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Andreas Joseph, Chiara Osbat

How you export matters: the disassortative structure of international trade

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Abstract

The local network structure of international trade relations offers a new dimension for understanding a country's competitive position vis-á-vis its trade partners and competitors, supporting economic policy analysis. We introduce two network measures that can be used to analyse comparative advantage and price competitiveness, called relative export density and export price assortativity, respectively. The novelty of these measures is that they consider the embedding of a country into its local trade environment. They are computed based on unit values and sector concentrations at a highly granular level and they help to uncover general patterns of the global organisation of international trade. Countries have a strong tendency to arrange their exports to form local monopolies by focusing on products and markets, usually - but not exclusively - where they have a price advantage. Price (dis)assortativity turns out to be an important factor for export growth, even after controlling for a large set of macroeconomic and structural determinants. This effect is particularly strong for catching-up CESEE countries, with potential implications for industrial policy. The relationship between the two export assortativity metrics for different groups of countries and for varying technological content of exports indicates a tipping point in a country's development from price-driven competition to non-price factors.

Keywords: Export growth, Comparative advantage, World trade network, Export sophistication

JEL Codes: F14, F63, D85

Non-technical summary

The product and geographical structure of international trade has been the subject of study since the early days of Economics. As soon as 1817 Ricardo showed that there are welfare gains from specialisation and trade over autarchy, even when one country is better in absolute terms at making each good. The modern interpretation of this idea of comparative advantage and of the gains from trade refers to a complex world of many countries with different characteristics and trade barriers between them, exchanging many goods, formulated in terms of labour, technology and geography. A natural question is to what extent comparative advantage can evolve and how it affects the export performance and consequently the long-term growth of a country. The evidence is conflicting, see e.g. Imbs and Wacziarg (2003); Batista and Potin (2014); Imbs et al. (2014); Papageorgiou and Parmeter (2015).

Comparative advantage depends on unobservable technology differences. To operationalise this concept, it was recast in terms of relative export specialisation by Balassa (1965), with further refinements by Laursen (2015) among others. This approach - referred to as "Revealed Comparative Advantage" (RCA) - is central to the relatively new literature that uses network theory to estimate the complexity of export structure and to link it with economic development (see for instance Hausmann and Hidalgo (2011)).

Why do we look at the topology, that is the shape, of how bilateral trade links organise? Trade relations between countries at a single-product level are sparse, implying that markets are fragmented. In such a situation measures based on global comparisons are less informative than measures that take into account a country's embedding into the international trade network, see e.g. Joseph and Chen (2014). The investigation of the detailed structure of trade links can provide valuable insights, not only on global trade, but also on a country's integration into global value chains and on globalization itself.

In this study we set out to combine the ideas behind RCA and local trade integration. Our approach to operationalise the concept of comparative advantage is to depart from just measuring the concentration of a country's exports relative to the rest of the world, which is a global measure, and to look at metrics of export assortativity, which are local properties. In network theory assortative mixing or assortativity is the tendency of nodes that are similar according to some metric to establish links among themselves. In international trade, the so-called Linder hypothesis is a conjecture that echoes the concept of assortativity: The more similar the demand structures of countries, the more they will trade with one another (Linder (1961)). Indeed, export assortativity can be broadly associated with a country's similarity to its neighbours in terms of export composition. However, we do not only look at the size and composition of export flows, which is closer to the original idea of RCA, but also at the price characteristics of those flows, which can be associated with differences in technology and quality. Hence, the novel metrics that we propose look at the price and product composition of a country's exports and compare them to those of its partners and competitors (defined as a partner's third-party import and export partners). The final objective is to obtain indicators for a country's relative export prices and product specializations, not relative to the rest of the world, but conditioned on the destinations it actually trades with and the competitors it actually faces.

The questions are now how relative prices and product compositions are related for different groups of countries and for different technological content. Are there general principles for the organisation of international trade? Ultimately, how does the integration of a country in the global trade network affect its export growth and, indirectly, its growth path?

We identify two general principles of international trade which seem to hold regardless of the country of interest. They show rather a disassortative than an assortative pattern, especially concerning prices: The average product is cheaper than those of competitors and countries strongly concentrate their exports on a few products which they sell to only some destinations. In other words countries have a strong tendency to organise their exports such that they form "local monopolies" for individual products. Taken together these principles can be interpreted as avoiding competition, with global trade arranging itself in the form of mutual wholesale markets.

However, there are rich variations and exceptions between countries and for different products. For instance, the price distributions of developed countries tend to be either centred around parity or be skewed towards higher relative prices. By contrast, catching-up and developing countries tend to have price distributions that are skewed towards lower relative prices, as one may expect.

In addition to uncovering these general principles of trade we investigate the relation between export assortativity and export growth which often constitutes an important component of a country's development path. Because the determinants of export growth are complex and vary considerably and to take an unbiased approach to address this issue, we chose a Bayesian model averaging framework including a large set of variables, accounting for economic structure, human capital, innovation, business and government efficiency and structural variables. This enables one to let the data decide what are the most likely covariates to enter a model. Export price assortativity is found to be one of the highest-ranking variables and it is positively associated with export growth, especially for catching-up CESEE countries. Its importance seems to be less significant for more developed EU15 countries. That the evolution of relative prices captures the catching-up process in Europe, where the average relative price stabilises at or slightly below parity for all countries, indicates that price is a necessary, but not sufficient, component of export competitiveness. The convergence towards price parity indicates a transition from mere price-driven to monopolistic competition, where more qualitative features gain importance.

The literature on the analysis of global trade has also formed a theoretical and empirical basis for formulating industrial policy advice, see e.g. in "The Atlas of Economic Complexity: Mapping paths to prosperity" Hausmann et al. (2013). Based on our analysis, the consideration of the structure of international trade indeed introduces a topological component into industrial policy. Besides addressing one's export prices or industry composition - generally a difficult long-term process - decision makers in policy and industry might address the structure of trade links. For instance, using the proposed methodology, one can evaluate a country's competitive position (in terms of prices and specialisation), for entering (or exiting) any specific market, enabling "What-if-Analyses" of export decisions.

1 Introduction: A local measure of revealed comparative advantage

The product and geographical structure of international trade has been the subject of study since the early days of Economics. As soon as 1817 Ricardo showed that there are welfare gains from specialisation and trade over autarchy, even when one country is better in absolute terms at making each good. The modern interpretation of this idea of comparative advantage and of the gains from trade refers to a complex world of many countries with different characteristics and trade barriers between them, exchanging many goods, and it is formulated in terms of labour, technology and geography (as distance is a good indicator of trade costs between two locations), see e.g. Eaton and Kortum (2002). A natural question is to what extent comparative advantage can evolve, and how it affects the long-term growth of a country. The evidence is conflicting: E.g. Imbs and Wacziarg (2003) find that the relation of product concentration to the level of per capita income is U-shaped: As they grow, countries first diversify across products, then they start specializing again after a certain threshold of per capita income has been reached. This empirical finding runs counter to the theoretical prediction of a monotonic relationship between income and specialisation. Alternative explanations have been offered for this "hump shape", e.g. in terms of capital intensity by Batista and Potin (2014) or of local and global economic integration by Imbs et al. (2014), but its validity has also been questioned, e.g. by Papageorgiou and Parmeter (2015).
The concept of comparative advantage depends on unobservable technology differences. For operationalisation it was recast in terms of relative export specialisation by Balassa (1965), with further refinements by Laursen (2015) among others. This approach - referred to as "Revealed Comparative Advantage" (RCA) - is central to the relatively new literature that uses network theory to estimate the complexity of export structure and to link it with economic development (see for instance Hausmann and Hidalgo (2011)). This literature has in turn formed a theoretical and empirical basis for formulating industrial policy advice, e.g. in "The Atlas of Economic Complexity: Mapping paths to prosperity" Hausmann et al. (2013).

Hausmann and Hidalgo were among the first to exploit the network structure of international trade to draw policy conclusions on a country's development path. Their approach is closely linked with the intention of this study, which uses newly developed network measures to analyse a country's competitiveness.
Why do we look at the topology, that is the shape, of how bilateral trade links organise? Trade relations between countries at a single-product level are very sparse, implying that markets are fragmented. In such a situation measures based on global comparisons are less informative than measures that take into account a country's embedding into the international trade network, see e.g. Joseph and Chen (2014). In this sense, the investigation of the detailed structure of trade links can provide valuable information, not only on global trade, but also on a country's integration into global value chains and on globalization itself.

Our approach to measuring comparative advantage is to depart from just looking at the concentration of a country's exports relative to the rest of the world, which is a global measure, but to look at metrics of export assortativity which are local properties. Export assortativity can be broadly associated with a country's similarity to its neighbours in terms of export composition. We do not only look at the size and composition of export flows, which is closer to the original idea of RCA, but also at the price characteristics of those flows. Our metrics look at the price and product composition of a country's exports and compare them to those of its partners and competitors (defined as a partner's third-party import and export partners). The final objective is to obtain indicators for a country's relative export prices and product specializations, not relative to the rest of the world but conditioned on the destinations it actually trades with and the competitors it actually faces.
The next interesting question is how the integration of a country in the global trade network affects its growth path. This line of research was pioneered by Hausmann et al. (2007) and we look at the impact of our measures of integration in a similar spirit, but using state-of-the-art growth regressions econometrics.

This study is structured as follows. In section 2, we introduce the methodology behind export assortativity metrics and give some examples for their application. In section 3, we uncover general trends in these measures, focusing on the euro area (EA). We also look at simple relations between relative export prices and concentrations for different groups of countries and technological content. We observe that there is a tipping point during the development process of a country at which export competition shifts from being driven by relative prices to non-price factors. This might explain the U-shape observed by Imbs and Wacziarg (2003). In section 4, we investigate the importance of trade assortativity metrics as determinants of export growth where we find that relative export prices are a leading indicator, especially for catching-up economies. We conclude in section 5.

To paraphrase much of the literature and in response to the question "does what you export matter?" (see Lederman and Maloney (2012)), we find rather that *how* you export matters.

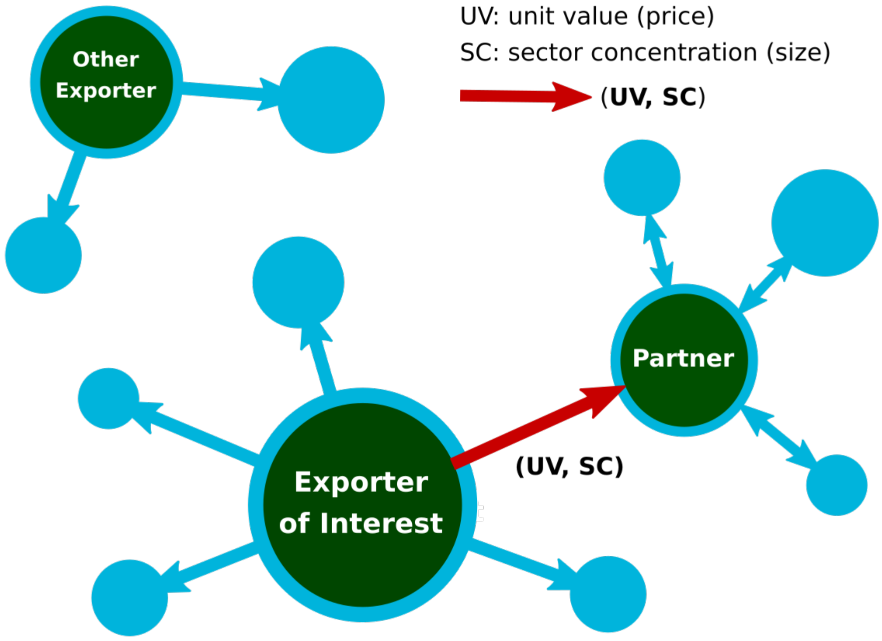
2 Methodology: Export assortativity metrics

The network structure of international trade can be represented formally by a graph consisting of nodes connected by links. In their most general form for the international trade network (ITN) nodes are given by countries and links are given by weighted and directed trade flows between them[1]. A single trade link for a single product is usually evaluated by its total value (TV) as an indicator for its importance. We also consider its unit value (UV) as an indicator for price, which is also assumed to contain some

[1]Links can be either binary (on/off) or carry some weight, and can either be symmetric (mutual) or directed (unidirectional).

information about quality (see Fontagné et al. (2009), but also Pula and Santabárbara (2011) for a different view).

Figure 1: Principles of export assortativity metrics: Stylised international trade for a single product.



In network science, assortativity is the general property of a node to attach to nodes that are similar in some characteristic. Assortative mixing (assortativity) indicates the preference for connecting to nodes that are similar and disassortative mixing (disassortativity) the tendency to connect to nodes that are different in some property or characteristic. For example, social networks tend to exhibit assortativity in terms of the degree of nodes: People who are known by many tend to connect to other people who are known by many ("celebrity dating"). By contrast, biological networks tend to be disassortative: Highly connected nodes tend to connect to nodes with few links ("hub and spoke").[2] In terms of other economic networks, research has found that interbank credit networks also exhibit disassortative mixing, i.e. a few hubs trade with many separated banks. In economic terms, this kind of structure is what one would expect in a situation of monopsony or monopoly (see e.g. Fricke et al. (2013)).

With that in mind, the theory of comparative advantage would lead to a structure of international trade where disassortative mixing prevails: In the limit, each country would tend to become a monopolist in a few goods.

We look at the (dis)assortativity properties of a country's exports in terms of prices (unit values, or UV) and sector concentration (SC). A country's export price assorta-

[2]See e.g. Piraveenan et al. (2010) and Singh and Dhar (2015).

tivity (EPA) is defined in terms of its price for each single product compared to the corresponding average UV of its trade partners. A country's relative export density (RED) is similarly defined for its SC. Conceptually, this is shown in Figure 1, which sketches the observed structure for highly disaggregate trade flows: It paints a picture of "balkanisation", in the sense that most exporters export each single product only to a small group of partner countries. In such a situation, the price and industry composition of the rest of world ("other exporter") might be irrelevant. Therefore, focusing on the local network structure can provide the most relevant information.
Technically, for a country a and a product p, EPA and RED can be written in the same way. Let X denote either EPA or RED and x be either UV or SC: For example, for the SC, we first evaluate every trade partner's b average SC in Equation 1 by summing its exports and imports with third-party countries c to approximate the level of specialization in that market. Here, f_{ij}^{p} stands for the trade flow from a country i to a country j of product p in terms of total value at a given moment in time, and T_X and T_M are the values of total exports (X) and imports (M), respectively, of the left-hand-side country. This is to control for country size, as only trade shares enter the calculation.

$$x_b^p \quad = \quad \frac{1}{T_X^b + T_M^b}\left(\sum_{c \in X} f_{bc}^p * x_b^p + \sum_{c \in M} f_{cb}^p * x_c^p\right), \tag{1}$$

After having defined the property x for every product p and partner b, Equation 2 defines the assortativity factor of country a with respect to property x and relative to its export partner b. For example, looking at SC, $A_{a,b}^p$ can tell if country a is more specialised (positive $A_{a,b}^p$) or less (negative $A_{a,b}^p$) than country b with respect to product p. The same reasoning holds for relative prices: Country a can be more expensive (positive $A_{a,b}^p$) or less expensive (negative $A_{a,b}^p$) than country b with respect to its UV of product p.

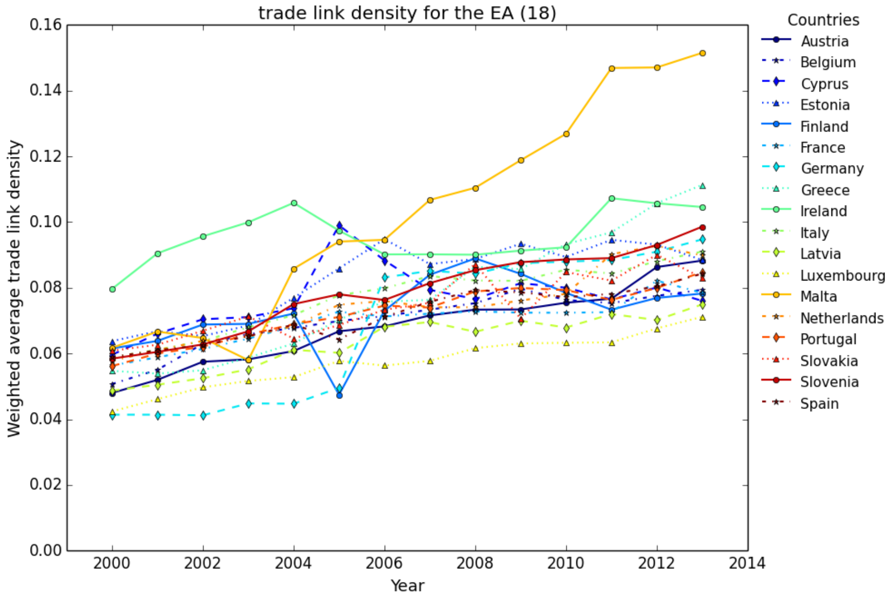
$$A_{a,b}^p \quad \equiv \quad \frac{x_a^p - x_b^p}{x_a^p + x_b^p} \in (-1, 1], \tag{2}$$

The next step is to take the weighted average of single-partner assortativity factors from Equation 2. This is done in Equation 3.

$$X_a^p \quad = \quad \frac{1}{T_X^a} \sum_{b \in X} A_{a,b}^p * f_{ab}^p \in (-1, 1], \tag{3}$$

Equation 1 and Equation 3 account for the network structure of trade links, as only elements where $f_{ij}^p \neq 0$ enter the sums. The assortativity factor (Equation 2) can be interpreted as follows: A value of -1 means that a product is actually not exported. This situation is excluded by construction. A value of $+1$ means that the exporter has a monopoly in market b, while a value around 0 indicates equality (similarity) of countries

Figure 2: Average trade link densities for EA countries.



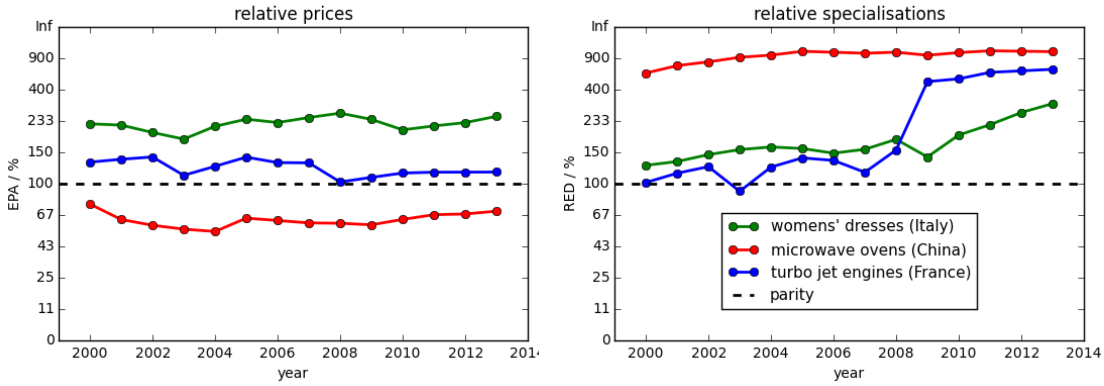
a and b with respect to the property of interest x. This is closer to a situation of perfect competition[3].

Finally, Equation 4 offers a representation of Equation 2 and Equation 3 in terms of a percentage scale of the *average competitor* whose value of either EPA or RED has been set to 1.

$$\tilde{X}_a^p \quad = \quad (\frac{1 + X_a^p}{1 - X_a^p}) * 100 \in (0, \infty] \qquad (4)$$

Assortativity values of -1, 0 and 1 are now mapped to 0, 100 and infinity, again meaning no export, parity and monopoly, respectively. Next, we will investigate how export assortativity measures look and evolved on a global scale with a particular focus on Europe.

[3]More generally, we can describe the network structure of international trade for a single product p by the real matrix $f_a b^p$, where a and b are country indices. A general assortativity measure for country a and some property x can then be formulated as $A_x^a =< f_{ab}^p * \frac{x_a - x_b}{x_a + x_b} >_b \in (-1, 1]$, where $< . >_b$ is chosen such that the norm is fulfilled.



(a) EPA comparison

(b) RED comparison

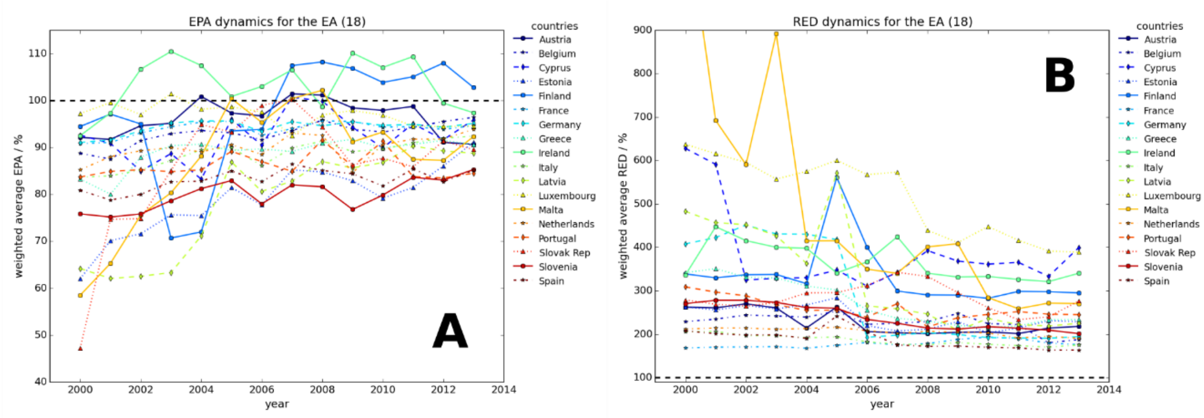
Figure 3: EPA (left) and RED (right) dynamics for three different products and countries.

3 A stylised fact emerges: Countries exhibit disassortative mixing and concentrate exports in products where they have a price and a local comparative advantage.

Our empirical analysis is based on the United Nations Commodity and Trade Statistics (Comtrade) at the 6-digit level of the HS-1996 classification, which covers over 5000 product classes and about 100 million observations of bilateral trade links in our sample. Using these data we calculated EPA and RED according to Equation 1 - 4 and aggregated the results at the country level, using single-product export shares.
What does the disaggregated trade network look like? A first descriptive measure is the network density, i.e. the fraction of actual of all possible trade links. In our case, each product is characterised by a density in terms of the number of nodes that trade in it, compared to the total number of possibilities given by $N^2 - N$ where N is the number of countries in the sample. Then the average density of each country is calculated by taking the weighted average of the density of the products it exports, where the weights are the shares of each product in its exports. Figure 2 shows the evolution of this metric for 18 EA countries from 2000 to 2013. Malta stands out as having a very high density: This means that it exports a large share of products that are traded a lot. In a sense popularised by Hausmann and Hidalgo (see Hausmann and Hidalgo (2010), Hausmann and Hidalgo (2011)), this high density indicates that Malta exports a large share of ubiquitous products.

To provide some intuition for the two novel metrics EPA and RED, Figure 3 shows the corresponding dynamics of three 6-digit goods for three different exporters, namely microwave ovens from China, aircraft engines from France and women's dresses from Italy. Belonging to different technological content categories of goods, a point which will be addressed later, these goods show different levels and dynamics of the assortativity

Figure 4: Dynamics of weighted averages of EPA (left) and RED (right) for EA countries



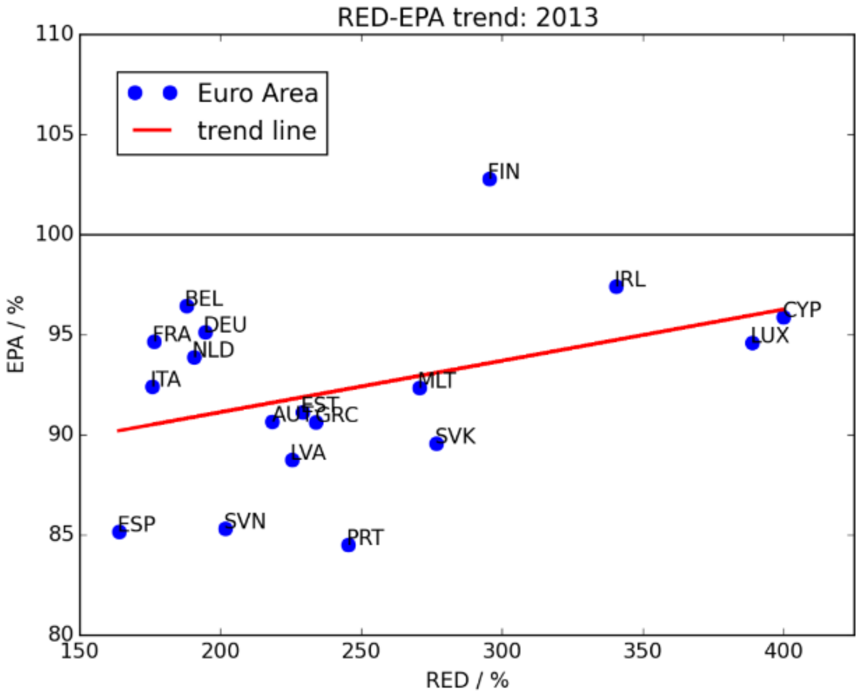
of relative prices (EPA) and export concentration (RED), where the zero line means equality with respect to one's average competitor. France's exports of aircraft engines have higher prices on average and have become progressively more concentrated than its neighbours in the ITN. Note that the sudden increase in its RED for aircraft engines happened at the time of the Great Trade Collapse associated with the Global Financial Crisis 2007-2008. This led to a drop in the global export density for this product, also seen for similar products, which seems to have resulted in a considerably strengthening of France's competitive position with respect to aircraft engines. One can see that Italy focuses much more on women's dresses than its competitors, and can also afford to charge considerably higher prices for them, which can be described as the typical characteristics of a premium exporter. By contrast, the export of Chinese microwave ovens can be described as a typical process of low-price-driven performance, as relative its UV stays far below those of the local network neighbourhood and the concentration is higher than that of its competitors. We dub this behaviour "wholesaling".

Two main stylised facts emerge at the aggregate level:

- Price disassortativity: EPA is generally below 100 for most exporters. This means that countries concentrate their exports in products where they have an advantage of price in the markets they serve.[4]
- Even stronger sector concentration disassortativity: RED is always much larger than 100. This implies a locally monopolistic structure, i.e. countries focus their exports on products and markets where they have clear advantages of specialisation (local comparative advantage). This finding is crucially coupled to the sparse network structure of trade at the single-product level, in the sense that highly specialised countries tend to export to destinations where a product is not prevalent in either exports or imports. This can be seen from Equation 2, where, by

[4] Numbers refer to Equation 4.

Figure 5: Positive correlation between price and concentration assortativity in the EA in 2013.



construction, it is impossible for all countries to simultaneously diverge from 100 in the same direction and for all products at a global level.

Both observations are exemplified in Figure 4, where EPA (A) and RED (B) for 18 EA countries are shown between 2000 and 2013. A possible interpretation of the fact that EPA is between 75 and 100 for most countries (notably including the industrialised ones) is the general importance of price competition. It seems basically impossible for countries to sell the *bulk* of their products at higher prices than their competitors. However, competition in international trade might tip from being price-driven to more non-price factors, such as quality or branding, as countries develop. First evidence for this can be seen in Figure 5, which shows a positive trend between export specialisation and relative export prices for the EA in 2013. As will be shown in greater detail, the story seems to be more complicated than that, suggesting that competitive (low) export prices are a necessary, but not sufficient, condition for trade competitiveness.

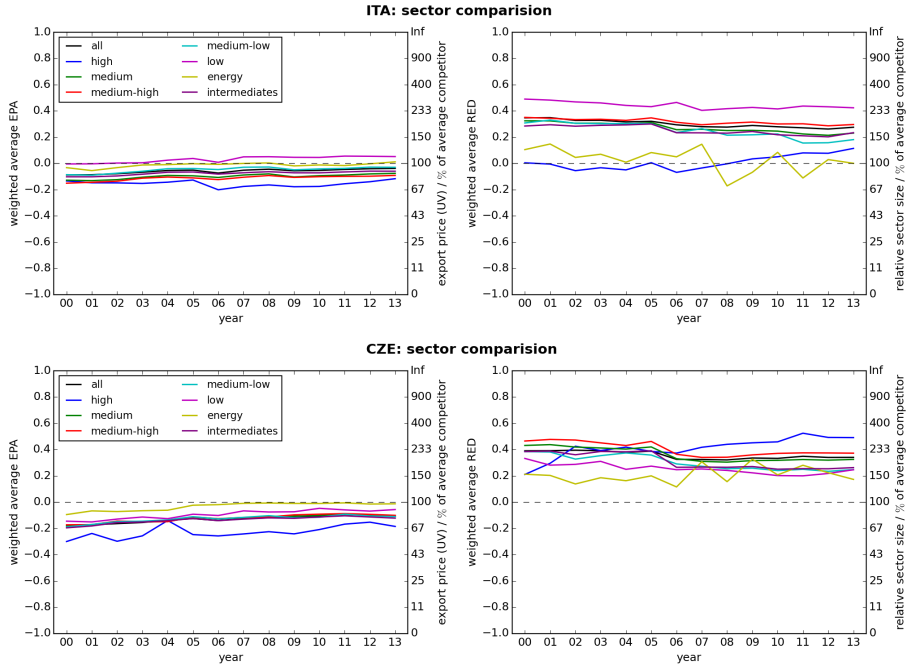
Investigating the time evolution of both export assortativity measures EPA and RED, two trends can be identified at the global and regional level. One is a general tendency of rising EPA and falling RED values, which can be attributed to the large increase of trade links (globalisation) during this period. Assuming that price and specialization are the main drivers of competitiveness, it becomes persistently harder to have both relatively lower prices and higher levels of specialisation than one's competitors, as there is an increasing density in trade relations. The other trend we observe is convergence within the EA, as the EPA values of Eastern European countries (Estonia, Latvia, Slovakia and Slovenia) rose much faster towards the 100-line (price equality) than those of the other EA countries. From a policy point of view, the consideration of the structure of global trade introduces a topological component into industrial policy. Besides addressing one's export prices or industry composition, generally a difficult long-term process, decision makers in policy and industry might address the structure of trade links. For instance, using the same methodology, one can evaluate one's competitive position (in terms of EPA and RED), for entering (or exiting) any specific market. That is to perform "What-if-Analyses" for export decisions. Another main advantage of export assortativity measures is that they carry an absolute meaning at any point in time, i.e. no base year indexing is needed for their representation and comparison over time.

3.1 Case Study: The exports of Italy and the Czech Republic by technological content

Sector-specific applications of export assortativity measures are given in Figure 6, which shows the dynamics of weighted average EPA and RED according to the technological content of exports for Italy and the Czech Republic. Again, EPA is generally below zero, meaning that export prices tend to be lower than those of partners and competitors. An exception to this rule is the low-tech sector of Italy, which averages prices about 20 % percent higher than those of the average competitor in recent years. This can be explained by the fact that low-tech product include food and clothing, which often fall under premium goods in the case of Italy.
For the EPA of the Czech Republic, one observes an overall convergence to the "upper-zero-bound" of equal prices (the dashed reference line) for all content groups. This can be explained by the fact that the Czech Republic is a catching-up (converging) economy inside Europe, which still offers lower prices than its average competitors. Note that energy goods (yellow line) are traded globally and, as such, tend to track zero.
Turning to RED, one can see that both Italy and the Czech Republic focus their export largely in products where they have a higher level of concentration than their average competitor, which is in line with our previous observations. Notably, the Italian low-tech sector is sticks out again, pointing to a large RCA or a good competitive position of this sector. Note that results regarding the high-tech sector need to be interpreted with caution due to its relatively small size and high volatility.

As our analysis is based on highly disaggregated data, we are able to further drill down into individual sectors. Italy's low-tech and the Czech Republic's intermediates sectors consist of about 1700 and 3100 single product classes, respectively. Figure 7 provides more detailed insights into both sectors by the means of inter-quartile box-plots. On can again see the particularity of Italy's low-tech sector (upper left). About three quarters of its products are exported at higher unit values than those of the average competitor. By contrast, at least half of the Czech Republic's intermediates (upper right)

Figure 6: EPA/RED sector comparison by technological content of exports for Italy and the Czech Republic .



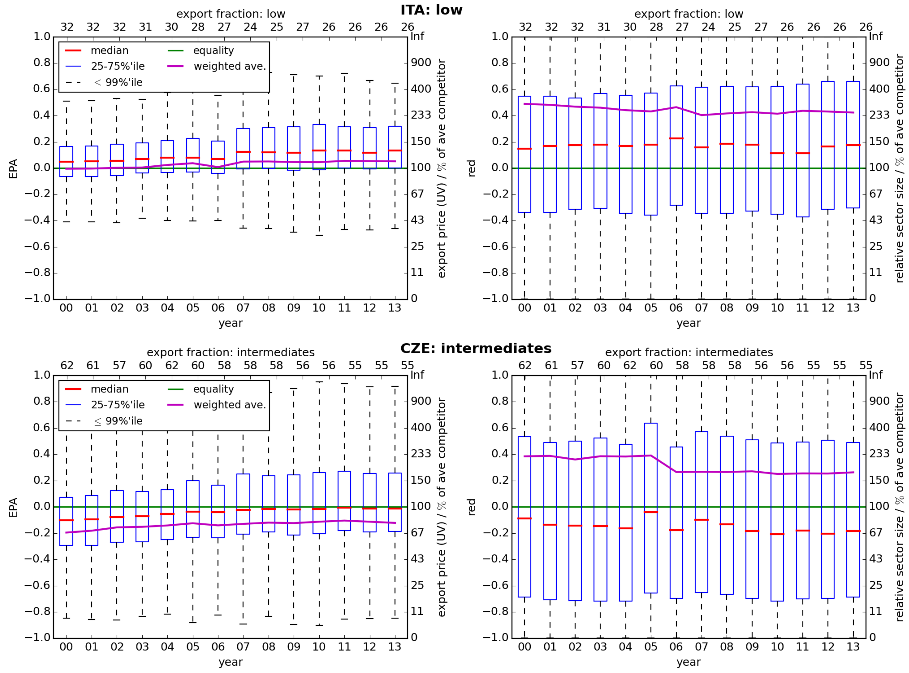
trade at unit values below those of the average competitor, pointing to price competition. In this sense, approaching and crossing of the parity-EPA line from below may be interpreted as advancing one's products' export competitiveness from being price-driven to non-price factors, such as quality or exclusivity.

Turning to the corresponding RED values, Italy has a much larger relative concentration throughout the whole low-tech sector than the Czech Republic has for its export of intermediates.
Generally, both sectors are in line with the globally uniform observation, in that they are concentrated on products with lower relative prices and high relative concentrations, corresponding to the lower and upper portions of the EPA and RED distributions, respectively.

3.2 Relation between RED and EPA: Local monopolies and price competition

The previous subsection looked at the relation between RED and EPA in two countries. Here we address the question of whether there is a basic relation between a country's assortativity in export price level (EPA) and specialisation (RED) more formally, using a panel regression of the form

Figure 7: Box plots of EPA/RED distribution for low-tech exports of Italy and intermediate goods from the Czech Republic



$$EPA_(group, tech, t) \;=\; \beta * RED_(group, tech, t) + \epsilon_(group, tech, t) \tag{5}$$

where t stands for the year, the β are coefficients and the ϵ are the corresponding error terms. We pool country groups[5] and technology sectors, while controlling for country fixed effects, and use robust regressions to account for outliers. The idea behind this approach is to identify groups of countries for which the concentration of exports in a certain technological level can be associated with either higher or lower relative export prices, or their changes.

[5]Using ISO 3-digit country codes, **All:** AUT, BEL, BGR, HRV, CYP, CZE, DNK, EST, FIN, FRA, DEU, GRC, HUN, IRL, ITA, LVA, LTU, LUX, MLT, NLD, POL, PRT, ROU, SVK, SVN, ESP, SWE, GBR, ISL, MKD, MNE, SRB, TUR, ALB, BIH, ARG, AUS, BRA, CAN, CHN, IND, IDN, JPN, KOR, MEX, RUS, SAU, ZAF, USA, CHL, ISR, NZL, NOR, CHE.
EU-28: AUT, BEL, BGR, CYP, CZE, DEU, DNK, ESP, EST, FRA, FIN, GBR, GRC, HRV, HUN, IRL, ITA, LTU, LVA, LUX, MLT, NLD, POL, PRT, ROU, SVK, SVN, SWE.
EU-15: AUT, BEL, DEU, DNK, ESP, FRA, FIN, GBR, IRL, ITA, LUX, NLD, POL, PRT, SWE.
RichNoOil: AUT, BEL, DEU, DNK, FRA, FIN, IRL, LUX, NLD, SWE, CAN, JPN, USA, AUS, SGP, CHE, HKG.
EA: AUT, BEL, CYP, DEU, ESP, EST, FRA, FIN, GRC, IRL, ITA, LVA, LUX, MLT, NLD, PRT, SVK, SVN.
CESEE: CZE, HRV, HUN, POL, ROU, SVK, SVN, BGR.
Baltics: EST, LTU, LVA.
BRIC: BRA, CHN, IND, RUS.

Several conclusions can be drawn from this simple exercise (see β coefficients in Table 1):

- Assortativity in price levels and in export concentration are significantly related across all countries and within some groups of countries, such as Central Eastern and South-Eastern Europe (CESEE) and the Baltics, or the EU-28, but the association is not significant for other group of countries, such as rich and energy-non-exporting countries (RichNoOil). This may be related to how much price-and-cost factors matter for a country's export competitiveness. While for converging countries (CESEE and the Baltics) export concentration is mostly associated with lower prices, there is no such relation for developed countries (EU-15 and RichNoOil), which may point to the importance of non-price factors in these countries.

- In terms of magnitude, the relation between EPA and RED levels (upper table) is strongest for high-tech (generally positive) and intermediate goods (generally negative). From this, one may conclude that the specialisation in high-tech goods corresponds to relatively higher price levels, while in intermediate (and most other goods), countries specialise more in goods and markets where they have a relative price competitiveness.

- Looking at the relation between first differences of relative export prices and levels of specialization (lower table), the main distinction can again be observed between groups at different stages of development. While for RichNoOil countries an increase in specialization is associated with an increase of export price assortativity, the opposite is observed for converging or developing counties (Baltics and BRIC). This points again to variations in the importance of price versus non-price factors of competition.

- EPA-RED-relations are particularly strong for intermediate goods, which points to the price sensitivity of global value chains.

Overall, the lesson from this exercise is that countries "look for monopolies" in their products (high RED disassortativity), but depending on the type of product, this monopoly power can be achieved either by undercutting competitors' prices or by non-price competition. The latter could take the form of higher quality, enabling the exporter to charge a premium price for its goods and at the same time claim a high market share.

4 Export growth regressions

Does the classification based on EPA and RED help to derive deeper insights into competitiveness, as measured by export growth? To answer this, we look at the long-term export growth across a subset of EU countries.[6] We follow the approach that has become standard for growth regressions since the work of Sala-i Martin (1997). However, we look at a large range of potential drivers of export growth, focusing in particular

[6]Croatia, Cyprus and Malta were excluded due to lack of complete data.

on whether the characteristics of a country's export structure, as described by EPA and RED, appear as important determinants over and above other macroeconomic and structural characteristics.

Most studies of export performance focus on relative prices and costs, but a price increase could correspond to a trade competitiveness improvement if it derives from an upgrade of the quality of the export bundle. For example, Benkovskis and Woerz (2014) find that controlling for upgrades in taste and quality has a strong effect on the dynamics of trade prices. To tease out the importance of relative prices and of our proposed indicators, we control not only for various structural and macroeconomic aspects of the country's economy in our export growth regressions, but also for some exogenous country characteristics and for catching-up effects. The controls that we used can be separated into several blocks. These account for cost competitiveness, for the structure of GDP, for institutional characteristics such as governance, rule of law, ease of doing business, for human capital, labour productivity and TFP, and for structural characteristics that reflect to some extent endowments, such as arable land, availability of natural resources and the presence of ports. Table 2 lists all variables, organised according to these main blocks.

4.1 Methodology

Previous influential work by Sala-i Martin et al. (2004) and Sala-i Martin (1997) used a Bayesian averaging of classical estimates (BACE) to study the determinants of long-term growth. Their approach differs from the one we use as they combine the averaging of estimates across models, which is a Bayesian concept, with classical OLS estimation of the parameters within each possible model. Successive work that used a fully Bayesian approach, Fernandez et al. (2001), found similar results within a cohesive statistical framework, which was also adopted, inter alia, by Moral-Benito (2012) and Danquah et al. (2014) on growth regressions and by Gonzàlez-Aguado and Moral-Benito (2012) on corporate defaults. Previous applications to competitiveness and export growth were by Osbat and Formai (2013) in a cross-section setting and by Benkovskis et al. (2015).

The methodology used in this paper closely follows the framework adopted for growth regression by Fernandez et al. (2001). We consider a panel linear regression model where an indicator of trade performance for n countries, grouped in a vector y, is regressed on an intercept α and k potential explanatory variables in a matrix X of dimension $n \times k$. Throughout, we assume that $rank(X) = k$, and define β as the full k-dimensional vector of regression coefficients. A problem of model uncertainty arises when we don't know which variables $X_i \in X$ are included in the true sampling model M_i:

$$y_{jt} = \alpha_i + \beta_i * X_{i,jt} + \epsilon_{i,jt} \tag{6}$$

where i indexes models and j indexes countries, $\beta_i \in \Re_{k_i}(0 \leq k_i \leq k)$ groups the relevant regression coefficients and ϵ is a Gaussian iid error term with variance σ_j^2, $\epsilon \sim \mathcal{N}(0, \sigma_j^2 I)$. Considering a single linear model that includes all variables is inefficient or even infeasible with a limited number of observations, hence we use a Bayesian model selection/averaging (BMS/A) approach. We estimate many different models specified as a

subset of all the possible combinations of the variables, then we either take a weighted average of the estimated models (BMA) or choose the "best" one (BMS). As X contains k potential variables, there are 2^K variable combinations and, thus, models.
The model weights are posterior model probabilities (PMP) and the framework gives us also posterior distributions of any statistic of interest based on these posterior model probabilities. Of particular interest is the marginal posterior probability of including a certain variable (PIP), which is simply the sum of the posterior probabilities of all models that contain that regressor. Details on how these quantities are estimated are given in the Appendix; the computations were performed using BMS, a package described in Zeugner and Feldkircher (2015). We estimate the panel regression in Equation 7 on annual data from 2002 to 2013 by regressing the annual growth rate of each country's exports on subsets of the variables in Table 2, also including country and time fixed effects.

4.2 Estimation results

Some variables almost always enter the the top models selected by the algorithm, and the most frequently included variables always enter with the same sign (either positive or negative). This is shown in Figure 8, where variables are ordered according to their PIP (top to bottom) and model are ordered left-to-right according to their PMP. For variables blue indicates a positive sign, red a negative sign and white the absence of a variable in a given model. The vertical space associated with each variable is proportional to its posterior inclusion probability (PIP). Only the variables with the highest PIP are shown.[7] The overall summary statistics, including convergence statistics and explanatory power for individual countries, are shown in Table 4.

Three variables enter all models (PIP=1): The stock of FDI inflows as a proportion of GDP and the sophistication of goods exports[8] increase export growth, while demographics measured by the age dependency decreases it. A revealed comparative advantage in the exports of intermediate goods also increases export growth, as would be expected when thinking of the importance, especially for converging economies, of establishing themselves as parts of global value chains. Another variable that appears in 97% of the selected models, with a positive sign, is the diffusion of broadband connections, which typically proxies for a developed infrastructure and an ICT-literate workforce. Similarly, total factor productivity increases exports, as expected, and has an 84% inclusion probability. The cost of investment, measured by the price of capital formation and long-term interest rates, weigh on export growth, while the cost of labour does not appear in the list of variables with the highest posterior probability. Some coefficient signs, such as that of government consumption as a percentage of GDP and stock market capitalisation, or those related to governance, are different than one would expect based on economic theory. However, they can be rationalised if one thinks that the sample contains both "old" and "new" EU Member States. The latter, though scoring lower over the sample

[7]Note that the variable ranking can slightly vary from the actual calculated ranking, as only the top models, but not all visited models are considered.

[8]Calculated according to Hausmann et al. (2007)

Figure 8: Variable inclusion (top to bottom) of the 10000 best models (left to right).

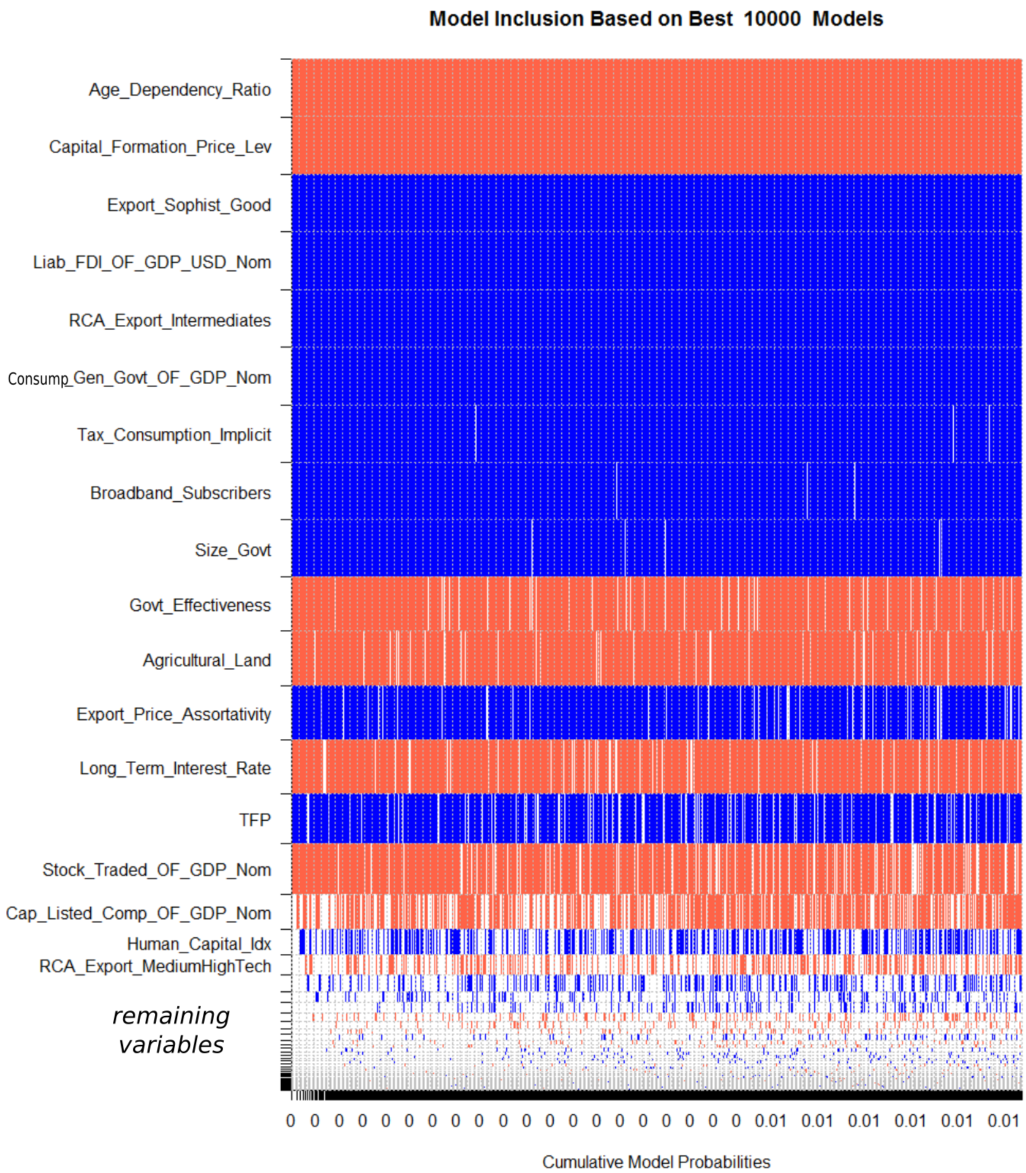
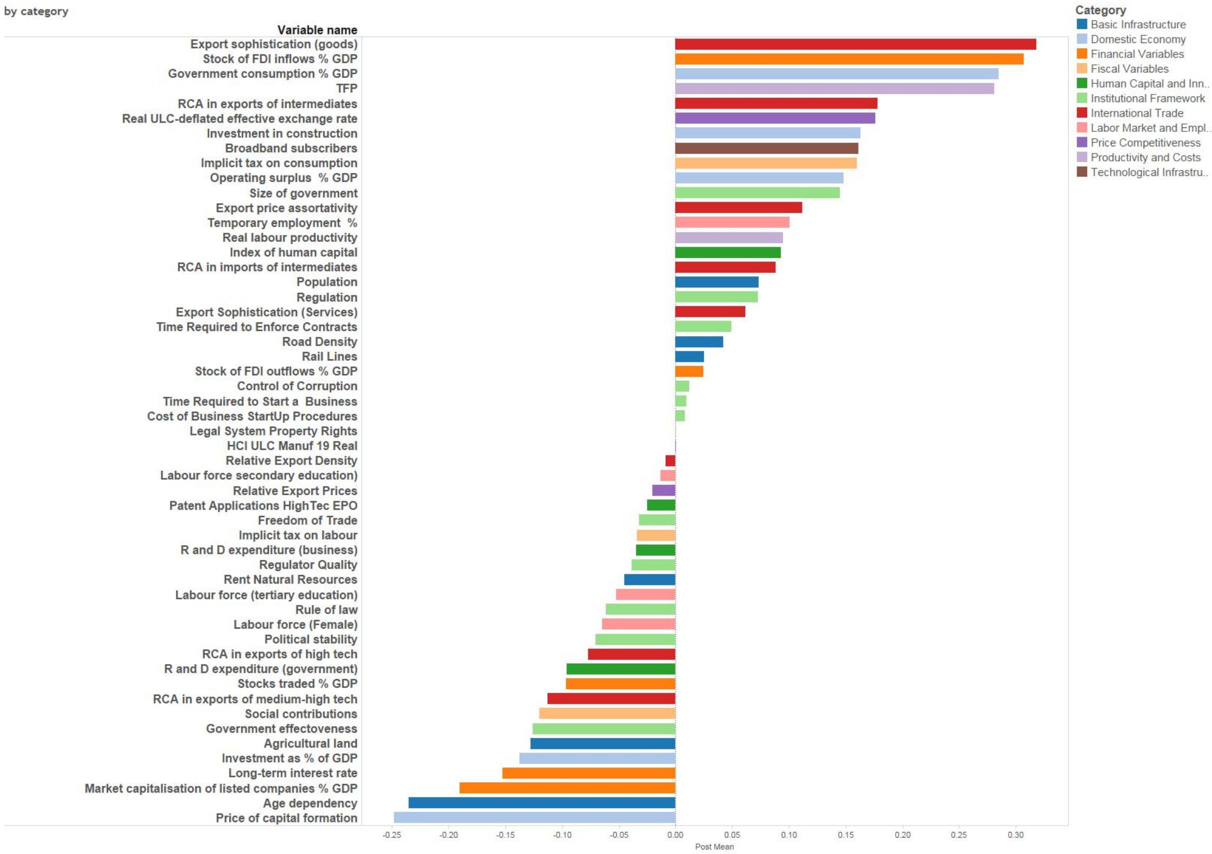


Figure 9: Estimated average coefficients across models by category



on those variables, experienced a very sharp rise in exports as they integrated in global trade from a very low position.

It is also interesting to look at the posterior coefficient estimates of the groups of variables identified in section 4: These are summarised in Figure 9 showing that indeed, many variables that relate to institutions and governance appear with a negative sign. This could be explained by the heterogeneous country groupings.

Figure 10 offers another view of the categories of variables, in term of posterior inclusion probability: Variables related to the domestic economy, to financial conditions and to the structure of trade appear very often, whilst those related to the institutional framework appear less often. This would also confirm that different characteristics have different effects and importance at the various levels of economic development, calling for a split-sample analysis, as conducted by Benkovskis et al. (2015).

How do the assortativity measures fare in terms of explanatory power? Export price assortativity is the 14^{th} variable in term of PIP, at 85%, with a consistently positive coefficient, meaning that higher prices than competitors in the ITN neighborhood do

Figure 10: Estimated average coefficients across models by category, sorted by posterior inclusion probability

by category and PIP

PIP 0.1968 – 1.0000

Category	Variable name	
Basic Infrastructure	Age dependency	-0.2351
	Agricultural land	-0.1279
	Population	0.0731
	Road Density	0.0418
	Rent Natural Resources	-0.0449
	Rail Lines	0.0249
Domestic Economy	Price of capital formation	-0.2485
	Government consumption % GDP	0.2849
	Operating surplus % GDP	0.1484
	Investment in construction	0.1633
	Investment as % of GDP	-0.1374
Financial Variables	Stock of FDI inflows % GDP	0.3071
	Long-term interest rate	-0.1527
	Market capitalisation of listed companies % GDP	-0.1904
	Stocks traded % GDP	-0.0965
	Stock of FDI outflows % GDP	0.0243
Fiscal Variables	Implicit tax on consumption	0.1596
	Social contributions	-0.1198
	Implicit tax on labour	-0.0343
Human Capital and Innovation	Index of human capital	0.0930
	R and D expenditure (government)	-0.0960
	R and D expenditure (business)	-0.0346
	Patent Applications HighTec EPO	-0.0250
Institutional Framework	Size of government	0.1449
	Government effectoveness	-0.1259
	Political stability	-0.0703
	Regulation	0.0729
	Rule of law	-0.0617
	Time Required to Enforce Contracts	0.0491
	Regulator Quality	-0.0383
	Freedom of Trade	-0.0322
	Time Required to Start a Business	0.0092
	Cost of Business StartUp Procedures	0.0084
	Control of Corruption	0.0121
	Legal System Property Rights	0.0005
International Trade	Export sophistication (goods)	0.3177
	RCA in exports of intermediates	0.1778
	Export price assortativity	0.1120
	RCA in exports of medium-high tech	-0.1128
	RCA in imports of intermediates	0.0885
	RCA in exports of high tech	-0.0771
	Export Sophistication (Services)	0.0617
	Relative Export Density	-0.0089
Labor Market and Employment	Temporary employment %	0.1004
	Labour force (Female)	-0.0646
	Labour force (tertiary education)	-0.0525
	Labour force secondary education)	-0.0131
Price Competitiveness	Real ULC-deflated effective exchange rate	0.1760
	HCI ULC Manuf 19 Real	0.0000
	Relative Export Prices	-0.0205
Productivity and Costs	TFP	0.2808
	Real labour productivity	0.0951
Technological Infr..	Broadband subscribers	0.1611

not necessarily imply a loss of exporting strength, but they could be associated with specialisation and market power. This is only a conjecture, however, and it should be tested by more detailed analysis, possibly at the sectoral level.

Figure 11 shows the results for CESEE countries alone: The main difference is that variables that have to do with integration in global value chains, such as RCA in intermediates, as well as our EPA measure have higher inclusion probability and higher importance. The stock of FDI inflows and total factor productivity are also more important than in the "Old" member states (EU15: See Figure 12), where the variables that measure the cost of investment and the financial markets situation are more important. Importantly, EPA does not appear to be nearly as important in the EU15 as in CESEE: This confirms our conclusion that export competitiveness matters more for countries that are catching up than for the more mature economies.

4.3 Jointness analysis

The BMA algorithm we use in this paper is affected by collinearity between variables. We have shown in subsection 3.2 that our proposed measures (RED and EPA) are related. This does not by any means imply that they are collinear. To study whether correlations between variables are a problem in our setup, we perform a jointness analysis, following Ley and Steel (2007) and Doppelhofer and Weeks (2009). A jointness analysis looks at whether pairs of variables have a high probability of being included in a model together, in which case they are complements (positive jointness) or whether they tend to be substitutes, i.e. have a higher probability of being excluded when the other variable is included (negative jointness). The analysis is thus based on the joint posterior distribution of variables over the model space. If RED and EPA captured the same characteristics they would turn out as substitutes.

We use the measure proposed by Ley and Steel (2007), which corresponds to the posterior odds ratio of the models including both variables at the same time versus the models that include them only individually. We take the base 10 logarithm of the posterior odds ratio, so that a value of 1 means that there is a 10:1 probability that the two variables are complements. Similarly, a log odds ratio of -1 indicates that two variables are substitutes. A log ratio of 0 means that there are equal odds of including the variables together or separately.

The results of this exercise are shown in Figure 13. Each dot represents a variables pair and the sizes of the dots are proportional to the average sum of the two PIPs. Clearly, variables that have a high PIP are also more likely to be included together with other variables. EPA is signaled by red dots and tends to be a complement to all highest ranking variables. RED (indicated by blue dots) is on the disjointness side, indicating collinearity or substitutability. As we move towards the right of the odds-ratio diagram, we must bear in mind that high disjointness is likely due to low PIPs of most variables in that part of the chart (indicated by the small dot sizes).

How do we interpret these results? While RED, which is our proxy for comparative advantage, has a relatively low posterior inclusion probability and appears as a substitute of various other variables, EPA, which is a measure of the local price competitiveness of

Figure 11: Central and Eastern European countries: Estimated average coefficients across models by category, sorted by posterior inclusion probability

by category and PIP

PIP 0.1049 – 0.8709

Category	Variable name	
Basic Infrastructure	Age dependency	-0.3318
	Road Density	0.3423
	Rent Natural Resources	-0.1335
	Rail Lines	0.0915
	Population	0.0046
	Agricultural land	-0.0176
Domestic Economy	Government consumption % GDP	0.4050
	Price of capital formation	-0.2604
	Investment as % of GDP	-0.1461
	Investment in construction	0.1384
	Operating surplus % GDP	0.0813
Financial Variables	Stock of FDI inflows % GDP	0.3064
	Long-term interest rate	-0.1956
	Market capitalisation of listed companies % GDP	-0.1741
	Stocks traded % GDP	-0.0768
	Stock of FDI outflows % GDP	0.0332
Fiscal Variables	Implicit tax on consumption	0.1227
	Social contributions	-0.1660
	Implicit tax on labour	0.0035
Human Capital and Innovation	Index of human capital	0.0799
	R and D expenditure (government)	-0.0596
	Patent Applications HighTec EPO	-0.0401
	R and D expenditure (business)	0.0201
Institutional Framework	Government effectoveness	-0.1697
	Political stability	0.3308
	Regulation	0.1221
	Cost of Business StartUp Procedures	0.1004
	Time Required to Start a Business	-0.0756
	Control of Corruption	0.0720
	Regulator Quality	-0.0657
	Size of government	0.0689
	Time Required to Enforce Contracts	0.0375
	Freedom of Trade	-0.0173
	Legal System Property Rights	0.0042
	Rule of law	-0.0314
International Trade	RCA in exports of intermediates	0.2193
	Export sophistication (goods)	0.3157
	Export price assortativity	0.1634
	RCA in exports of medium-high tech	-0.1347
	Export Sophistication (Services)	-0.0903
	RCA in exports of high tech	-0.0688
	Relative Export Density	-0.0658
	RCA in imports of intermediates	0.0419
Labor Market and Employment	Labour force (tertiary education)	-0.0977
	Temporary employment %	0.1007
	Labour force (Female)	-0.0694
	Labour force secondary education)	0.0549
Price Competitiveness	Relative Export Prices	0.0860
	HCI ULC Manuf 19 Real	-0.1036
	Real ULC-deflated effective exchange rate	-0.0203
Productivity and Costs	TFP	0.5007
	Real labour productivity	0.1393
Technological Infr..	Broadband subscribers	0.1221

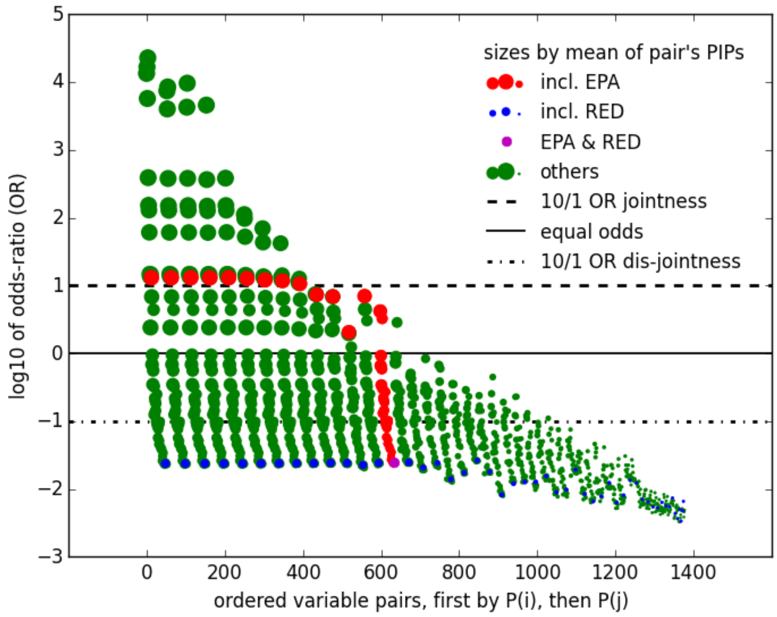
Figure 12: EU15: Estimated average coefficients across models by category, sorted by posterior inclusion probability

by category and PIP

PIP
0.1432 1.0000

Category	Variable name	
Basic Infrastructure	Age dependency	-0.1952
	Agricultural land	-0.1540
	Road Density	-0.1199
	Population	0.1402
	Rent Natural Resources	0.0801
	Rail Lines	0.0081
Domestic Economy	Price of capital formation	-0.2429
	Operating surplus % GDP	0.0510
	Investment in construction	-0.0257
	Government consumption % GDP	0.0052
	Investment as % of GDP	0.0323
Financial Variables	Stock of FDI inflows % GDP	0.5712
	Stocks traded % GDP	-0.3428
	Long-term interest rate	-0.2094
	Stock of FDI outflows % GDP	-0.2708
	Market capitalisation of listed companies % GDP	-0.0738
Fiscal Variables	Implicit tax on consumption	0.1456
	Social contributions	-0.1188
	Implicit tax on labour	-0.0440
Human Capital and Innovation	R and D expenditure (business)	-0.1737
	Index of human capital	0.1252
	Patent Applications HighTec EPO	-0.0418
	R and D expenditure (government)	-0.0353
Institutional Framework	Political stability	-0.1298
	Size of government	0.1402
	Regulation	-0.0605
	Freedom of Trade	-0.0408
	Rule of law	-0.0359
	Government effectoveness	-0.0368
	Legal System Property Rights	0.0221
	Time Required to Enforce Contracts	0.0017
	Time Required to Start a Business	-0.0197
	Regulator Quality	0.0116
	Cost of Business StartUp Procedures	0.0036
	Control of Corruption	-0.0080
International Trade	Export sophistication (goods)	0.2862
	Export Sophistication (Services)	0.2095
	RCA in imports of intermediates	0.1590
	RCA in exports of high tech	-0.1094
	RCA in exports of medium-high tech	-0.0717
	RCA in exports of intermediates	0.0769
	Relative Export Density	0.0225
	Export price assortativity	0.0068
Labor Market and Employment	Labour force secondary education)	-0.0952
	Labour force (tertiary education)	-0.0530
	Temporary employment %	0.0354
	Labour force (Female)	-0.0357
Price Competitiveness	Real ULC-deflated effective exchange rate	0.1952
	HCI ULC Manuf 19 Real	0.0663
	Relative Export Prices	-0.0300
Productivity and Costs	Real labour productivity	0.2405
	TFP	-0.1940
Technological Infr..	Broadband subscribers	0.1922

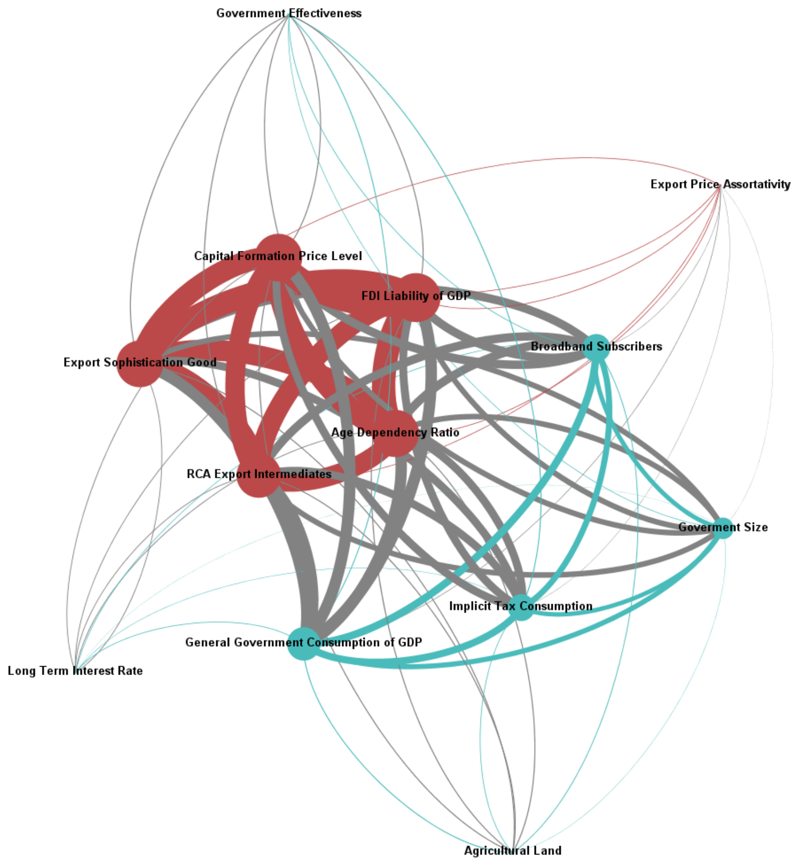
Figure 13: Estimated jointness of variables, sorted by posterior inclusion probability.



a country, has a high PIP and is seen as complementary to many other variables with high PIP.

Another way to look at these results is to use a network diagram. Figure 14 shows the backbone network of highest ranking variables by PIP. That is those pairs located above the 10/1 odds ratio line in Figure 13. The edge strength between two variables is given by their jointness value (the thickness of the lines) and the size of the nodes by the sum of adjacent edges. Variable node colors represent segmentation by a modularity-based node clustering algorithm Barabási (2016), while edge colours are the mixture of node colours. We can identify two clusters of variables that have high PIP and high jointness, forming so to say the "backbone" of the model space: One (in red) contains export sophistication, exports of intermediaries, the cost of investment and FDI liabilities as a ratio of GDP. The export of intermediaries and FDI liabilities point to the leverage that observations from the so-called new member states of the EU may have in our sample: These countries received large FDI inflows, integrated very tightly in global supply chains and experienced high export growth. They also tend to be aging societies. The results in Figure 11 and Figure 12 show that age dependency has a higher impact in the CESEE countries than in the EU15. The other cluster contains variables that are related to the size of government in the economy, which we find - somewhat puzzling - to increase export growth. Again, this may be related to the presence of catching-up CESEE countries in our sample. We also observe a peripheral layer of high-ranking variables in Figure 13, which are connected to all core variables, but not to each other.

Figure 14: Backbone network of model space from highest ranking variables in BMA results.



EPA is seen part of this set of complimentary variables. This observation strengthens its relation to the export performance of a country, especially being the only high-ranking export price indicator.

5 Conclusions

The structure of international trade relations at a highly disaggregate product level is very sparse. Based on this, we have identified two (self-)organisational principles of international trade, which hold regardless of the country of interest. Despite large variations across products, a country's average export product is characterised by being cheaper and more specialised (as measured by sector concentration) relative to its competitors in the local trade network. We uncovered these insights using two novel measures based on the mixing properties of product concentration and of relative prices: Export price assortativity (EPA) and relative export density (RED). These are not only based on the comparison of a country to its direct trade partners, but also to its partners' partners, hence its competitors. According to both measures we uncovered disassortative mixing: Countries tend to be cheaper and more specialised than their competitors. However, there remain interesting variations within a country's export basket and between countries. For example, Italy's low-tech sector trades at above-average prices. This can be explained by the relative abundance of premium products, e.g. in clothing.

In terms of prices, although the distributions of relative prices and specialisations are very broad for most countries, there is a difference between more and less developed economies in the skewness of EPA distributions. For more developed countries these tend to be either centred around parity or to be skewed towards higher relative prices. By contrast, catching-up countries tend to have price distributions that are skewed towards lower relative prices (though with upward trends).

In terms of product concentration, the distributions of RED are heavily skewed towards lower values, while their weighted averages lie far above parity in most cases. This means that countries focus their exports on destinations where they have an advantage of scale. By construction, this would not be possible if most countries specialised in exporting similar products to similar markets. This indicates that an underlying principle of self-organisation of international trade is the avoidance of competition by focusing one's products on a few destination markets, leading to a fragmentation of international trade.

A notable exception from this rule is the high-tech sector of some developing countries, where average concentrations stay below or at parity. This is related to the relatively small size of this sector in these countries. Apart from these general principles, we analysed the relationship between export assortativity metrics and export growth, which often constitutes an important component of a country's development path. Because the determinants of export growth are complex and vary considerably and to take an unbiased approach to address this issue, we chose a Bayesian model averaging framework including EPA and RED in a larger set of variables. Using variables accounting for economic structure, human capital, innovation, business and government efficiency and structural variables, it turns out that EPA is one of the highest ranking variables in terms of inclusion probability and that it is positively associated with export growth. We interpret EPA as a leading outcome-based indicator for trade growth, capturing a country's international competitiveness. This is underlined by EPA being the only high-ranking price variable, especially for catching-up CESEE countries. Its significance seems to be smaller for more developed EU15 countries.[9] Taken together with the fact that relative prices stabilise at or slightly below the average for all countries, this indicates that price competitiveness is a necessary, but not sufficient, component of export competitiveness. Convergence towards relative price parity indicates a transition from mere price-driven to monopolistic competition, where more qualitative features gain importance. The same principle seems to apply to RED which almost universally assumes relatively high values. A practical application of export assortativity metrics which we

[9] The results on separate old and new EU member states data are not shown in this paper but available upon request.

do not discuss at length in this paper is their use for “What-if analyses” for trade policy. For instance an exporter could evaluate its competitive position with respect to its relative price for a product and different export destinations. Based on these results, it may decide to enter or exit a particular market. That is, export assortativity metrics may be helpful to calibrate industrial policy, especially for catching-up economies, reducing the risk of costly experiments in development.

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Appendix: Bayesian model averaging and selection methodology

A specific type of model uncertainty arises if the modeller does not know which variables $X_i \in X$ are included in the true sampling model M_i:

$$y_{jt} = \alpha_i + \beta_i * X_{i,jt} + \epsilon_{i,jt} \tag{7}$$

where i indexes models and j indexes countries, $\beta_i \in \Re_{k_i}(0 \leq k_i \leq k)$ groups the relevant regression coefficients and ϵ is a Gaussian iid error term with variance σ_j^2, $\epsilon \sim \mathcal{N}(0, \sigma_j^2 I)$. Considering a single linear model that includes all variables is inefficient or even infeasible with a limited number of observations. A possible approach is to use Bayesian model selection or averaging. This involves estimating many different models specified as a subset of all the possible combinations of the variables, then either taking a weighted average of the estimated models (BMA) or choosing the modal model, i.e. the model with highest posterior probability (BMS).

The model weights are posterior model probabilities that arise from Bayes' theorem:

$$p(M_i|y, X) = \frac{p(y|M_i, X)p(M_i)}{p(y|X)} = \frac{p(y|M_i, X)p(M_i)}{\sum_{s=1}^{s=2^k} p(y|M_s, X)p(M_s)}. \tag{8}$$

where $p(y|M_i, X)$ is the marginal likelihood of model M_i and $p(y|X)$ denotes the integrated likelihood which is constant over all models and is thus simply a multiplicative term. The marginal likelihood $p(y|M_i, X)$ is obtained as:

$$p(y|M_i, X) = \int p(y|\alpha_i, \beta_i, \sigma, M_i)p(\alpha_i, \sigma)p(\beta_i|\alpha_i, \sigma, M_i)d\alpha_i d\beta_i d\sigma, \tag{9}$$

where $p(\alpha_i, \sigma)$ and $p(\beta_i|\alpha_i, \sigma, M_i)$ are the priors for the parameters of model M_i. The posterior model probability (henceforth PMP) in (Equation 8) is thus proportional to the marginal likelihood of the model (the probability of the data given the model M_i) times a prior model probability $p(M_i)$. The posterior distribution of any quantity of interest, say Δ, is an average of the posterior distributions of that quantity under each of the models with weights given by the posterior model probabilities. Thus

$$p(\Delta|y, X) = \sum_{s=1}^{s=2^k} p(\Delta|M_i, y, X)p(M_i|y, X) \tag{10}$$

gives the posterior distribution of parameters such as the regression coefficients or the predictive distribution that allows to forecast future or missing observables. The marginal posterior probability of including a certain variable is simply the sum of the posterior probabilities of all models that contain the regressor. In order to apply the BMA procedure described above, we need to specify priors for both the generic model M_i and for the model's parameters α_i, β_i and σ. Model selection (BMS) chooses the model with highest posterior probability instead of the posterior-weighted average.

The Priors

In the Bayesian framework, we need to complete the sampling model in (7) with a prior distribution for the parameters in M_i , namely α_i, β_i and σ. In the context of model uncertainty, the choice of this distribution can have a substantial impact on posterior model probabilities (see e.g., Kass and Raftery (1995), and George (1999)). We follow Fernandez et al. (2001) who propose to use "improper-noninformative" priors on the constant and error variance, which means they are evenly distributed over their domain: $p(\alpha_i) \propto 1$, i.e. complete prior uncertainty where the prior is located. Similarly, $p(\sigma) \propto 1$. The crucial prior is the one on regression coefficients β_i. The literature standard is to use a g-prior structure originally proposed by Zellner (1986):

$$\beta_i|g \sim \mathcal{N}\left(0, \sigma^2\left(\frac{1}{g}X_i'X_i\right)^{-1}\right)$$

This means that the researcher assumes that coefficients are zero, and that their variance-covariance structure is broadly in line with that of the data X_i. The hyper-parameter g captures how certain the researcher is that coefficients are indeed zero: A small g means a small coefficient variance and therefore implies the researcher is conservative, i.e. quite certain that the coefficients are zero. The opposite is true when g is large.[10] A popular "default" choice for the hyper-parameter g is the "unit information prior" (UIP), which sets $g = n$ for all models and thus attributes about the same information to the prior as is contained in one observation. Fernàndez et al. (2001a) investigate many possible choices for g and conclude that when n is small taking $g = max(n; K^2)$ leads to reasonable results. Finally, we need to specify a prior distribution over the space $\mathcal{M}$ of all 2^k possible models. In the absence of prior information, a popular choice (see also Fernàndez et al. (2001b)) is a uniform model prior $p(M_i) = 2^{-K}$. This choice implies a prior expected model size equal to $K/2$, meaning that the uniform model prior puts more mass on intermediate model sizes. The binomial model prior constitutes a simple and popular alternative to the uniform prior. It starts from a covariate viewpoint, placing a common and fixed inclusion probability θ on each regressor. Since expected model size is $\bar{m} = K\theta$, the researcher's prior choice reduces to eliciting a prior expected model size $\bar{m}$. Ley and Steel (2012) note that to reflect prior uncertainty about model size, one should rather impose a prior that is less tight around prior expected model size. Therefore, they propose a hyperprior on the inclusion probability θ, effectively drawing it from a Beta distribution. In terms of researcher input, this prior again only requires to choose the prior expected model size. However, the resulting prior distribution (called "Beta-Binomial") is considerably less tight and should thus reduce the risk of unintended consequences from imposing a particular prior model size. The baseline choice of our computation is given by $g = max(n; K^2)$ and by a a Beta-Binomal model prior. Nevertheless, we can check the robustness of our results against other choices.

[10] The posterior distribution of coefficients reflects prior uncertainty: Given g, a posterior t-distribution follows, with expected value $E(\beta_i|y; X_i; g; M_i) = \frac{g}{1+g}\hat{\beta}_i$, where $\hat{\beta}_i$ is the standard OLS estimator for model (7).

The sampler algorithm

Fernandez et al. (2001) show that for the linear model in (7) with the parameter priors described above the marginal likelihood (9) can be solved analytically. It follows that the same holds for the posterior model probabilities and the posterior parameters in (10). In practice, however, computing the relevant posterior distribution analytically is hampered by the very large amount of terms involved in the computations. In our application, we have K = 53, and we would thus need to calculate posterior probabilities for each of the 2^{53} models. Exhaustive evaluation of all these terms is computationally prohibitive. Monte Carlo Markov Chain (MCMC) samplers are used. These explore the model space in order to approximate it as closely as possible. BMS mostly relies on the Metropolis-Hastings algorithm, which "walks' through the model space as follows: Given that the chain is currently at model M_s, a new model M_i is proposed randomly through a uniform distribution on the space containing M_s and all models with either one regressor more or one regressor less than M_s. The chain moves to M_i with probability $p = min\{1, [p(y|M_i, X)p(M_i)]/[p(y|M_s, X)p(M_s)]\}$ and remains at M_s with probability $1 - p$. If model M_i is accepted, it becomes the current model and has to survive against further candidate models in the next step.[11] In this manner, the number of times each model is kept will converge to the posterior model probability $p(M_i|y; X)$. Thus, we shall use the chain to identify the models with high posterior probability. Then for the top models, analytical derivations can be considered and the correlation between the analytical and "the numerical" PMPs gives a measure of the quality of the approximation. This depends, among other things, on the number of draws the MCMC sampler runs through.

[11] MCMC samplers can differ in the way they propose candidate models. See Zeugner (2011) for a more detailed description of this issue.

Tables

Table 1: Estimates of Equation 5 using robust fit weights for outliers. For each country group, the first line shows the coefficients for each technological content level of exports and the second line the corresponding values of R^2. Statistical significance is indicated by: ***1%, **5%, *10%).

		all	high	medium	med-high	med-low	low	energy	intermed.
Level	all	-0.11***	0.10***	-0.05*	-	-	-0.08***	-0.03***	-0.09***
		0.04	0.02	0.03	-	-	0.03	0.01	0.02
	EU	-0.17***	0.12***	-0.08**	-	-0.06**	-0.10***	-0.05***	-0.12***
		0.05	0.02	0.02	-	0.01	0.02	0.04	0.03
	EU15	-	-	-	-	-	-	-	-
		-	-	-	-	-	-	-	
	RichNoOil	-	-	-	-	-	-	-	-
		-	-	-	-	-	-	-	
	EA	-	0.23***	-	-	-0.06**	-	-0.06***	-0.09***
		-	0.09	-	-	0.02	-	0.06	0.03
	CESEE	-0.29***	0.38***	-0.19***	-0.18***	-0.21***	-0.16**	-	-0.25***
		0.19	0.23	0.09	0.08	0.10	0.05	-	0.17
	Baltics	-0.52***	-0.26**	-0.38***	-0.40***	-	-0.22***	-	-0.36***
		0.74	-	0.31	0.26	-	0.29	-	0.70
	BRIC	-	0.31*	-	-	-	-	-0.08***	-
		-	0.06	-	-	-	-	0.15	-
Growth rate	all	0.56***	-	-	0.04***	-	-	-	-0.16***
		0.04	-	-	0.10	-	-	-	0.05
	EU	0.60***	-	-	-0.63***	-	-	-	-0.17*
		0.03	-	-	0.18	-	-	-	0.04
	EU15	0.71***	-	-	-	-	-	-	-
		0.09	-	-	-	-	-	-	0
	RichNoOil	0.66***	0.08***	1.**	-	-	-	-	0.86***
		0.16	0.15	0.21	-	-	-	-	0.10
	EA	-	-	-	-0.67***	-	-	-	-
		-	-	-	0.08	-	-	-	
	CESEE	-	-	-	-0.64***	-	-	-	-
		-	-	-	0.39	-	-	-	
	Baltics	-	-	-	-	-	-0.53**	-0.82**	-0.56**
		-	-	-	-	-	0.09	0.12	0.20
	BRIC	-0.16*	-	-0.36***	-0.27***	-	-	-	-0.31***
		0.15	-	0.42	0.54	-	-	-	0.50

Table 2: List of variables

Group	Variable name
Business Efficiency	Government Bond Yield
Business Efficiency	Domestic Credit to Private Sector
Business Efficiency	Market capitalization to GDP
Business Efficiency	Stock traded to GDP
Business Efficiency	NFC debt as ratio of GDP
Business Efficiency	Household debt as ratio to GDP
Business Efficiency	Interest Rate Spread
Business Efficiency	Long-term Interest Rate
Business Efficiency	Bank Capital to Assets Ratio
Business Efficiency	Chinn-Ito index , financial openness
Business Efficiency	FDI Liabilities as share to GDP
Business Efficiency	FDI Assets as share of GDP
Business Efficiency	Real long-term interest rates, deflator GDP
Business Efficiency	Private bond market capitalization
Business Efficiency	Public bond market capitalization
Business Efficiency	Total Venture Capital investment by country of portfolio company
Business Efficiency	Total Factor Productivity as proxied by the Solow residual
Business Efficiency	Real Labour productivity
Economic Structure	Share of investment if GDP
Economic Structure	Ratio of investment that goes to construction
Economic Structure	Share of public consumption in GDP
Economic Structure	Profits as a share of GDP
Economic Structure	Temporary employees
Economic Structure	Female Labor Participation Rate
Economic Structure	Labor Force with Secondary Education
Economic Structure	Labor Force with Tertiary Education
Economic Structure	New Businesses Registered
Economic Structure	Price level of capital formation
Economic Structure	Relative export price
Economic Structure	HCI ULC manufacturing, vs EU18 EER-19
Economic Structure	HCI ULC total economy vs EU17 EER-20
Economic Structure	House price index, new and existing, deflated by the private consumption deflator
Economic Structure	Export market share
Economic Structure	Relative Export Density
Economic Structure	Export Price Assortativity
Economic Structure	Goods Export sophistication Index
Economic Structure	Services Export sophistication Index
Economic Structure	RCA in high-tech industries exports
Economic Structure	RCA in Medium High Tech Exports
Economic Structure	RCA Exports, Intermediates
Economic Structure	RCA imports, Intermediates
Economic Structure	Public Spending on Education
Government Efficiency	Implicit Tax Rate by economic function: Consumption
Government Efficiency	Implicit Tax Rate by economic function - Capital
Government Efficiency	Implicit Tax Rate by economic function - Labor
Government Efficiency	Social contributions
Government Efficiency	Control of Corruption, WGI
Government Efficiency	Rule of Law, WGI
Government Efficiency	Regulatory Quality
Government Efficiency	Government Effectiveness
Government Efficiency	Political Stability & Absence of Violence/Terrorism
Government Efficiency	Size of Government
Government Efficiency	Legal System and Property Right
Government Efficiency	Freedom of Trade
Government Efficiency	Regulation
Government Efficiency	Strength of Legal Rights
Government Efficiency	Cost of Business Start-Up Procedures
Government Efficiency	Time Required to Enforce A Contract
Government Efficiency	Time Required to Register Property
Government Efficiency	Time Required to Start A Business
Government Efficiency	Time to Resolve Insolvency
Human capital and Innovation	Broadband Subscribers
Human capital and Innovation	Index of human capital per person
Human capital and Innovation	High-tech patent applications to EPO
Human capital and Innovation	High-tech patents granted by USPTO
Human capital and Innovation	R&D expenditure intramural - Business enterprise sector
Human capital and Innovation	R&D expenditure intramural - Government sector
Structural Variables	Landlocked Dummy
Structural Variables	Remoteness
Structural Variables	Population
Structural Variables	Total Natural Resources Rents
Structural Variables	Age dependency ratio
Structural Variables	Agricultural Land
Structural Variables	Rail Lines
Structural Variables	Road density
Structural Variables	Lead time to export

Table 3: Posterior inclusion probability and coefficients for variables with a PIP larger than 0.5. Mean quantities over all visited models.

Variable	PIP	Post Mean	Mean/SD	Cond.Pos.Sign
Stock of FDI inflows % GDP	1.00	0.31	5.83	1.00
Export sophistication (goods)	1.00	0.32	4.47	1.00
Age dependency	1.00	-0.24	-3.83	0.00
RCA in exports of intermediates	0.99	0.18	3.62	1.00
Price of capital formation	0.99	-0.25	-3.45	0.00
Government consumption % GDP	0.98	0.28	3.37	1.00
Broadband subscribers	0.97	0.16	3.26	1.00
Implicit tax on consumption	0.95	0.16	2.96	1.00
Size of government	0.94	0.14	2.94	1.00
Agricultural land	0.94	-0.13	-2.90	0.00
Long-term interest rate	0.93	-0.15	-2.87	0.00
Market capitalisation of listed companies % GDP	0.90	-0.19	-2.81	0.00
Government effectiveness	0.90	-0.13	-2.76	0.00
Export price assortativity	0.85	0.11	2.50	1.00
TFP	0.84	0.28	2.54	1.00
RCA in exports of medium-high tech	0.70	-0.11	-2.17	0.00
Index of human capital	0.66	0.09	2.10	1.00
Real ULC-deflated effective exchange rate	0.65	0.18	2.00	1.00
Operating surplus % GDP	0.59	0.15	1.88	1.00
Stocks traded % GDP	0.59	-0.10	-1.79	0.00
Temporary employment %	0.54	0.10	1.79	1.00
Investment in construction	0.54	0.16	1.69	1.00
R and D expenditure (government)	0.50	-0.10	-1.73	0.00
RCA in imports intermediates	0.50	0.09	1.73	1.00

Table 4: Left: BMA R^2 for individual countries. Note that values can be negative, as R^2 is calculated on a subset of observations. Right: BMA summary statistics.

Country	R^2	statistic	name
Netherlands	0.90	Mean no. regressors	28
Czech Republic	0.88		
Spain	0.86	Draws	1.00E+08
Poland	0.85	Burnins	1.00E+06
France	0.84	Time	17.45544 hours
Lithuania	0.82	No. models visited	41082966
Greece	0.82	Modelspace 2^K	9.00E+15
Portugal	0.80	% visited	4.60E-07
Belgium	0.72	% Topmodels	2.2
Latvia	0.72	Corr PMP	0.9659
Estonia	0.71	No. Obs.	216
Finland	0.70	Model Prior	random / 5
Slovenia	0.66	g-Prior	EBL
Italy	0.65	Shrinkage-Stats	Av=0.9319
Slovak Republic	0.65		
Sweden	0.64		
Bulgaria	0.59		
Austria	0.59		
Romania	0.56		
Germany	0.50		
Denmark	0.50		
Hungary	0.36		
United Kingdom	0.34		
Ireland	-1.08		

Competitiveness Research Network

This paper presents research conducted within the Competitiveness Research Network (CompNet). The network is composed of economists from the European System of Central Banks (ESCB) - i.e. the 29 national central banks of the European Union (EU) and the European Central Bank – a number of international organisations (World Bank, OECD, EU Commission) universities and think-tanks, as well as a number of non-European Central Banks (Argentina and Peru) and organisations (US International Trade Commission). The objective of CompNet is to develop a more consistent analytical framework for assessing competitiveness, one which allows for a better correspondence between determinants and outcomes. The research is carried out in three workstreams: 1) Aggregate Measures of Competitiveness; 2) Firm Level; 3) Global Value Chains CompNet is chaired by Filippo di Mauro (ECB). Workstream 1 is headed by Pavlos Karadeloglou (ECB) and Konstantins Benkovskis (Bank of Latvia); workstream 2 by Antoine Berthou (Banque de France) and Paloma Lopez-Garcia (ECB); workstream 3 by João Amador (Banco de Portugal) and Frauke Skudelny (ECB). Monika Herb (ECB) is responsible for the CompNet Secretariat. The refereeing process of CompNet papers is coordinated by a team composed of Filippo di Mauro (ECB), Konstantins Benkovskis (Bank of Latvia), João Amador (Banco de Portugal), Vincent Vicard (Banque de France) and Martina Lawless (Central Bank of Ireland). The paper is released in order to make the research of CompNet generally available, in preliminary form, to encourage comments and suggestions prior to final publication. The views expressed in the paper are the ones of the author(s) and do not necessarily reflect those of the ECB, the ESCB, and of other organisations associated with the Network.

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Andreas Joseph (corresponding author)

Advanced Analytics Division, Bank of England, London, United Kingdom; email: andreas.joseph@bankofengland.co.uk

Chiara Osbat

Prices and Costs Division, European Central Bank; email: chiara.osbat@ecb.europa.eu

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Postal address	60640 Frankfurt am Main, Germany
Telephone	+49 69 1344 0
Website	www.ecb.europa.eu

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