Work Project presented as a part of the requirements for the Award of a Master Degree in Economics from NOVA – School of Business and Economics

Structural Transformation in the Product Space: Patterns and Implications

André Ferreira Coelho

Student no. 526

A project carried on Macroeconomics and International Economics under the supervision of:

Professor Luís Catela Nunes

Professor Miguel Lebre de Freitas

Lisbon, January 7th, 2013

Table of Contents

1. Abstract

Product fundamentals are essential in explaining heterogeneity in the product space. The scope for adapting and transferring capabilities into the production of different goods determines the speed and intensity of the structural transformation process and entails dissimilar development opportunities for nations. Future specialization patterns become then partly determined by the current network of products' relatedness. Building on previous literature, this paper explicitly compares methodological concepts of product connectivity to conclude in favor of the density measure we propose combined with the Revealed Relatedness Index (RRI) approach presented by Freitas and Salvado (2011). Overall, RRI specifications displayed more consistent behavior when different time horizons are equated.

Keywords: comparative advantage; structural transformation; learning-by-doing

2. Introduction

Models of structural transformation have privileged the role of product fundamentals in explaining similarity amongst products. At micro (firm) level, firms are likely to invest in new products if there is scope for adapting and transferring existing capabilities and resources into the production of that good. At a country level, achieving Revealed Comparative Advantage (RCA) in a given good at a certain point in time is likely to be the reflex of past adjustments of productive factors towards different goods and perhaps sectors.

Building on Hausmann and Klinger (2006, 2007) and Freitas and Salvado (2011) outcomes-based and product specific measures of proximity and relatedness, this paper tries to convey some light to the extent to which these concepts are valid approaches to capture product connectivity in the product space. Once the product space is defined, different product density definitions are proposed to capture aggregate network spillover effects triggered by the products exported with RCA within a country. This measures summarize how related each product is to the core capabilities of economies and the scope for adapting and transfer capabilities such that the process of structural transformation is reflected in different specialization patterns along time and heterogeneous potential for countries' economic growth. This paper contributes to the literature by proposing an alternative, more intuitive, concept of product density whose consistency is exhaustively tested against concepts already proposed in the literature.

This paper is organized as follows: Section 3 briefly surveys relevant literature; Section 4 relates RCAs with product density and introduces relevant concepts and definitions; Section 5 describes the data used; Section 6 clarifies methodological aspects and the empirical approach pursuit; Section 7 presents the main results; Section 8 concludes an Section 9 discuss some limitations while suggest further improvements.

3. Literature Review

It is been a long journey since Adam Smith (1776) and David Ricardo's (1819) models of comparative advantages for economic theory to explain why countries specialize in the production of different goods and how countries' specialization patterns evolve over time. Particularly relevant is to understand what governs the process of structural transformation (i.e. the process of changes in countries' structure of comparative advantages and patterns of specialization) and its implications in future specialization patterns and in countries' related economic performance.

Relevant economic literature goes back to the second half of 20th century where changes in productive structure and production patterns were recovered to the center of academic discussion. For Rostow (1956, 1959) economic take-offs were driven by self-sustained growth in a limited number of productive sectors that set in motion a chain of spillover effects diffusing industrial techniques into the remaining sectors. Kuznets (1957) claimed that the association of international differences in economic efficiency and increases in factor productivity drove the evolution of sectorial composition of modern economies and ultimately in the nation's income levels. Similar reasoning for economic growth can be found in Lewis (1955) where differences in factor's productivity were the main drivers of resource reallocation among sectors. Building on these ideas, Chenery and Taylor (1968) advocated uniform patterns of change in countries' productive structure as income levels have historically risen controlling for different countries' industry-oriented patterns and Kaldor (1967) drawing on Young's (1928) framework for macroeconomic spillovers, matched supply and demand side of structural transformation. Also based on Young (1928), Matsuyama (1995) expanded the notion of demand side spillovers that generate horizontal and vertical complementarities in the presence of endogenized sectoral induced shocks.

More recently, economic sectorial interactions and their resultant impacts on patterns of production have been addressed from microeconomic models of learning-by-doing and information externalities. Departing from Arrow (1962) and Verdoom (1956), Barro and Sala-i-Martin (1995) claimed that learning-by-doing works through a gear mechanism where firms' capital stocks increase workers stock of knowledge that is disseminated through the economy at zero cost. Romer (1986) summarized: once discovered, knowledge and capabilities are prone to spill across sectors in economies. Stokey (1988) developed a DGE model where goods are ranked according their fundamentals and production becomes endogenously determined by learning spillovers leading to the introduction of new goods. Haussman, Hwang and Rodrik (2007) proposed a model of local cost discovery with knowledge spillovers where specialization patterns become partly undetermined and countries' export basket produce important implications on economic growth: "countries become what they produce".

Based on data at product disaggregated level, Lall (2000) suggested that countries' economic performance is ultimately conditional on cumulative processes, knowledge spillovers and technological agglomeration, factors neglected by neoclassical theories. Departing from Wacziarg and Welch (2003) where evidence in favor of u-shaped form relating export diversification and income was presented, Rodrik (2004) exhaustively reviewed industrial policy practices claiming that its' effectiveness is conditional on privates' information perception regarding latent externalities as it is on implemented micro-oriented policies. Hausmann, Hwang and Rodrik (2007) and Hausmann and Klinger (2006) went further in relating product sophistication and exports' income content and the value of countries' unexploited specialization opportunities to the scope for future economic growth.

Proposing a model of structural transformation in the product space based on Diamond (1989), Cabral (2000), Laezer (2003) and Hausmann and Klinger (2006, 2007), hereafter HK, departed from an heterogeneous product space in the spirit of Segerstrom (1991), to complement Romer's (1988) varieties model and Grossman and Helpman (1989, 1991) and Aghion and Howitt (1992) ladders models. Although not empirically tested, the model of structural transformation proposed by HK (2006, 2007) assumed linear profits from leapfrogging while costs are quadratic in distance, implying a heterogeneous product space entailing diverse consequences for economic growth where stagnation can occur. Previous works, namely Young (1991), contemplated improvements within products (vertical improvements) as well as vertical shifts while neglecting product heterogeneity. Jovanovic and Nyarko (1996) integrated vertical and horizontal shifts induced by technological improvements in a learning-by-doing model where the bounded scope for product quality improvements trigger spillover effects to different products based on factor similarities.

HK (2006, 2007) proposed pairwise conditional probabilities of two any products being simultaneously exported by the same country to assess product proximity. In prior literature, Ditezebacher and Lahr (2001) and Jaffe (1986) presented alternative concepts based on I-O tables and technology spillovers. Freitas and Salvado (2011), hereafter FS, argued that estimating product-based measures of product relatedness through latent variables models presents significant improvements comparing with alternative approaches. This comparison is central in this paper. For these authors, the general degree of relatedness among products, called "density", in the product space determines the speed and intensity of the structural transformation process which translates in a continuous (but heterogeneous) upgrading of countries' export basket as unexploited opportunities ("open forest value" for HK (2006), "upscale opportunities" for FS (2011)) in the productive structure are being explored.

Hausmann and Klinger (2006, 2007) also draw some intra industry conclusions by applying

Leamer (1984) and Lall (2000) cluster classifications frameworks. Earlier contributions include Hirschmann (1957) industry forward and backward linkages, V.P. de la Potterie (1997), Krugman (1991), and Krugman and Venables (1986) on patterns of industrial conglomeration and clustering and Porter (1990, 1998) framework of critical mass for geographical clusters induced by common institutional environment, knowledge sharing and public goods.

Products' income content and export sophistication levels were proposed in the literature by Hausmann, Hwang and Rodrik (2007) with the purpose of evaluating countries' unexploited opportunities and to evaluate whether they are determinant in driving the process of structural transformation. These concepts have been widely adopted and tested in relevant literature since there. Empirical applications of product density as a driver of specialization patterns have been combined with product sophistication literature and include Portugal (FS, 2011) and (Freitas e Mamede, 2011), South Africa (Haussman, Rodrik, Sabel, 2008), Brazil (Hausmann, 2008), Peru, Colombia, Equador and Chile (HK, 2007, 2008 and 2010), China, Malaysia and Ghana (Badibanga, 2009) and Latvia (Vitola and Dãvidsons, 2008).

More recently, Hidalgo (2009) and Hausmann and Hidalgo (2010, 2011) proposed a capabilities theory with increasing returns using a "method of reflections" and economic spectral complexity where product sophistication and exports' income content are proxied respectively by product ubiquity and export diversification. The number of complementary capabilities required by each product and available within a country becomes central in determining current specialization patterns and potential for fostering subsequent economic growth. Hausmann and Hidalgo (2010, 2011) method of reflections was empirically applied using HS product classification by Felipe et. al. (2012). The Atlas of Economic Complexity (2011) and Jankawska et. al. (2012) survey several countries.

This section presents a survey of the relevant literature developed in the last decades. In the next section essential product connectivity and density concepts will be presented.

4. Product Density

4.1 Product Connectivity and Revealed Comparative Advantage

Connectivity amongst goods in the product space framed in the context of structural transformation process are both conceived as the extent to which existing capabilities and resources may be adapted and transferred into the production of different goods.

Rather than making à-priori beliefs of how each product contributes to the production of another (eg. factor endowments, technological sophistication) in a heterogeneous product space, the empirical strategy to be used in this paper relies on outcomes-based and product specific measures that assume an agnostic position by letting data to give us some empirical notion of the magnitude of such connectivity network, e. Rather than being a drawback, requiring such invariability across countries is a condition to focus on trade export flows instead of internal demand for domestically produced goods. The underlying reasoning is that proximity and relatedness are uniquely motivated by product fundamentals and the degree to which they are imperfect substitutes in the production of different goods, irrespectively of country-specific considerations.

Further, proximity and relatedness measures should be harsh in capturing similarities in product fundamentals and factor endowments in the product space, excluding marginal impacts and similarities resulting from inefficient combinations of endowments and capabilities. Both conditions are assured by requiring countries to have revealed comparative advantage in the products they export.

Formally, RCA of country c in good i at time t is defined following Balassa (1965):

$$RCA_{c,i,t} = \frac{v_{c,i,t} / \sum_i v_{c,i,t}}{\sum_c v_{c,i,t} / \sum_i \sum_c v_{c,i,t}} \quad (1)$$

Where:

$v_{c,i,t}$	is the value of country c exports of product i at time t;
$\sum_i v_{c,i,t}$	is the sum of country's c exports at time t;
$\sum_c v_{c,i,t}$	is the total of worldwide exports of product i at time t;
$\sum_i \sum_c v_{c,i,t}$	is the sum of worldwide exports at time t;

It was created a dummy variable x_{ict} taking the value 1 if country c at time t has revealed comparative advantage in product i.

$$x_{c,i,t} = \begin{cases} 1 \; if \; RCA_{c,i,t} > 1 \\ 0 \; if \; otherwise \end{cases} \quad (2)$$

Hence, RCA is used in both the construction of pairwise proximity and relatedness measures that this paper wants to compare in order to extract some conclusions of how accurately they give an empirical basis to predict structural transformation.

4.2 Product Proximity measures

Departing from a symmetric measure of distance between each pair of products, HK (2006, 2007), argue that conditional probabilities (hereafter CP) would capture the contribution of having revealed comparative advantage in one good associated with a revealed comparative advantage in another good. The minimum between pairwise conditional probabilities would ensure a proximity measure (i.e. equal contributions between products i and j) and tackle cases where a limited range of goods worldwide exported would overstate conditional probabilities involving a good with low ubiquity.

$$\varphi_{i,j,t} = min\{P(x_{i,j,t}|x_{j,i,t}), P(x_{j,i,t}|x_{i,j,t})\} \quad (3)$$

Following HK (2006, 2007), the product space at time t is therefore represented by a squared matrix of pairwise distances $\varphi_{i,j}$ among products, which is shown to be highly heterogeneous. Higher similarity in terms of capabilities and resources between a given pair of goods should be reflected in a lower distance connecting them, captured by a higher conditional probability.

$$\Delta_t = \begin{bmatrix} 1 & \varphi_{1,2} & \varphi_{1,3} & \cdots & \varphi_{1,n} \\ & 1 & \varphi_{2,3} & \cdots & \varphi_{2,n} \\ & & 1 & \ddots & \varphi_{3,n} \\ & & & \ddots & \vdots \\ & & & & 1 \end{bmatrix}$$

4.3 Product Relatedness measures

Departing from not imposing symmetry in the matrix of pairwise distances, FS (2011), presented an alternative method for disentangling the increment in the probability of having

RCA in one product conditional on having RCA in another product. A Probit model was proposed to capture this marginal effect, where the notation used above holds. For any two products i and j:

$$P\left(x_{j,t} = 1 | x_{i,t}\right) = \Phi\left(\alpha_0 + \alpha_1 x_{i,t}\right) \quad (4)$$

$$P\left(x_{i,t} = 1 | x_{j,t}\right) = \Phi\left(\alpha_0 + \alpha_1 x_{j,t}\right) \quad (5)$$

Where $P\left(x_{jc} = 1 | x_{ic}\right)$ is not necessarily equal to $P\left(x_{ic} = 1 | x_{jc}\right)$, Φ represents the standard normal cumulative distribution function and α_1 is the strength of the stimulus in $i(j)$ associated with RCA in $j(i)$.

Individual two-sided significance tests were performed in each coefficient and whenever they were proven to be statistically significant at 5% significance level, the marginal effect was computed. All the cases where coefficients were not proved to be statistically significant, a missing value in the pairwise relatedness matrix was generated. FS (2011) contrast therefore a "Revealed Relatedness Index" (hereafter RRI) with HK (2006, 2007) proximity concept.

$$RRI_{i,j,t} = \Phi(\hat{\alpha}_0 + \hat{\alpha}_1) - \Phi(\hat{\alpha}_0) \quad (6)$$

Under this approach, the correspondent matrix of RRIs where non-significant effects were disregarded can be obtained[1].

$$\Omega_t = \begin{bmatrix} 1 & RRI_{1,2} & RRI_{1,3} & \cdots & RRI_{1,n} \\ RRI_{2,1} & 1 & RRI_{2,3} & \cdots & RRI_{2,n} \\ RRI_{3,1} & RRI_{2,3} & 1 & \cdots & RRI_{3,n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ RRI_{n,1} & RRI_{n,2} & RRI_{n,3} & \ldots & 1 \end{bmatrix}$$

4.4 Product Proximity and Relatedness – a brief comparison

While departing from different assumptions HK (2006, 2007) and FS (2011) modeling approaches to assess product connectivity and relatedness produce notably diverse and somehow contradictory implications.

By resorting to a parametric procedure to estimate relatedness across products in the product space, FS (2011) were able to perform significance tests and disregard all the pairwise

[1] Excluding circular probits equations and conditional probabilities (i.e when $i = j$) a total of 1070×1069 relationships we obtained per year under each methodology. Overall, this yields more than 89 million estimated equations over the time frame considered. Detailed information can be found in section 5. Data.

relatedness proven not to be statistically significant. Taking into account different data sources (FS used disaggregated data under the Harmonized System (HS) product classification while HK (2006, 2007) papers relies on data at SITC product classification) the proportion of statistically significant RRIs was shown to be only about 16.1%. Albeit the fact that FS (2011) study employs only 2005 data, this figure challenges the assumption beyond HK (2006, 2007) CPs approach, where every single pairwise proximity was validated and considered in the construction of further concepts.

Provided that the more disconnected is a set of goods in the product space the more costly is to adapt existing assets and technologies between them, efficiency in the productive process using emulated assets and technologies will be a decreasing function of product's distance. And since countries have limited endowments of resources and capabilities available it is intuitive to think that having RCA in one product might actually result in negative probability increments in having RCA in a set of products differing considerably in terms of fundamentals. Following Leamer's (1984) commodity cluster classification, having RCA in some agricultural products, for instance, might reduce the likelihood of having RCA in chemical industry. Also, by construction a country cannot have RCA in all the products it exports. If a country achieves RCA in a given good then, ceteris paribus, it has to be counteracted by a proportional decrease in the RCA ratio for some remaining products. Those whose share decreases more would be the least correlated in terms of product fundamentals. Contrary to HK (2006, 2007), who restrict marginal contributions to be necessarily positive, parameterization of a Probit models carried out by FS (2011) relaxes this assumption by allowing increments in probability in having RCAs associated with simultaneous RCA in other products to be negative. Still, FS (2011) claimed that marginal effects were found to be indeed negative only for 2.3% relationships out of the total pairwise combinations of products and 0.4% if non-significant ones were neglected.

HK (2006, 2007) rational behind imposing symmetry was to avoid situations where CPs computed over products with considerably low (high) ubiquity – products exported by few countries – become artificially upwards (downwards) biased, “reflecting the peculiarity of the country and not similarity of goods” (HK, 2006). However, conceiving that the valuable experience of producing i in the production of j equals the contribution of producing j in the production of i would not capture true similarities between countries. Think about a final and an intermediate good: producing the intermediate good is likely to endow a country with some knowledge and capabilities useful in the production of the final good, whereas the opposite is not necessarily true. FS (2011) pairwise contemporaneous estimation captures this dissimilarity in crossed marginal effects, reflecting a more accurate perception of product relatedness.

Henceforth, RRIs might consist in a more precise measure of product relatedness by (i) imposing significance tests, (ii) allowing for negative marginal contributions and (iii) by not imposing symmetric relatedness. Notwithstanding, the possibility of representing graphically the product space as it was originally done by Hidalgo et. al. (2007), Hidalgo (2009) and Hausmann and Hidalgo (2011) is restricted to a symmetric notion of distance in the product space.

4.5 Product Density measures

Once proximity and relatedness concepts were clarified and some of its implications were presented, we now turn our attention for measures that capture their implications at more aggregated levels. Product density is defined following an inward perspective within a country and it was first applied by HK (2006).

This measure captures the overall contemporaneous usefulness of all products in which a country possess RCA to each product individually considered. The same is to say that density condenses all the active spillover effects within a country motivated by product relatedness “received” by a certain product. Further, similarity in terms of capabilities and assets with countries’ overall specialization patterns would be translated in higher product density and consequently in a higher likelihood of having (either attaining or sustaining) RCA in subsequent periods.

4.5.1 Proximity-based density

Product density was first developed by HK (2006) in the context of their proximity concept to illustrate that products' proximity to a country's export basket has some explanatory power over the probability of developing RCA in the future. Formally, these authors defined density of product i at time t as the sum of a country's revealed comparative advantages excluding good i, weighted by the strength of their respective (non-negative) spillover effect towards product i, divided by product's i total received spillover effects.

$$scaled\ density_{c,i,t} = \frac{\sum_k \varphi_{i,k,t} x_{c,k,t}}{\sum_k \varphi_{i,k,t}} \tag{7}$$

Even though this is a valid measure to capture product density, proximities should be the main focus for relatedness with respect to a specific product instead of being the weight for the sum of comparative advantages per country, which will be biased against countries with fewer but more developed RCAs in comparison with countries with more and necessarily less significant RCAs.

Recognizing this limitation, FS (2011) propose an alternative definition of density applied to their RRI concept where the joint active relatedness involving product i is divided by the number of RCA present in a given country at a certain point in time. Despite the focus on relatedness (here proximities) instead of on number of RCAs, we shall argue that this measure may alternatively present some bias against products exported by countries with more but weaker RCAs when compared with those products exported by countries with less and stronger RCAs. In other words, two products with equivalent incoming paths strength, $\sum_k x_{i,k,t}\varphi_{i,k,t}$, will have different density levels, conditional on the number of active spillovers. Here, we adapted the original formula to fit proximity as HK (2006, 2007) defined it and hereafter it will be referred as weighted density.

$$weighted\ density_{c,i,t} = \frac{\sum_k x_{c,k,t}\varphi_{i,k,t}}{\sum_k x_{c,k,t}} \tag{8}$$

In order to address the drawbacks embodied in both formulas this paper, rather than complexify, simplify. We propose a crude density measure that captures aggregate product proximity by summing the knowledge, capabilities and resources spillovers intrinsic to all products containing RCA that surround product i without the need to be weighted by anything else. The underlying reasoning is that product density should be captured by proximity (or relatedness) with the major products exported by one country – products in which a country has RCA – instead of reflecting a weighted average of the number of products with RCA within a country or a weighted average of proximity. The same is to say that density is best given by the strength and number of active spillovers than by the average spillover effect.

$$crude\ density_{c,i,t} = \sum_k x_{i,k,t}\varphi_{i,k,t} \tag{9}$$

4.5.2 Relatedness-based density

Similarly to the product proximity approach, density concepts may be applied under the context of product relatedness. There are, however, some differences in their application that are worthwhile to note. In contrast with conditional probabilities, should be recalled that RRI are allowed to capture negative marginal contributions between products. Henceforth, the summation by product of their incoming paths, $\sum_i RRI_{i,k,t}$, might diverge remarkably from their respective counterpart obtained under conditional probabilities. More concretely, while $\sum_i \varphi_{i,k,t}$ is dependent on the number of (non-negative) spillovers, $\sum_i RRI_{i,k,t}$, consists in an aggregation of positive and negative effects, resulting that a vast majority of them will cancel-out reciprocally. For this reason, scaled density has no meaning if computed using product relatedness and is left outside from this analysis.

At a cost of the natural and mentioned limitations in comparing densities measures between product proximity and relatedness dimensions, density definitions will be tested against each other.

$$weighthed\ density_{c,i,t} = \frac{\sum_k x_{i,k,t}RRI_{i,k,t}}{\sum_k x_{i,k,t}} \tag{10}$$

$$crude\ density_{c,i,t} = \sum_k x_{i,k,t}RRI_{i,k,t} \tag{11}$$

Now that we have presented the two alternative approaches to measure product connectivity and their respective concepts capturing aggregated inward spillover effects, next section presents the data employed in this paper.

5. Data

Data employed in this study are yearly world trade export flows retrieved from Feenstra et. al. (2005) available at NBER, ranging from 1962 to 2000 at 4-digit Standard International Trade Classification (SITC4), Revision 2, consisting in 1070 products covering a total of 164 countries. This dataset was integrally constructed and complemented with an original product sophistication variable, exports' basket income-content variable and cluster commodity cluster variables in the spirit of Leamer (2005) not employed in this work.

Trade flows are employed as reported (in nominal thousands of $US Dollars) since by construction the methodological statistics computed and extensively applied throughout this study do not require deflating nominal into real trade flows. Density-related variables applied in sections 6.1. to 6.3. were exclusively derived from Feenstra et. al. (2005).

Although export datasets are available at higher level of product category disaggregation, they generally either cover narrower periods of time or include a narrow sample of countries. Further, databases constructed at higher disaggregation levels are not widely implemented and the likelihood of misreporting in the actual export trade flows is enhanced. Also, data panels are frequently not strongly balanced over time. Databases constructed from diverse product classifications systems include the United Nations Harmonized System (HS), the North American Product Classification System (NAPCS) or the Central Product Classification (CPC) at diverse revision schedules.

While drawing on the UN Trade Commodity Trade Statistics Database (COMTRADE), Feenstra et. al. (2005) gave primacy to importers' reports over exporters' reports as source of bilateral trade flows, whenever they were available, assuming that the formers report data more accurately. Trade flows reported by importers are "Cost, Insurance and Freight" (CIF) while data reported by exporters is “Free on Board” (FOB).

Several other adjustments to verify consistency in data and to avoid double counting were performed and are discussed in detail by the authors. UN-COMTRADE were merged and compared against US Trade Statistics when US was a partner country in bilateral trade flows; aggregate imports were cross-checked against the summation of reports at product level and reporting from unidentified partners were adjusted.

From 1984 onwards, Feenstra et. al. (2005) only report bilateral data exceeding US $100,000 for several reasons. In order to address this issue two additional product categories were added at SITC disaggregated level in this paper. Whenever trade flows at disaggregated level are included but do not match the sum of higher product aggregation category, an extra category accounting for that difference was created. By the same token, whenever trade flows are only available at higher aggregation levels, an additional aggregate category at SITC4 was created. Provided that it is not possible to observe SITC4 level products contained in both these categories as it is our purpose in this paper, they were disregarded with exception for RCA computations.

6. Empirical Approach

Recovering the initial intuition behind product density, at micro (firm) level, firms are likely to invest in new products if there is scope for adapting and transferring existing capabilities and resources into the production of those goods. At a country level, achieving RCA in a given good at a certain point in time is likely to be the reflex of past adjustments of productive factors towards different goods and perhaps sectors.

The Empirical approach used in this paper tries then to validate product-specific measures in assessing proximity and relatedness in the product space[2] by (i) to assess which density concept fits best the data within RRI and CP approaches, (ii) to provide a notion of different density magnitudes for transition and static products, to (iii) give a notion of inertia patterns in

[2] Due to different variables’ metrics and different observations included in different specifications due to the use of FE Logit models a direct comparison between methods is unfortunately not valid.

structural transformation across specifications. For robustness, tests and regressions were repeated for different time-lag structures simulating short, medium and long run horizons which provide some idea of persistency and consistency of results.

Results are divided in three sections. Section 7.1 presents some non-parametric empirical evidence trying to capture dynamics in RCAs by restricting the analysis to the cases where countries developed RCA in certain products between two different periods in time and splitting the sample into products with and without prior RCA. Essentially, this approach was designed to test whether products in which countries acquired RCA should be motivated by higher past density levels comparing with cases in which countries did not developed RCA. However, the inverse reasoning does not apply[3]. Different time-horizons corresponding to short-run (1 year), medium-run (3 years) and long-run (5 years) are used to attest time-consistency in product transitions.

In section 7.2 logit models were estimated using the within estimator (fixed effects), random effects (individual effects) and the pooled (population average) models. Table 2 describes the variables used. Given the time-varying nature of product density and the limited predictive power of time-invariant variables in explaining RCA dynamics, Fixed Effect (FE) estimators are expected to be consistent while Random Effects (RE) and Population Average (PA) estimators are likely to inconsistent.[4] In the context of ML estimation performed by binary outcomes models, fixed, random and population-averaged non-nested models can compared essentially on the basis of likelihood-derived criteria. Akaike's (1974) Information Criterion (AIC) and Bayesian Information Criteria (BIC) (Schwarz, 1978) are by far the most diffused methods in the literature. With no exception both criterions favored FE models over alternative

[3] At micro firm level, product density becomes irrelevant to explain which products have lost RCA between to different points in time. That is, density is relevant when firms perceive new opportunities probably with higher implicit PRODY; once firms are already producing a given good, they must be endowed with the required resources and knowledge, so that density around those goods does not play any role in explaining product's discontinuity. Accordingly, no particular trend is expected to be found when looking at the dynamics behind losses in RCA. Nevertheless, this exercise was performed and it is available on request.

[4] FE models allow for a limited form of endogeneity by letting explanatory variables to be correlated with the time-invariant component of the error term while they are still deemed to be uncorrelated with the idiosyncratic error. RE and PA models, on the other side, requires explanatory variables to uncorrelated with the error term. In FE models individual effects are assumed to be only captured by the intercept term whereas in RE models individual heterogeneity is captured by an i.i.d. intercept (the random effect) and a random error component. PA models do not disentangle between idiosyncratic and time invariant errors and require only orthogonality between predictive variables and the error. In the absence of correlation with the time-invariant error RE models produce more efficient estimators than FE models.

models, implying that most of the variation is indeed captured by the within estimator[5].

Results presented in next section consider altogether density measures derived from proximity (CP) and relatedness measures (RRI). Time persistency and revealed comparative advantage inertia are tested by running model specifications over the three different time-lag structures previously introduced.

Table 2 – Description of Variables

Variable	Description
$\boldsymbol{xkc_{i,c,t+n}}$	*Dummy variable taking the value 1 if country c has RCA in product i at time t+n*
$\boldsymbol{xkc_{i,c,t}}$	*Dummy variable taking the value 1 if country c has RCA in product i at time t*
lnden	*Logarithm of crude density (either with CP or RRI)*
lnwden	*Logarithm of weighted density (either with CP or RRI)*
lnhden	*Logarithm of scaled density (only available for CP)*

7. Results

7.1 Non-parametric approach

In order to focus in consistent changes in RCA over time and leave aside the noise caused by products swinging around the boundaries of RCA index, we generalize Hidalgo et. al. (2007) approach of restricting the sample to contain only products without RCA at t, splited into "transition products" and "underdeveloped products" at time $t+n$, to cover the entire sample.

$$transition\,product \equiv\ RCA_{c,i,t} < 0.5 \land RCA_{c,i,t+n} \geq 1 \tag{12}$$

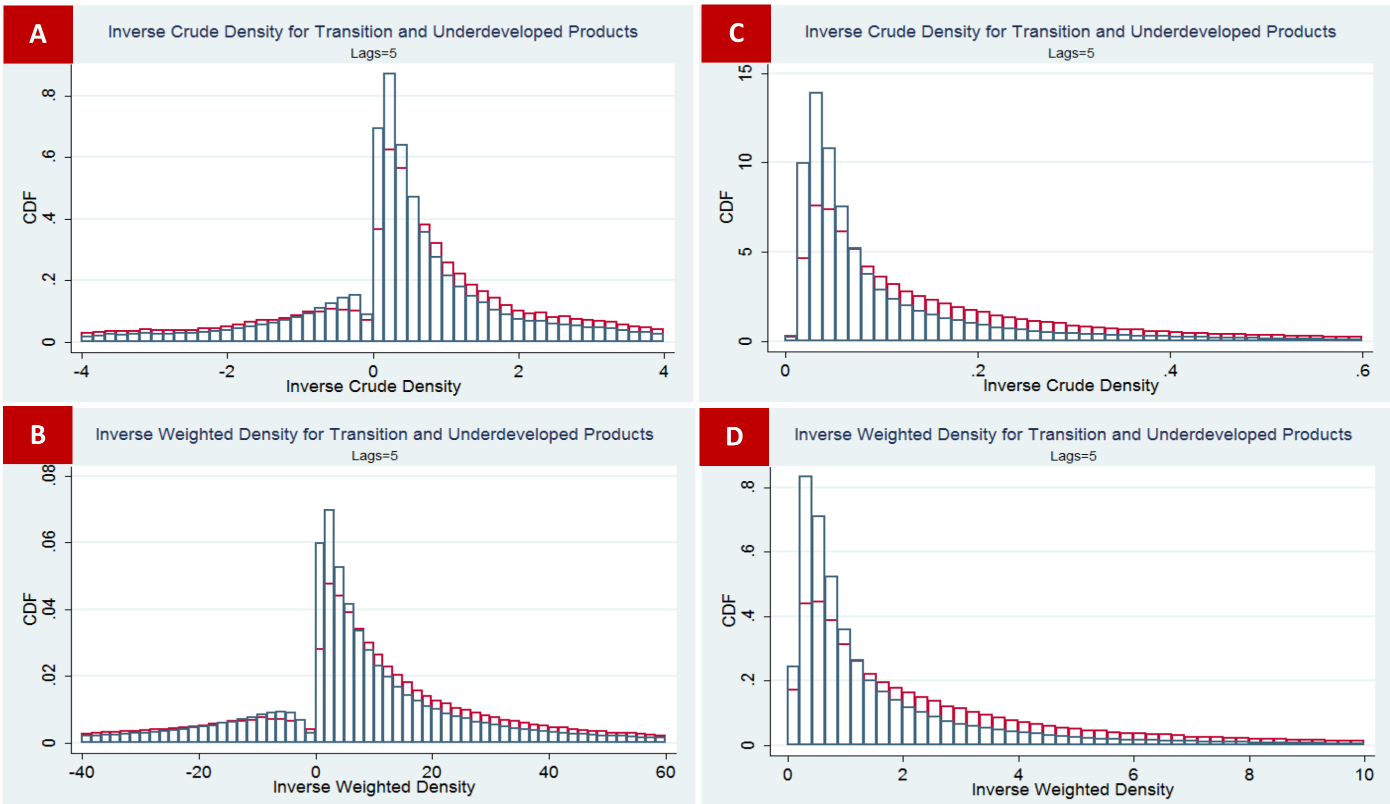
$$underdeveloped\,product \equiv\ RCA_{c,i,t} < 0.5 \land RCA_{c,i,t+n} < 0.5 \tag{13}$$

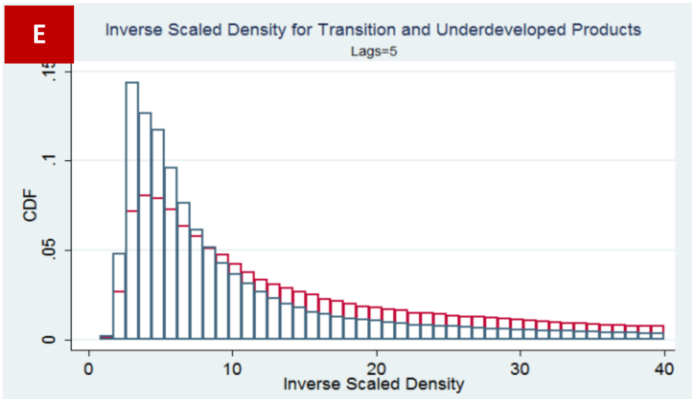
Figure 1 presents the results. Panels A. and B. are restricted to RRI based densities and display the histograms of past inverse density comparing their alternative definitions, while panels C to E focus on CP derived densities. Al panels display inverse densities at t and product groups were defined according to whether at time $t+5$ (long- run) products have acquired RCA (blue bars) or staid with $RCA < 0.5$ (red bars). Inverse densities were used for graphical convenience. To test whether transition and underdeveloped products follow the same distribution under the different cases, Wilcoxon Rank-Sum tests were conducted, leading with

[5] Some limitations behind FE ML estimator survived by Greene (2002) cannot be ruled out for small samples. This should not be a concern in this work.

no exception to the rejection at 1% significance level of the null hypothesis of equal

Figure 1 – Density and Transition vs. Underdeveloped products





Legend: density histograms for transition products (blue bars) and underdeveloped products (red bars) comparing RCA 5 years apart. Panels A and B refer to RRI approach using Crude and Weighted density definitions, respectively; panels C, D and E refer to CP approach using Crude, Weighted and Scaled definition, respectively.

Source: Own computations.

medians both groups somehow between t and $t + 5$ (blue bars) and those that stayed with RCA lower than 0.5 (red bars) at time $t + 5$. Invariability in Wilcoxon Rank-Sum test results across the different cases justifies its omission.

When comparing relatedness derived density distributions against proximity based density distributions, apart the logical differences implied by both methods, there is no major evidence favoring one approach. Products in which countries developed RCA were on average placed at lower inverse densities (meaning higher densities) than those products in which countries did not developed RCA. This pattern presents some evidence supporting the role of product density in determining subsequent specialization patterns across countries. Albeit the different specifications used, there is no evidence favoring one particular concept of density in capturing future RCA against the alternative concepts. Similar results do not allow for the election of a particular density measure as capture dynamics of RCA based on product connectivity more sharply. This is the first stylized fact presented in this paper. Following Hidalgo et. al (2007), at the single product level we test whether average density of a given product was higher in those countries where this product was a transition product than in countries where the product was underdeveloped. If this is the case, we expect that the ratio between both averages – the Discovery Ratio (H_j), be higher than one for most of the cases in our panel. Formally,

$$H_j = \frac{[\sum_{k=1}^{T} \omega_{jc}{}^{k}]\frac{1}{T}}{[\sum_{k=T+1}^{N} \omega_{jc}{}^{k}]\frac{1}{N-T}} \qquad (14)$$

Where $\omega_{jc}{}^{k}$ stands for the density definition to be used, T is the number of countries at time $t+n$ where product j was a transition product and N is the total number of countries contained in the panel. Tests were performed under multiple time-lag structures yielding similar results. Table 1 displays the results.

Table 1 – $\boldsymbol{RRI_{i,j,t}}$ and $\boldsymbol{\varphi_{i,j,t}}$ Discovery Factors (% Products with $H_j > 1$)

Time-Lag structure	Density measure	$\boldsymbol{RRI_{i,j,t}}$	$\boldsymbol{\varphi_{i,j,t}}$
$\{t; t+1\}$	$crude\ density_{c,i,t}$	**58.32%**	**86.94%**
$\{t; t+3\}$	$crude\ density_{c,i,t}$	**59.58%**	**87.81%**
$\{t; t+5\}$	$crude\ density_{c,i,t}$	**62.06%**	**87.89%**
$\{t; t+1\}$	$weighted\ density_{c,i,t}$	49.82%	73.30%
$\{t; t+3\}$	$weighted\ density_{c,i,t}$	51.74%	71.69%
$\{t; t+5\}$	$weighted\ density_{c,i,t}$	60.84%	71.29%
$\{t; t+1\}$	$scaled\ density_{c,i,t}$	—	85.97%
$\{t; t+3\}$	$scaled\ density_{c,i,t}$	—	86.99%
$\{t; t+5\}$	$scaled\ density_{c,i,t}$	—	87.06%

Source: Author's calculations

Discovery factors were shown to be always greater than its counterpart specifications for equivalent time-lag structures under both RRI and CP specifications. Provided that product j average crude density was higher in countries were j was a transition product compared with countries where j was underdeveloped vis-à-vis alternative density concepts, these results support that a stronger association between past density and present RCA is indeed captured by the concept this paper proposes. This is the second stylized fact in our work. Differences in general absolute magnitudes between RRI and CP methods should however be noted and interpreted with caution.

7.2 Panel data Maximum Likelihood estimator

In this section, logit models[6] were used to assess how past product density under different specifications determines the probability of a country possessing RCA in a subsequent period controlling for whether countries had already RCA in a certain product in a previous period. Sample descriptive statistics are displayed in table 3.A for RRIs and table 3.B for CPs. Results are displayed in table 5.

Table 3.A – $RRI_{i,j,t}$ Summary Statistics

Variable	Short-run				Medium-run				Long-run			
	Obs.	Mean	Median	St.dev	Obs.	Mean	Median	St.dev	Obs.	Mean	Median	St.dev
$xkc_{i,c,t+n}$	1611159	0.283	0	0.45	521178	0.286	0	0.452	307164	0.293	0	0.455
$xkc_{i,c,t}$	1643646	0.282	0	0.45	556373	0.283	0	0.45	343511	0.287	0	0.452
lnden	2656340	0.391	0.32	1.424	908587	0.402	0.338	1.42	559189	0.428	0.369	1.447
lnwden	2656340	-3.825	-3.715	1.2	908587	-3.825	-3.714	1.199	559189	-3.806	-3.689	1.217
lnden* $xkc_{i,c,t}$	1262310	0.662	0	1.144	430901	0.667	0	1.143	264728	0.683	0	1.168
lnwden* $xkc_{i,c,t}$	1262310	-1.022	0	1.498	430901	-1.018	0	1.49	264728	-1.029	0	1.5

Source: Author's calculations

Specifications (1) to (5) of table 5 show the results restricted for short-run impacts (two consecutive years) of density on the probability of a future RCA, specifications 5 to 10 focus on the medium-run impacts (3-year lag) and specifications 10 to 15 approach long-run impacts (5-year lag).

Interaction terms between density variables and lagged RCA were included to test whether past density has stronger predictive power explaining maintenance of or transitions into product comparative advantage. Model specifications covering RRI and CP approaches were separated

[6] Fitted probabilities computed through Logit and Probit models are remarkably similar and present only some discrepancy in tails of the distribution for big enough samples. Given the less computationally demanding requirements behind the logistic cumulative distribution function, logit models were preferred over probit models. Logit coefficients are roughly 1.6 times the equivalent probit coefficients (Amemiya, 1981).

Table 3.B – $\varphi_{i,j,t}$ Summary Statistics

Variable	Short-run				Medium-run				Long-run			
	Obs.	Mean	Median	St.dev	Obs.	Mean	Median	St.dev	Obs.	Mean	Median	St.dev
$xkc_{i,c,t+n}$	1611159	0.283	0	0.45	521178	0.286	0	0.452	307164	0.293	0	0.455
$xkc_{i,c,t}$	1643646	0.282	0	0.45	556373	0.283	0	0.45	343511	0.287	0	0.452
$lnden$	4534615	1.78	1.803	1.395	1515765	1.819	1.852	1.371	940794	1.84	1.882	1.372
$lnwden$	4534615	-2.171	-2.03	0.701	1515765	-2.16	-2.019	0.691	940794	-2.151	-2.01	0.69
$lnhden$	5426423	-2.974	-2.93	1.333	1511648	-2.931	-2.88	1.303	940794	-2.921	-2.866	1.306
$lnden* xkc_{i,c,t}$	1639559	0.954	0	1.59	552813	0.952	0	1.584	339867	0.968	0	1.595
$lnwden* xkc_{i,c,t}$	1639559	-0.406	0	0.663	552813	-0.411	0	0.673	339867	-0.419	0	0.682
$lnhden* xkc_{i,c,t}$	1622935	-0.41	0	0.756	544417	-0.417	0	0.769	339867	-0.413	0	0.754

Source: Author's calculations

for convenience. The inclusion of time controls was jointly tested through conventional wald tests, leading with no exception to the rejection of the null hypothesis at 0.1% significance level. Given the nature of binary outcomes models, coefficients do not provide direct interpretation[7] of the impact on the probability of having RCA associated with changes in density or lagged RCAs. Instead, probabilities are obtained evaluating the logistic cumulative distribution function at particular values. This is the major limitation behind latent dependent variable models.

In order to provide a more meaningful interpretation of the results, odds ratios were displayed in addition to marginal effects, since in the context of logit models they allow a straightforward interpretation[8] [9] of the odds for a future RCA divided into static and transition products and allow us to confront the same specification over different time-horizons. Notice that for interactions, no marginal effect is produced. Rather, marginal effects of interactions are embedded in the individual marginal effects for the variables that generate the interaction. This is why table 5 does not assign marginal effects to the interactions.

[7] Only signs are valid indicators of the strength of the stimulus for future RCA.

[8] In particular, marginal effects (ME) of interaction terms may be somehow difficult to interpret in the context of non-linear models (Ai and Norton (2003), Norton et. al. (2004) , Corneliβen and Sonderhof (2009) and Greene et al. (2010)). MEs of interaction terms report variations from a global baseline while odds-ratios (i.e. multiplicative effects) disentangle effects departing from particular category's baseline. MEs have becomingly suppressed from interaction terms to be absorbed by individual explanatory variables marginal effects in the literature. This is also discussed in Buis (2010) and Newson (2003). Panel data non-linear models pose additional challenges on interpreting interaction effects. Unobserved group level variables are dropped out from the model, being captured in the group level variance term. MEs under these situations fix unobserved group variables at their means while averaging over observed explanatory variables. Marginal effects become computed in a predictive basis assuming different specifications according to the model to be estimated. Additionally, Drukker (2008) cited by Cameron and Trivedi (2010) arguments in favor of using PA models in non-linear models.

[9] MEs computed over latent variable FE models may mislead the "true" effects. We thank J.M.C. Santos Silva for pointing this out. Kitazawa (2012) proposes to calculate hyperbolic transformations for FE models allowing the calculus of average elasticities.

Information criteria (IC) for non-nested model comparison were obtained and are displayed in table 5. Akaike' (1974) IC and Schwarz' (1978) Bayesian IC favored unanimously crude density specifications over weighted density specifications in both in RRI and CP approaches for equivalent lag structure as the number of parameters is constant across specifications[10]. However, under CP context HK (2006, 2007) density definition appears to provide a better fit of the data. We can find here our third stylized fact highlighted by this paper.

As far as density is individually considered[11], when crude, scaled and weighted densities are confronted for equivalent approaches and time-lag structures, crude density specification applied to RRI approach shown to have the behavior most compatible with economic intuition (specs. 1, 6 and 11). This can be seen both in density coefficients or in corresponding marginal effects (elasticities) and odds ratios. A 10% increase in crude density, contributes, on average and ceteris paribus, to an increase of 1.25% in the probability of having future RCA in the short run, 2.15% in the medium run and 2.99% in the long run. Odds ratios provide similar conclusions some somehow less intuitive: a 1 unit increase in the logarithm of crude density (roughly 2.56 units on density evaluated at mean), induces an increase in the odds of having future RCA by 9% in the short run, 11,1% in the medium run and 12.7% in the long run. Opposite results were obtained for CP approach applied to crude density (specs. 3, 8 and 13). Here, the equivalent percentual variations in density led to variations of 2.39%, 1.91% and 1.55%, respectively in the long, medium and short run, in the probability of having RCA in a subsequent period. All the remaining specifications (weighted and scaled definition) surprisingly presented erratic patterns along time. In weighted run and the reverse case is verified under scaled specifications. Overall, density measures show therefore to fit reasonably well the data, showing to be highly significant in explaining future specialization patterns, translated in a stronger impact in future RCA in long run. However, crude density as a measure of connection between products that condensate the absolute sum of significant

[10] Comparisons including scaled densities and among different time-lag structures are not valid measures of the general quality fit of the model since different observations were included in the models. For similar specifications covering different time-lag structure this happens naturally as lagged observations are missing for the initial years in our database while for equal time-lag but different model specifications this happens since the FE estimator excludes observations with no within variation..

[11] For now we ignore interaction effects.

Table 5: Logit Fixed effects (FE) results for Short, Medium and Long Run

Impact	Method	Spec.	xkc	lnden	lnden*xkc	lnwden	lnwden*xkc	lnhden	lnhden*xkc	LL	AIC	BIC	Obs.
Short-run	Relatedness measure (RRI)	(1)	2.179*** *1.736* [8.837] (160.18)	0.086*** *0.125* [1.09] (15.44)	0.188*** – [1.207] (27.82)					-171935.6	343951	344401	569578
		(2)	2.818*** *2.39* [16.740] (100.48)			0.088*** *0.128* [1.092] (15.23)	0.095*** – [1.100] (11.96)			-172462.0	345004	345454	569578
	Proximity measure (CP)	(3)	1.306*** *0.959* [3.691] (42.33)	0.450*** *0.239* [1.568] (36.23)	0.335*** – [1.398] (37.15)					-204739.1	409558	410016	684207
		(4)	3.009*** *4.098* [20.264] (74.54)			0.389*** *0.911* [1.475] (20.58)	0.356*** – [1.427] (13.70)			-205948.8	411978	412435	684207
		(5)	3.049*** *3.729* [21.099] (168.86)					0.306*** *0.702* [1.358] (27.24)	0.361*** – [1.435] (35.80)	-20408.1	404896	405353	675492
Medium-run	Relatedness measure (RRI)	(6)	0.903*** *1.344* [2.468] (36.37)	.106*** *0.215* [1.111] (11.29)	0.150*** – [1.162] (12.74)					-49560.2	99148.4	99286	136722
		(7)	1.556*** *2.888* [4.740] (32.15)			0.097*** *0.378* [1.102] (10.04)	0.117*** – [1.124] (8.28)			-49658.3	99344.7	99482.2	136722
	Proximity measure (CP)	(8)	2.373*** *1.084* [10.727] (34.06)	0.438*** *0.191* [1.550] (18.39)	0.172*** – [1.189] (8.45)					-42574.7	85177.4	85318.2	172716
		(9)	2.764*** *4.278* [15.868] (33.35)			0.473*** *0.582* [1.605] (12.64)	-0.146** – [0.864] (-2.80)			-42754.3	85536.6	85677.4	172716
		(10)	3.422*** *2.81* [30.630] (86.06)					0.233*** *0.322* [1.263] (11.26)	0.249*** – [1.283] (11.28)	-41473.8	82975.5	83116	168868
Long-run	Relatedness measure (RRI)	(11)	0.344*** *0.873* [1.411] (10.00)	0.119*** *0.299* [1.127] (9.53)	0.064*** – [1.067] (4.04)					-23936.4	47890.7	47972.2	63355
		(12)	0.731*** *0.467* [2.078] (11.40)			0.094*** *0.132* [1.100] (7.31)	0.077*** – [1.080] (4.12)			-23961.0	47940	48021.4	63355
	Proximity measure (CP)	(13)	2.601*** *1.288* [13.480] (25.06)	0.303*** *0.155* [1.350] (9.12)	0.165*** – [1.179] (5.43)					-18082.6	36183.1	36267.2	84750
		(14)	3.062*** *3.322* [21.360] (26.37)			0.375*** *0.359* [1.455] (7.07)	-0.071 – [0.932] (-0.98)			-18129.0	36276.1	36360.2	84750
		(15)	3.535*** *3.812* [34.312] (57.17)					0.408*** *0.654* [1.504] (10.68)	0.272*** – [1.312] (7.63)	-18043.8	36105.5	36189.7	84750

Logit coefficients are predictive marginal effects of a positive outcome conditional on one positive outcome within group. [Odds ratio are reported in squared brackets.]
Marginal effects in italics. Z-statistics in parentheses (* $p<0.05$, ** $p<0.01$, *** $p<0.001$) Standard errors use observed information matrix (OIM).
AIC and BIC are respectively Akaike's (1974) and Schwarz's (1978) information criteria. Time controls included in all estimates.

inward impacts proved to offer a more reasonable behavior of structural transformation over time while Information Criteria favors these specifications for RRI approaches. This is our fourth stylized result.

Density interaction terms display positive coefficients' signs for Crude and Scaled densities in all time-lag structures, meaning that density has prominent role in explaining static behavior (i.e. maintenance of RCA over time) rather than transitions from underdeveloped and boundary products. Marginal effects as computed are not a valid indicator of these differences since they are (correctly) embodied in the density variable marginal effect[12]. Odds ratios were then computed to validate comparisons between transition and static products along time and are presented in table 5 in squared brackets[13]. Irrespectively of the time horizon under analysis, the gap between the probability of sustaining RCA and the probability of countries to develop RCA in products without RCA in a previous period, shrinks for longer time horizons. This is a consistent result for crude density equations for CP (specs. 3, 8 and 13) and for RRI approach (specs. 1, 6 and 11) and also for weighted density specifications for CP (specs. 4, 9 and 14). For instance, differences in odds ratios' magnitudes range from 2.192 in the short run to 1.592 in the long run for Crude density CP specifications (specs. 3, 8 and 13), meaning that for a unit increase in the logarithm of crude density and a given product in the short run, countries with prior RCA in that product have 2.19 times more probability of sustaining comparative advantage in the next year than countries without prior RCA have of developing it within the same time period. Taking the same specification this gap between products with and without previous RCA is reduced to is 1.8 times in the medium run and 1.69 times in the long run. These results suggest that reallocation of resources and assets into the production of alternative products with higher density (i.e. density for transition products) takes some time to produce effects such that they are strong enough to overcome inertia favoring maintenance rather

[12] See explanation in footnote 7.

[13] For continuous variables, the odds ratio does not compare with a baseline or control group. Valid interpretations are obtained by comparing $exp^{\beta \times q}$ and $exp^{\beta \times (q+1)}$ where q is given by any value of ln(density). Given the different metrics behind the alternative density definitions, comparisons across them are not valid. Thus odds are only a valid way of comparing differences along time within the same estimated equation. Density differences in transition versus static products are obtained by the multiplication of odds ratios in the density and interaction terms. This obeys to the odds-ratios multiplicative property. Multiplication results are suppressed for simplicity.

transformation in specialization patterns. Our fifth stylized fact is that although density is more decisive in explaining maintenance of present RCAs than it is in contributing for the development of new RCAs, this gap is remarkably shrunk in the long run.

In all specifications performed lagged RCA proved to be a strong predictor of future probability of having RCA[14]. this path dependence is shown to be not only smaller for models controlling for RRI derived density than for models controlling for CP derived density, as the persistency of their autocorrelation function tends to decay as we move towards long-run impacts. The implicit reasoning is that the impact of inertia in explaining the structure of comparative advantages is remarkably reduced when time is given to firms to perceive and adjust investments such that they can reach some production level enough for a country to have developed a comparative advantage. The dynamics behind the process of structural transformation in the product space is essentially static in the short run, becoming progressively more flexible in the long run. How to verify this?

The odds[15] for the probability of maintaining a previously obtained RCA relatively to the probability of developing a comparative advantage in a new product decrease from 10.67 (short run) to 2.87 (medium run) and 1.7 (long run) for crude density specifications using RRI approach (specs. 1, 6 and 11). The same is to say that in the short run products with past RCA have 10.7 times more chances of sustaining RCA in than countries without previous RCA have of developing it, while this difference is reduced to 1.7 in the long run. Similar results are obtained when crude density is measured through CP approaches (specs. 2, 7 and 12). RCA statics proved not have a stable decreasing impact under CP approaches throughout time as it is intuitively expected. Altogether, these findings present strong evidence towards RCAs' time persistent behavior, strengthen further the evidence towards a strong inertia pattern in density impacts mostly in the short and medium run. RRI approaches appear to capture more

[14] Since binary outcomes models are being used, this is only directly evident from the magnitude of Z-statistics for previous RCA dummy variables in table 5**.**

[15] Construction and interpretation of odds ratio done as in footnote 12. Differences in probability of developing subsequent RCA relatively to the probability of sustaining prior RCA is given by the multiplication of odds ratios for the dummy variable of lagged RCA and the interaction term. This obeys to the odds-ratios multiplicative property. Multiplication results are suppressed for simplicity.

accurately this pattern over time. This is our sixth and last stylized result.

8. Conclusions

Departing from previous works by HK (2006, 2007) and FS (2011) this paper represents an attempt to bring some light on the validity of Conditional Probabilities and Revealed Relatedness Index as measures of product connectivity. Additionally, a new measure of product density was proposed and compared against alternative concepts in determining future specialization patterns for different time horizons. Some stylized results were produced but remarkable dissimilarities behind CP and RRI methodological approaches and econometric applicability severely limited reaching clear-cut result favoring one approach.

Non-parametric results presented in section 7.1 followed previous tests conducted by HK (2006, 2007) and Hidalgo et.al. (2007) and confirm prior findings in which structural transformation does indeed depend on product density. Discovery ratios comparing average density for transition and underdeveloped products shown strong evidence supporting our crude density measure as best capturing subsequent RCAs.

Econometric specifications presented in section 7.2. provide mixed evidence. Information criteria invariably elected crude density specifications as providing a more robust fit of specialization patterns' dynamics than the concept proposed by FS (2011) under CP and RRI approaches for short, medium and long run as we have measured them. Despite a weaker economic reasoning behind HK (2006, 2007) density definition in our view, it proved to provide the best fit under the CP approach also proposed by the authors.

Overall, lagged crude density under RRI approach shown to have produced the most consistent effects in the probability of future RCA along time. Density has a reinforced explanatory power over specialization patters for longer time horizons where firms have time to adjust their decisions and reallocate assets into the production of different goods.

The inclusion of an interaction term between density and prior RCA allowed to conclude that the probability of a country maintain a RCA is strikingly higher that the probability of a country developing RCA in new products even though this difference is relaxed in the long run. Density odds for future RCA proved, however, to be reduced by about 11% between the short and the long run for crude density in RRI specification and by about 80% for CP specifications. Density is determinant in explaining specialization patterns, particularly under an inertia context where products have historically been produced with comparative advantage. In the long run inertia in density impacts for transition and static products is drastically loosened.

Mostly under CP approaches, path dependency static behavior in specialization patterns ignoring density impacts was proved to be remarkably strong. In fact only RRI specifications displayed a decreasing static impact of current RCA structure in future specialization patterns. Here, the odds of having RCA in a subsequent period given contemporaneous RCA decrease from 10.7 (crude density) and from 18.4 (weighted density) in the long run to respectively 1.7 and 2.2 in the long run.

Overall, this paper presents somehow strong evidence favoring RRI approaches over CP approaches and elected our crude measure facing alternative concepts as the one presenting a behavior more compatible with economic intuition.

9. Limitations and Further Research

While an eminently empirical paper that departs from the postulate whereby products are related in the product space in terms of capabilities and assets without a formal model for structural transformation, this work is somehow conditional on hypothesis accepted but not directly tested. Models of learning-by-doing, cost discovery and information spillovers are the main references for the theoretical framework presented by HK (2006).

Substantial presumption and hypothesis taken as given should always be subject to discussion: (i) whether historical trade disaggregated data has been reported with acceptable accuracy, (ii) whether CPs and RRIs are valid concepts of product connectivity given that they are simply measured or regressed in a contemporaneous basis, (iii) whether a bounded product space assuming vertical improvements but neglecting horizontal innovations are representative of the product space empirically observed in daily routines, (iv) weather it makes sense to exclude non-tradable goods and internationally traded services from models of structural transformation in a globalized world, (v) whether firms can effectively perceive new opportunities in the product space if they rationally (have ability to) guide their investment decisions based in density and income content criteria, just to name a few, are questions that should always make academia to question the extent to which the models it proposes are suitable, tough partial, representations of reality.

Further research may extend this work by integrating product-based density measures with product's sophistication (Prody) and country's income content implicit in their export basket (Expy) in order to verify whether structural transformation is being made towards upscale products, benefiting nation's economic performance. In addition, drawing a framework where future specialization patterns are conditional on variables with some predictive power (i.e. Prody, Expy, GDP, industrial product classification) allow empirical research to confront past observed structural dynamics with an out-of-sample forecasting experiment or an alternative partial adjustment model where patterns of specialization evolve as a fraction of the predicted evolution.

10. References

[1] **Aghion**, P. Howitt, P. 1992. "A model of growth through creative destruction". *Econometrica* 60(2): 323-351.

[2] **Akaike**, H. 1974. "A new look at the statistical model identification". *IEEE Transactions on Automatic Control*, 19(6): 716–23.

[3] **Amemiya**, T. 1981. "Qualitative response models: A survey". *Journal of Economics Literature*, 19: 1483-1536.

[4] **Arrow**, K. 1962."The economic implications of learning by doing". *Review of Economic Studies*, 29(3): 155 - 173.

[5] **Badibanga**, T., Diao, X., Roe, T., Somwaru, A. 2009. "Dynamics of Structural Transformation: Na Empirical Characterization in the Case of China, Malaysia, and Ghana". IFPRI Discussion Paper No. 00856, April.

[6] **Balassa** B. (1965) "Trade Liberalization and Revealed Comparative Advantage." The Manchester School of Economic and Social Studies 3(2), 99-123.

[7] **Barro**, R. J., Sala-i-Martin, Xavier. 1997. "Technological Diffusion, Convergence and Growth". *Journal of Economic Growth*, Spinger, vol. 2(1), 1-26.

[8] **Cabral**, L. 2000. "Stretching firm and brand reputation" *RAND Journal of economics*, 31(4): 954-73.

[9] **Cameron**, A., Trivedi, P. 2010. "Microeconometrics Using Stata". Texas: Stata Press.

[10] **Chenery**, H., Taylor, L. 1968. "Development Patterns: Among Countries and Over Time". *The Review of Economics and Statistics*, 50(4): 391-416.

[11] **Dietzenbacher**, E., Lahr. 2001 "Input-output analysis: frontiers and extensions" Palgrave, NY

[12] **Feenstra**, R., Lipsey, R., Deng, H., Ma, A., Mo, H. 2005. "World Trade Flows: 1962-2000". NBER Working Paper No. 11040, January.

[13] **Felipe**, J., Kumar, U., Abdon, A., Bacate, M. 2012. "Product Complexity and Economic Development". *Structural Change and Economic Dynamics,* 23: 36-68.

[14] **Freitas**, M., Mamede, R. 2011."Structural Transformation of Portuguese Exports and the Role of Foreign-Owned Firms: A Descriptive Analysis for the period 1995-2005". *Notas Económicas,* Junho: 20-43.

[15] **Freitas**, M., Salvado, S. 2011. "Industry Similarities and Upscale Opportunities for Portugal: an Empirical Assessment Based on 2005 Trade Data". Working Paper, May.

[16] **Grossman**, G. & E. Helpman. 1989. "Product development and international trade" *The Journal of Political Economy* 97(6): 1261-1283.

[17] **Grossman**, G. & E. Helpman. 1991. "Quality ladders in the theory of growth" *Review of Economic Studies* 58(1): 43-61.

[18] **Hausmann**, R. 2008. "In Search of the chains that hold Brazil back". CID Working Paper No. 180, September.

[19] **Hausmann**, R., Hidalgo, C. 2010. "Country Diversification, Product Ubiquity, and Economic Divergence". CID Working Paper No. 201, October.

[20] **Hausmann**, R., Hidalgo, C. 2011. "The Network Structure of Economic Output". *Journal of Economic Growth*, 16: 309-42.

[21] **Hausmann**, R., Hidalgo, C. et al. 2011. "The Atlas of Economic Complexity: Mapping Path to Prosperity". New Hampshire: Puritan Press.

[22] **Hausmann**, R., Hwang, J., Rodrik, D. 2007. "What you export matters". *Journal of Economic Growth,* 12(1): 1-25.

[23] **Hausmann**, R., Klinger, B. 2006. "Structural Transformation and Patterns of Comparative Advantage in the Product Space". CID Working Paper No. 128, August.

[24] **Hausmann**, R., Klinger, B. 2007. "The Structure of the Product Space and the Evolution of Comparative Advantage". CID Working Paper No. 146, April.

[25] **Hausmann**, R., Klinger, B. 2007. "Structural Transformation in Chile". Quantum Advisory Group, Analytics for a Discontinuous World, June.

[26] **Hausmann**, R., Klinger, B. 2008. "Achieving Export-Led Growth in Colombia". CID Working Paper No. 112, September.

[27] **Hausmann**, R., Klinger, B. 2008. "Growth Diagnostics in Peru". CID Working Paper No. 181, September.

[28] **Hausmann**, R., Klinger, B. 2010. "Structural Transformation in Ecuador". Inter-American Development Bank, Country Department Andean Group, Policy Brief No. 112, April.

[29] **Hausmann**, R., Rodrick, D., Sabel, C. 2008. "Reconfiguring Industrial Policy; A Framework with an Application to South Africa". CID Working Paper No. 168, May.

[30] **Hidalgo**, C. 2009. "The Dynamics of Economic Complexity and the Product Space over a 42 year period". CID Working Paper No. 189, December.

[31] **Hidalgo**, C., Klinger, B., Barabási, A., Hausmann, R. 2007. "The Product Space Conditions the Development of Nations". *Science*, 317: 482-487.

[32] **Hirschman**, A.1958 "The Strategy of Economic Development". New Haven, Conn,:Yale University Press

[33] **Jaffe**, A. 1986 “Technological opportunity and spillovers of R&D: evidence from firm’s patents, profits and market value”. *American Economic Review*, 76(5):984-1001.

[34] **Jankowska**, A., Nagengast, A., Perea, J. 2012. “The Product Space and The Middle-Income Trap: Comparing Asian and Latin American Experiences”. OECD Development Center Working Paper No. 311, April.

[35] **Jovanovic**, B., Nyarko, Y. 1996. “Learning by doing and the choice of technology”. *Econometrica*, 64(6): 1299-1310

[36] **Kaldor**, N. 1967. “Strategic Factors in Economic Development”. New York State School of Industrial and Labor Relations, Cornell University, Ithaca, NY.

[37] **Kitazawa**, Y. 2012. “Hyperbolic Transformation and Average Elasticity in the Framework of the Fixed Effects Logit Model”. *Theoretical Economics Letters*, 2: 192-99.

[38] **Krugman**, P., Venables, J., 1996. "Integration, specialization, and adjustment" *European Economic Review*, Elsevier, vol. 40(3-5): 959-967

[39] **Kuznets**, S. 1966. “Modern Economic Growth”. Yale University Press, New Haven, CT.

[40] **Lall**, S. 2000. “The Technological Structure and Performance of Developing Country Manufactured Exports, 1985-98”. *Oxford Development Studies*, 28(3): 337-369.

[41] **Leamer**, E. 1984. “Sources of Comparative Advantage: Theory and Evidence”. Cambridge MA: *The MIT Press*.

[42] **Lewis**, A. 1955. “The Theory of Economic Growth”. Irwin, Homewood, IL.

[43] **Matsuyama**, K. 1995. “Complementarities and Cumulative Processes in Models of Monopolistic Competition”. *Journal of Economic Literature*, 33(2): 701-29.

[44] **Porter**, M. 1990. “The Competitive Advantage of Nations”. *Harvard Business Review*, 68(2): 73-93.

[45] **Porter**, M. 1998. “Clusters and Competition: New Agendas for Companies, Governments and Institutions”. Harvard Business School Working Paper, No. 98–080, March.

[46] **Rodrick**, D. 2004. “Industrial Policy for the Twenty-first Century”. Discussion Paper No. 4767, November.

[47] **Romer**, P. 1986. “Increasing Returns and Long Run Growth”. *Journal of Political Economy*, 94(5): 1002:1037

[48] **Rostow**, W. 1956. “The Take-Off Into Self-Sustained Growth”. *The Economic Journal*, 66(261): 25-48.

[49] **Rostow**, W. 1959. “The Stages of Economic Growth”. *The Economic History Review*, 12(1): 1-16.

[50] **Schwarz**, G. 1978. “Estimating the dimension of a model”. *Annals of Statistics*, 6: 461–464.

[51] **Segerstrom**, P. 1991. “Innovation, Imitation and Economic Growth”. *Journal of Political Economy*, 99(4): 807-827.

[52] **Stokey**, N. 1988. “Learning by Doing and the Introduction of New Goods”. *The Journal of Political Economy*, 96(4): 701-717.

[53] **Van Pottelsberghe de la Potterie**, B. 1997. “Issues in assessing the effect of interindustry R&D spillovers”. *Economic Systems Research*, 9(4): 331-356.

[54] **Vitola**, K., Dãvidsons, G. 2008. “Structural Transformation of Exports in a Product Space Model”. Latvijas Banka Working Paper, April.

[55] **Wacziarg**, R., Welch, K. 2003. “Trade Liberalization and Growth: New Evidence”. NBER Working Paper No. 10152, December.

[56] **Wang**, Z., Wei, S., Wong, A. 2010. “Does a Leapfrogging Growth Strategy Raise Growth Rate? Some International Evidence”. ADB Working Paper Series on Regional Economic Integration No. 47, April.

[57] **Young**, A. 1991. “Learning by Doing and the Dynamic Effects of International Trade”. *The Quarterly Journal of Economics*, 106(2): 369-405.