policies of related diversification will be discussed in detail in the next section.

Relying on this evidence a counterfactual analysis has analysed the potential development trajectories of European countries in the environmental technologies. The results indicate that some countries that up to recent times have been pioneers in environmental technologies may lose their strong position in these technologies due to a weak embedding of the related economic activities in the overall productive structure of their economies. In other countries instead the results indicate that new strenghts in environmental technologies have the potential to emerge, as some environmental technologies can draw on untraded interdependencies that have not been brought to full fruition so far.

5.2 Policy implications: Using path dependencies to overcome path dependencies

These insights are important if one is to assess how innovation or more broadly speaking industrial policy should intervene to drive technical change towards paths that promote sustainable economic development while safeguarding and strengthening the competitiveness of firms. It shows that subsidies and price signals alone are not sufficient in themselves to shift productive systems to new ecologically sustainable trajectories.

The concept of relatedness as outlined in the previous sections therefore provides both a tool to characterise the direction technical change and innovation in a country, and to identify potential avenues for future development. Policies aiming at the promotion of sustainable technical should exploit relatedness and complementarities both at the technological and institutional levels. They should promote the renewal of established economic activities as well as innovation and diversification into products or technologies supporting substainability goals that are related to established competencies.

A premise to implement such policies is to extensively analyse and assess existing competencies and to identify promising areas of activity into which an established productive system can diversify through related diversification. The present paper has used the concept of relatedness in product space to identify "opportunity sets" to broaden and deepen the presence of the EU28 countries in environmental technologies that can support the development of trajectories of sustainable industrial development.

A companion study (see Unterlass, Reinstaller, Vogel, and Friesenbichler, 2015) has analysed potential policy approaches to promote related diversification mostly through the recombination of existing capabilities with new ones. It identifies tha most important channels of diversification as:

1. Mission oriented policies,

2. policies supporting entrepreneurship, discovery and recombinant technical change in industries, and
3. research and technology policies targeting relatedness and recombination.

These broadly defined fields of action are interdependent and have all taken by themselves a number of strengths and weaknesses.

Mission oriented policies that focus on societal challenges may trigger recombination of competencies across technological fields and sectors. Mission oriented policies in the context of Smart Diversification strategies however should explicitly take into account local competencies. This means that new missions should build on these capabilities and aim at achieving the mission's goals by developing these capabilities further through ambitious technological search and recombination.

One potential danger is that the goals set out by the mission rely too heavily on undeveloped capabilities (e.g. new principles of operation or materials) or on capabilities that are not related to existing capabilities. In this case it is likely that the mission fails, or that considerable long-term investments and public risk taking in building up capabilities and human capital to accomplish the mission are needed while there is no guarantee that these investments contribute to achieve the mission's goals. Nevertheless, challenging missions and challenging domains of application of technologies are often important to achieve significant technological breakthroughs.

Mission orientation comes with a trade-off that has no easy solution: The policy design has to find the right balance between mission driven diversification relying on related technologies and mission driven diversification relying on weakly or unrelated technologies. In this regard, one has to take into account that on the one hand, technological practice often throws up important questions requiring further scientific investigation. On the other hand, scientific research often identifies opportunities from its own results that prime commercial application. Therefore there is a major reason for being concerned with the diversity of the research and the scientific portfolio, especially in the context of mission orientation.

This suggests that in the design of mission oriented programmes it is necessary to define goals broadly, while ensuring bottom up research on related problems both from a broad scientific and from more narrow technological and engineering perspectives. This is all the more important to avoid that mission orientation promotes technological lock-ins. It is also necessary that an exchange of findings and problems between these different domains to ensure cross fertilisation. While this may sound like what is nowadays known as "new" mission-orientation (as we see it for instance in the Horizon 2020 programmes), there is however an important difference. Mission orientation should capitalise on existing capabilities and try to exploit diversification potentials by means of the design of selection mechanisms and the specification of missions.

Other difficulties associated with mission-orientation should be considered as well. As Mowery (2009) works out, success in mission oriented programmes stands or falls with complementary market making measures. Public procurement policies are important complements to ensure that for products and technologies for which a-priori no or only very small markets exist markets are created. These publicly created market niches have to ensure that learning processes can take place that eventually lead to technological feasibility and economic viability of the related products and services (cf. Kemp, Schot, and Hoogma, 1998). However, such processes may require minimum market sizes and are thus not an option for small countries (unless coordination in larger economic areas like the EU takes place). In addition, they may also lead to rent seeking by large incumbents in the market. Furthermore, additional regulations and specific tax measures may also be needed to ensure that viable markets for these products eventually emerge.

In order to avoid "picking the winners" approaches policy promoting diversification towards technologies supporting sustainability goals should support entrepreneurship and entrepreneurial discovery. The emphasis should lie on innovation activities that aim recombining competencies across technological fields and sectors. Such processes are typically supported by a number of knowledge transfer mechanisms. Here we will emphasise labour mobility, entrepreneurial activities through spin-offs, and the promotion of foreign direct investment.

Labour mobility is an important mechanism for the transfer and recombination of knowledge. For instance with respect to geographical mobility the economic literature has repeatedly stressed that the mobility of highly qualified workers (such as researchers) has a positive impact on the competitiveness of countries, regions and firms. In this respect a number of studies have found that mobile researchers are an important resource pool, which help to improve national and firm level R&D performance as well as helping with integration into international R&D networks and increasing entrepreneurial and patenting activity (cf. Zucker, Darby, and Torero, 2002; Moen, 2005; Song, Almeida, and Wu, 2003; Hunt and Gauthier-Loiselle, 2008). Furthermore, a by now relative large body of empirical research (cf. Wadhwa, Saxenian, Rissing, and Gereffi, 2008; Fallick, Fleischman, and Rebitzer, 2006) shows that even within a region, mobility of researchers between sectors and firms may have a positive impact on competitiveness. Boschma, Eriksson, and Lindgren (2009) on the other hand show that employees recruited from related industries increase productivity whereas new recruits from the same industry have a negative impact on performance. Labour mobility is therefore not only a major source of knowledge spillovers but also a source that can contribute to recombinant technical change.

Even more important than labour mobility between related industries, may be mobility between industry and the academic sector. A recent study has shown that industry researchers often start their career in the public sector to then change into generally more applied industry research (Huber, Reinstaller, Unterlass, and Ebersberger, 2010). The relative majority (42.3%) of the industry researchers surveyed in the cited study describes their career path as one starting in the public sector and ending in the private sector. Hence, this type of mobility fosters knowledge flows and potential recombination between industrial capabilities and related academic knowledge bases. In addition, this type of mobility supports also the cooperation between academia and industry (Cohen, Nelson, and Walsh, 2002).

To support labour mobility labour market policies should on the one hand develop measures that support job mobility between related industries not only within a country but across EU 28 countries. On the other hand, framework conditions and regulations have to be screened in order to eliminate barriers to labour mobility between industries. Such barriers could be industry specific labour norms, non-compete clauses in labour contracts or differences in salaries for workers with comparable qualifications caused by industry specific collective agreements. In order to support mobility between the academic and the industrial sector cooperative research programmes seem to be an appropriate vehicle. Similarly, public policy should provide incentives and support collaborative research activities between companies in technologically related industries. However, while internationally good examples of such cooperative research programmes exist, it has to be acknowledged that such cooperative programmes often suffer from problems related to the overall objectives they pursue, to conflicts between short run and long run goals of the programmes and participating partners, or the repartition of IPRs between the involved partners. Hence, the potential of such measures to support diversification policies should be re-examined more in details in dedicated studies.

We have already discussed the importance of and the mechanisms through which spinoffs contribute to industrial restructuring and related diversification processes in the first part of this paper. While entrepreneurship policies are widespread across countries and most likely to be overrated (cf. Nightingale and Coad, 2013, 2014), the support of employee start-ups and spinoffs should be an integral part of policies promoting the diversification of industrial activities towards technologies supporting sustainable industrial development. Klepper (2001) argues that spinoffs inherit routines (and thereby specific capabilities) from their parent companies. While these transplanted routines will perform a subset of functions performed in the parent they will however combine with other different routines and both the performance and output will depart from their parents. As Klepper explains, this is also the reason why such firms have also a higher probability of survival than other types of start-ups. This is related to the experience their founders have accumulated in related industries (Klepper, 2007).

The processes Klepper (2001) describes are, viewed from a micro perspective, the essence of related diversification. Therefore, entrepreneurship policies should focus on or give priority to the support of employee start-ups in the context of Smart Diversification strategies. The downside of this approach is of course, that the promotion of employee start-ups is not equally possible across industries: generally technology intensive firms will have more routines than firms with low technological intensity because their activities are more complex, and hence, spinouts will be more likely for such types of companies. In industries where the technological intensity is low, the opportunities for employee start-ups may be more limited.

Finally, foreign direct investment (FDI) may be an important source for diversification and access to related capabilities that are not present at first in a country (or region). The potential impact of supporting FDI is however discussed controversially. Some authors find that foreign ownership of companies is often a predictor for both less local R&D cooperation and reduced in-house R&D (cf. Knell and Shrolec, 2005). Other studies in turn argue that this is mostly the case in industries with low technological intensity and that indeed foreign subsidiaries have a higher propensity to innovate when they are active in technology intensive sectors of the host country (cf. Damijan, Kostevc, and Rojec, 2010). Eventually, the impact FDI is likely to have on domestic industries boils down to the relatedness of these companies to existing capabilities and their embeddedness in the local productive system (Narula, 2011). This suggests that FDI policies targeting Smart Diversification should focus on companies whose technologies and capabilities are related to and complement to well-developed competences in the country. FDI policies should in addition be complemented by investments in (cooperative) research and education in fields that ensure that foreign subsidiaries can draw on a local pool of knowledge and human capital in order to develop their capabilities further in the host-country.

Established research and technology policies can also be modified to that they are better able to target relatedness and recombination. We have already discussed mission oriented and cooperative policies earlier. One can however also think of ways on how standard non-mission oriented bottom up type of research funding measures and programmes can target related and recombinant technical change more accurately through specifically designed review processes. Of course, one should not make the mistake to think that peer review processes can adequately distinguish between work with the potential for radical innovation and work that promises incremental advance of existing lines of scientific investigation and technological development. However, peer review process can be designed to limit incremental technical change (favouring specialisation) and promote recombinant technical change (favouring diversification).

More precisely the evaluation of research projects could be linked to the four distinct patterns of diversification (or more detailed description of thereof) discussed earlier in the paper. For instance, the intensity of the support of such projects could vary in function of these patterns, as they are likely to imply different risk profiles. Hence, they would require also varying degrees of support intensity. More ambitious types of diversification that are also more risky should ceteris paribus receive higher funding than less risky types of diversification. For instance, it is very likely that research projects that imply diversification through transition are technologically less risky than research projects that aim at diversification through re-domaining. Hence, the latter type of projects should typically receive - ceteris paribus - higher funding. While in practice it seems probable that it would be difficult to work out general principles of funding that would be able to take diversification processes fully into account, substantial knowledge on the patterns of technical change nowadays is available and should be used to design research funding. As recombinant technical change is a key ingredient of related diversification knowledge on this type of technical change should be used in the context of Smart Diversification approaches.

This section of the paper has outlined a few potential avenues for designing innovation policies that promote diversification processes to shift technological trajectories towards sustainability. They are of course only indicative and have focused rather on general principles and domains of policy rather than on specific policies to actually shift the productive systems of EU member states towards trajectories that are less energy and resource using while ensuring at the same time also social sustainability. Considerable work is still needed to assess much more in detail how diversification policies can contribute to the goal of achieving sustainable social and ecological development.

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Project Information

Welfare, Wealth and Work for Europe

A European research consortium is working on the analytical foundations for a socio-ecological transition

Abstract

Europe needs change. The financial crisis has exposed long-neglected deficiencies in the present growth path, most visibly in the areas of unemployment and public debt. At the same time, Europe has to cope with new challenges, ranging from globalisation and demographic shifts to new technologies and ecological challenges. Under the title of Welfare, Wealth and Work for Europe – WWWforEurope – a European research consortium is laying the analytical foundation for a new development strategy that will enable a socio-ecological transition to high levels of employment, social inclusion, gender equity and environmental sustainability. The four-year research project within the 7th Framework Programme funded by the European Commission was launched in April 2012. The consortium brings together researchers from 34 scientific institutions in 12 European countries and is coordinated by the Austrian Institute of Economic Research (WIFO). The project coordinator is Karl Aiginger, director of WIFO.

For details on WWWforEurope see: www.foreurope.eu

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