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EMPLOYMENT AND EXPORT SPECIALIZATION PATTERNS VERSUS GDP *PER CAPITA* PERFORMANCE - UNIFYING APPROACH

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Abstract

The underneath motivation of this study is based on the findings confirming that specialisation is non neutral on a country's growth performance. Consequently, it seems important to analyse the evolution of specialization patterns along the process of economic development. The scope of the paper is twofold: first of all, it aims at understanding if the evolution of employment specialisation is reflected in the same manner in trade specialisation patterns. Secondly, it explores the link between the degree of specialization on one side and cross country GDP *per capita* performance on the other. The paper challenges other empirical studies present in the specialization literature and contributes by presenting *simultaneously* the evolution of sectoral dispersion patterns emerging from employment and trade data. The sample of countries (32 world economies on different stages of economic development), the time span (1980 onwards) and the sectoral composition of the two datasets are retained constant. By comparing the results obtained with various inequality indicators, including a wide range of absolute and relative measures, we demonstrate the relevance of the methodological setting used for the assessment of economic activity dispersion. Next, we perform nonparametric and semiparametric estimations in order to reveal the 'specialization curve' which describes the evolution of specialization along the development path. We find a support for nonlinear relationship between the two dimensions of specialization and GDP *per capita* levels, with a tendency towards despecialization in the initial phase of economic growth.

Keywords: industrial specialisation, trade specialisation, comparative advantage

JEL: F16, J31, L6

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0. INTRODUCTION

Is the degree and the nature of specialization important from the point of view of GDP per capita performance? Both theoretical (Fujita, Krugman and Vanables, 1999; Grossman and Helpman, 1991; Lucas, 1998; Krugman and Venables, 1990; Krugman, 1991) and empirical (Bensidoun *et al.*, 2001; Plumper and Graff, 2001) literature states that the nature of specialization is non neutral on countries' development. However, existing contributions do not provide a clear and systematic evidence on the relationship between various dimensions of an economic structure of a country and its GDP *per capita* expansion.

One of the main problems is that the concept of specialization can be analysed from two very different perspectives: as a production/employment phenomenon or as a trade phenomenon. Consequently, it is not perfectly clear if the specialization - GDP *per capita* relationship has the same nature when looking at the structure of the economy from the 'internal' or 'external' perspective. The former can be described by the structure of labor force or production (output or value added); the latter manifests itself in the structure of trade (exports).

Most empirical studies are quite selective and present results based either only on easily available trade data (Amable, 2000; Bensidoun *et al.*, 2001; de Benedictis *et al.*, 2006; Hausmann *et al.*, 2005; Laursen, 1998; Plumper and Graff, 2001; Proudman and Redding, 2000) or on rather limited industrial production/employment data (Amiti, 1999; Imbs and Wacziarg, 2003; Kim, 1995; Koren and Tenreyro, 2004; Redding, 2002). The overview of existing evidence on the evolution of specialization gives very mixed picture, for example showing either increasing (Amiti, 1999) or constant (ECB, 2004) specialization trends observed in European industrial statistics. At the same time, decreasing specialization trend emerges from the analysis of international trade data (de Benedictis *et al.,* 2006; Laursen, 1998; Aiginger *et al.,* 1999). However, the differences in data sets, time periods and measurement techniques used by different authors make the comparisons between their results rather difficult.

Given these observations, two things seem to be important: first of all, to find out if the differences between the conclusions reached in various studies stem only from the differences in empirical settings. It can be done exclusively by applying the same procedure and methodology to various (but transformed into similar structures in order to allow for parallel comparisons) international data sets. To our knowledge, no systematic comparison of this kind has been made so far.[1] Secondly, we aim at revealing the nature of a relationship between various aspects of specialization on one side and GDP *per capita* on the other.

This study challenges the aforementioned limitations of the existing empirical evidence and proposes a unifying approach. We adopt the concept of specialization understood as the degree of inequality in the distribution of economic activity across manufacturing sectors. Two dimensions of specialization are analysed in parallel – the first one emerging from employment data and the other described by changes in countries' export structures. The analysis draws on the manufacturing industrial data for 32 world economies on various stages of economic development and goes back to the year 1980. The results obtained for employment and trade specialization are directly comparable thanks to the thorough reorganisation of the original datasets, the maintenance of the same set of countries and sectors as well as the application of a unique classification scheme (ISIC rev.2, 3 digit). Moreover, the use of a large set of specialization measures (both absolute and relative) allow us to check the robustness of the results according to the methodological and computational setting.

The structure of the paper is as follows: the first section presents a general overview of the theoretical and empirical considerations on the link between specialization and output *per capita* performance. The second part describes in details the approach followed in this paper and the composition of a dataset.[2] In the next, third section we confront employment and trade (export) patterns of specialization in manufacturing. It is evident that the choice of a particular index can influence the results – those obtained with various measures of specialization belonging to the same group

[1] Some specialization studies include 'sensitivity analysis' which extend the basic dataset and compare the outcomes obtained with various types of data (value added, output, employment and trade). However, as a result of the differences in the time span, the set countries or the level of sectoral disaggregation it is impossible to confront *directly* the growth effects of trade and employment specialization. Brülhart (1998 and 2001) matches employment and export data to study geographical location patterns in the EU; Midelfahrt-Knarvik *et al.* (2000) use EU production and trade data but they do not explore the link between emerging specialization patterns and GDP *per capita* performance.

[2] The original employment and export data series (coming from UNIDO Industrial Statistics Database and UN Comtrade Database available through World Bank's WITS, respectively) have been thoroughly analysed in order to find out how to construct the panel including the maximum number of observations and allowing for as homogeneous analysis as possible. Our general critical observation is that many previous studies seem to base the results on the datasets of a very poor quality which suggests that their conclusions should be treated with caution. The panel we choose goes back to 1980 and includes the data for 32 world economies for which the complete (or almost complete) employment and export data series were available. We have chosen to follow the rule of analysing complete data series for a smaller set of countries, rather that including a large number of countries but having data with a lot of missing values - it would have influenced the quality and the reliability of the final conclusions.

(absolute or relative) are highly correlated but the correlations are not so high *between* the two groups. Section four is dedicated to the econometric analysis of specialization - GDP *per capita* nexus: the outcomes obtained previously for the individual countries with regard to two distinct dimensions of manufacturing specialization are matched with their overall economic performance. We are particularly interested in the evolution of specialization patterns along the development path. In order to avoid imposing the nature of a relationship between the dependent and independent variables we have chosen to apply non parametric lowess procedure, as well as semi parametric GAM estimation. Traditional parametric estimation is used as a supporting tool. Thanks to the inclusion of controlling variables (country fixed effects) we can interpret the evolution of specialization trend as a behaviour of a 'typical' country along its development path.

Concluding remarks are presented in the last fifth section. We find a support for a nonlinear relationship between specialization and GDP *per capita* level, with a tendency towards despecialization at the initial phases of economic development. It is confirmed for both export and employment specialization. High degree of specialization is associated with low levels of GDP *per capita* but as countries develop, the tendency towards more equal distribution of economic activity across manufacturing sectors is expected.

1. THEORETICAL AND EMPIRICAL BACKGROUND

Specialization can be roughly defined as "the extent to which a given country specialises its activities in a small number of industries or sectors" (Aiginger *et al.*, 1999). Consequently, a country is said to be *specialised* in a particular industry if this industry has a high share in the total country manufacturing. The production structure is said to be highly specialised if a limited number of industries account for a large share of total production.[3] Analogical definitions can be formulated for export or trade specialization.

[3] Note the difference with the concept of concentration defined as "the extent to which activity in a given industry is concentrated in a few countries" (Aiginger *et.al*, 1999). The link between sectoral specialization and geographical concentration is presented in the *New Economic Geography* models (Krugman, 1991; Krugman and Venables, 1990; Fujita, Krugman and Vanables, 1999). In Krugman's model, which highlights the existence of economies of agglomeration, geographic concentration of economic activity may imply specialization. It happens if agglomeration forces (such as the existence of specialised suppliers or specific labor markets) originate from spillovers which affect firms belonging to the same industry.

Economic theory does not offer one unique explanation of the relationship between specialization and GDP *per capita* performance; in fact there are a few streams of literature which deal with this issue. Traditional approach originating from Solow-type setting predicts the impact of specialization on growth through the mechanism of more efficient allocation of resources between capital and labor intensive activities. New growth theories stress the importance of endogenous factors influencing economic performance and having long-run growth effect (rather than only a transitional level effect typical for classical theories). Within the class of new growth models two main approaches can be identified (Dowrick, 1997): the *Smithian* approach and the *Ricardian* approach. The former (Rivera-Batiz and Romer, 1991; Rivera-Batiz and Xie, 1993) is based on the importance of increasing returns to scale and the overall level of specialization. The latter (Grossman and Helpman, 1991) underlines the consequence of differences in innovation potential across distinct sectors and demonstrates that the nature of specialization is important - different sectors have different impact on productivity and growth performance. Countries specialising in high tech, dynamic and innovative industries would experience higher rates of growth than those locked in the production of traditional goods.

According to the vision presented in the literature on endogenous growth (Aghion and Howitt, 1992; Lucas, 1998) sectoral composition influences economic development through the impact on productivity growth. Again, as in new trade theories setting, different sectors may have different productivity potentials and major specialization in high productivity branches can lead to better performance of the economy on the whole. Secondly, structural change and shift of resources from low productivity towards high productivity sectors can be an important font of economic growth dynamics. The first effect is of a static nature while the second one is linked to the dynamic changes which regard the alteration of the economic structure of a country. Therefore, it is important not only *if* the country specialises but *in what*. According to this point of view, a country which specialises in a 'growth-engine' sector, characterised by strong potential for technological progress, can experience faster growth than countries which are locked in a production of low-tech goods. These predictions are in line with the class of growth literature which emphasises the importance of technological change, perceived as the key determinant of economic growth (for a complete overview see Dosi *et al.,* 1990). The impact of technological transformation on a country's performance includes a whole series of effects: higher levels of economic activity and higher national shares in world production, improvements in terms of balance of payments constraints, changes in sectoral composition of output and structural shifts towards sectors with higher value added, rise in allocative efficiency.

Trade literature offers contrasting views on the link between export and economic growth. According to the traditional approach a country's trade specialization patterns do not influence its performance measured in economic terms (Krugman, 1994). Recent contributions challenged this hypothesis both theoretically and empirically. It has been shown that industrial sectors are not identical in their influence on economic performance (Plumper and Graff, 2001). Also the nature of exported products can be important (Hausmann *et al.*, 2005) because export in certain goods may have a significant impact on the economic development and, consequently, competitive advantage in technology intensive goods can promote better output *per capita* performance.

Similarly, the theoretical literature on the effects of economic integration presents various contrasting views regarding specialization. Classical approach, based on the assumptions of perfect competition, constant returns to scale and homogeneity of goods, suggests that the elimination of obstacles to trade should lead to major inter-industry trade and divergence in production structures in the integrating countries. The fundamental concept here is the notion of comparative advantage according to which each country eventually specialises in producing those goods in production of which it is more efficient. Ricardian theory (Ricardo, 1817) focuses on the differences in productivity or technology as the main determinants of specialization. H-O (Heckscher, 1919; Ohlin, 1933) comparative advantage stems from the differences in relative factors endowments and works without any mobility of factors of production across nations. Trade liberalisation leads nations to specialize in the production of goods which require those factors they are relatively abundant of and this mechanism eventually leads to inter-industry pattern of specialization.

The story can be very different when factors of production are allowed to move across borders and when trade is not costless. New Trade Theory (Krugman, 1991) allows for the existence of imperfect competition on product markets, increasing returns to scale and network effects. Contrastingly to H-O setting, the result is less pronounced inter-industry specialization, more intra-industry trade and convergence in industrial structures between countries. Such tendency derives from the fact that sometimes the structure of the market is better characterised by the presence of monopolistically competitive firms which tend to specialise in producing different varieties of similar products. As a result intra-industry pattern of specialization gains importance and reduces cross-country sectoral specialization (measured at the aggregate industry level).

The results obtained in the empirical studies are far from being homogeneous and conclusive, even though it is rather clear that the nature of specialization in non neutral on countries' economic performance. Amable (2000) shows that inter-industry trade and comparative advantage in electronics have a positive impact on productivity growth. Bensidoun *et al.* (2001) demonstrate that growth effect of international integration depend on the type of products countries are specialised in. The main problem, however, is that while some authors find increasing (Amiti, 1999; Brülhart, 2001) or constant (ECB, 2004) specialization trends resulting from the industrial statistics, decreasing specialization trends emerge from the analysis of international trade data (Aiginger *et al.,* 1999; de Benedictis *et al.,* 2006; Laursen, 1998). Increase in the degree of production specialization does not necessarily imply rising export (or trade) specialization – in fact some evidence from the European countries demonstrates that two aspects of specialization may evolve in opposite directions with rise in production specialization and the tendency of de-specialization in exports during the 1990s (Aiginger *et al.*, 1999). Consequently, it is not perfectly clear what is the nature of the relationship between specialization and *per capita* GDP. Finally, it has been demonstrated that economies may undergo different stages of industrial specialization (first diversifying and then specialising again) as their economies grow (Imbs and Wacziarg, 2003).

The contradictions between various studies based on trade and industrial data recall for a unifying approach, providing an homogeneous empirical setting and enabling to perform a complete, fully comparable analysis of the evolution of various aspects of specialization along the GDP *per capita* development path and its link with inequality. This is the main scope of this paper.

2. VARIOUS DIMENSIONS OF SPECIALIZATION

Unifying approach

Empirical measures of industry size and 'industrial specialization' make use of output, value added or employment data. Patterns of 'trade specialization' are usually based on the measures drawing from export data *i.e.* widely used Balassa Revealed Comparative Advantage index (Balassa, 1965) but some authors use both import and export data series constructing so-called two flow or net trade indices *i.e.* Michaely index (Michaely, 1962) or Lafay index (Lafay, 1992).[4] Trade data is available at much more disaggregated level, allowing for deeper analysis, and usually is of a better quality that employment data.

As demonstrated above, empirical results obtained in different studies vary and this fact may have origins in the differences in the data used, time and countries' coverage or measurement techniques. Consequently, it is very difficult to make direct comparisons between the results based on industrial and trade statistics because the size and content of samples vary across studies, not to mention the levels of disaggregation and indicators used. The approach adopted here aims at providing an homogeneous empirical setting for the analysis of the relationship between the two types of specialization (the first one emerging from employment data and the other from export statistics). Afterwards, we proceed towards detecting the evolution of these two dimensions of manufacturing specialization along the development path of *per capita* GDP.

Data and panel composition

Main problems are linked to limited data availability which influenced strongly the final choice of countries, level of disaggregation and years included in the analysis. Considering a broad sample of countries is surely an advantage - for example trade patterns are more likely to appear among partners characterised by relatively high level of dissimilarity. Analysis based on highly disaggregated data provides much more

[4] See Iapadre (2003) for an overview of the taxonomy of statistical indicators for the analysis of international trade and production and De Benedictis and Tamberi (2001), Iapadre (2001) or Laursen (1998b) for a description of various measures of specialization.

information on specialization than aggregated industry-level data.[5] In addition to these difficulties, changes in specialization patterns and their relation with the evolution of output *per capita* are classical themes which require long run analysis.

However, it is practically impossible to have a balanced panel dataset including *both* trade and industrial sectoral statistics for very large sample of countries, covering long period of time and at high level of sectoral disaggregation. The final selection of countries and the time span is based on the thorough comparison of the two basic data sources we use – United Nations Industrial Statistics Database (UNIDO) and United Nations Commodity Trade Statistics Database (UN COMTRADE).[6] We have analysed the coverage of employment, value added and output series for every single country present in UNIDO Rev.2 database and what emerges is that sectoral statistics are complete only for a small sample of world economies.[7] Our general critical observation is that many existing empirical studies exploring the link between specialization and development seem to base the results on the datasets of a very poor quality which suggests that their conclusions should be treated with caution.

In the end, our analysis covers 32 world economies(Table 1) at various levels of GDP *per capita* for which we were able to obtain complete disaggregated industrial and export statistics.[8] The time span of more than two decades (we start the analysis with the data for 1980) is long enough to reveal some changes in production or trade structures and to link the emerging specialization patters with economic performance. Export data would have been available for the years preceding the 1980s (theoretically, UN COMTRADE reports data since 1962) but we wanted to have homogeneous trade and industrial statistics for the overlapping time periods. Hence, export statistics cover 26 years (1980-2005) while employment data is reported for 21 years (1980-2000). The analysis is restricted to manufacturing sectors only (ISIC codes 311 to 390 as in

[5] For example, 3-digit ISIC code 384 ('Manufacture of transport equipment') incorporates both 'Manufacture of motorcycles and bicycles' (3844) and 'Manufacture of aircraft' (3845). The latter includes the production of aircraft engines or space vehicles, surely products more advanced technologically than saddles, seat posts and frames classified under 3844 code. ISIC 3-digit and even 4-digit classification hide these differences thus lower levels of aggregation ignore a part of intra-industry product heterogeneity

[6] There are alternative fonts of disaggregated data, surely of a good quality (such as: OECD STAN or EUROSTAT PRODCOM) but they refer to a restricted set of developed countries. Instead, the scope of our analysis was to explore specialization-growth nexus in a broader context, taking into account as many world economies at different stages of economic development as possible.

[7] By 'complete' we mean that for a given year the employment, output or value added data is available for at least two thirds of ISIC Rev.2, 3-digit sectors. Theoretically, UNIDO database includes industrial statistics for more than 160 world economies. In reality, out of 150 countries we have looked at, only one-third report complete employment series for more that 20 years between 1980 and 2005. Complete output and value added data series are available for 20 years or more (always between 1980 and 2005) only in case of little more than one-fourth of all countries (42 and 41 out of 160, respectively).

[8] We do not report the results of export specialization for those countries/years for which in a given year the data was missing for more than one-third of the sectors.

Appendix 1) which are expected to be less dependant on geographical and climatic conditions.

Table 1. List of countries

BOL Bolivia[1)]	***FIN*** Finland	***IRN*** Iran, Islamic Rep. of [c) 5)]	***MAC*** China, Macao SAR
CAN Canada	***FRA*** France	***ISR*** Israel	***NOR*** Norway
CHL Chile[2)]	***GBR*** United Kingdom	***ITA*** Italy	***PRT*** Portugal
CHN China [a) 3)]	***HKG*** China, Hong Kong	***JOR*** Jordan	***SGP*** Singapore
COL Colombia	***HUN*** Hungary [b)4)]	***JPN*** Japan	***SWE*** Sweden
CYP Cyprus	***IND*** India	***KEN*** Kenya	***TUR*** Turkey [e)7)]
ECU Ecuador	***IDN*** Indonesia	***KOR*** Korea, Rep. of	***URY*** Uruguay [8)]
ESP Spain	***IRL*** Ireland	***KWT*** Kuwait [d) 6)]	***USA*** United States of America

a) not in export A dataset 1980-1984; b) not in export A dataset 1980-1991; c) not in export A dataset1980-1996; d) not in export A dataset1980-1986 and 2002-2005; e) not in export A dataset 1980-1984.
1).not in export B dataset 1980-1990; 2) not in export B dataset 1980-1982; 3) not in export B dataset 1980-1986; 4) not in export B dataset 1980-1991; 5) not in export B dataset 1980-1996; 6) not in export B dataset 1980-1986 and 2000-2005; 7) not in export B dataset 1980-1984; 8) not in export B dataset 1980-1982.

The very positive characteristics of the dataset which we use is the fact that both for employment and for export data we manage to maintain exactly the same sectoral disaggregation scheme (ISIC Rev.2, 3 digit).[9] Other data (GDP, GDP *per capita*, openness, population) come from Penn World Table 6.2. To sum up, we have perfectly comparable - across time, countries and industries - set of employment and export statistics. The unique characteristic of the data we use is the fact that by choosing this very set of countries, years and sectors we have managed to reduce noticeably the number of missing values (less than 1.4% of total 64654 sectoral observations). Hence, we can perform reliable specialization analysis, not distorted by the excessive presence of missing values which would have to be filled in artificially.

Measures of specialization

There are several measures of specialization, usually formulated as indexes constructed for a country in a given moment of time. These instruments can be divided

[9] It was possible thanks to the use of trade data classified not, as usual, according to the SITC system (Standard International Trade Classification) but according to the ISIC division (International Standard Industrial Classification). Such 'reclassified' export data series come from the World Bank's Database available through WITS[9] (World Integrated Trade Solutions).

into two broad categories distinguishing between *absolute* and *relative* measures. Absolute measures of specialization show how different is the distribution of sector shares from a uniform distribution. The indices of the second type – relative ones - refer the sectoral structure of a particular country to the common benchmark which may be perceived as a 'benchmark' in the country sample. Many studies present in the literature use the indices of one type only and as we will see later, the choice of specialization measure may be important for the conclusions drawn.

Lets consider *n* industries (sectors) present in *m* countries and define the share of employment (*E*) in industry i =1,2,…n in total employment of country j=1,2,…m as*:*

$$s_{ij} = E_{ij} / \sum_i E_{ij} \qquad (1.1)$$

Alternatively, in case of exports data (*X*) the share is specified as:

$$s_{ij} = X_{ij} / \sum_i X_{ij} \qquad (1.2)$$

As far as the relative measures of specialization are concerned, the main difference with the absolute ones is that the latter do not take into account the evolution of 'benchmark' specialization pattern in the sample. Relative measures, instead, define country's degree of sectoral division of economic activity referred to all other countries.

Hence, we define the 'world' typical share of industry *i* in total 'world' employment:

$$w_i = \sum_j E_{ij} / \sum_i \sum_j E_{ij} \qquad (2.1)$$

As before, in case of exports data (*X*) the 'world'[10] share is specified as:

$$w_i = \sum_j X_{ij} / \sum_i \sum_j X_{ij} \qquad (2.2)$$

We report four absolute and four relative indices of specialization- they are synthetically presented in Table 2; most of them are based on standard measures of economic inequality.[11] In the definitions we have adopted employment setting , analogical indices can be calculated for export data using (1.2) and (2.2) instead of (1.1) and (2.1), respectively. For the sake of completeness we have also calculated the median of Balassa index but because of relatively low degree of sectoral division (ISIC 3 digit) it resulted to be a weak indicator of specialization. Apart from BI median, all measures are

[10]Note that 'world' here is treated conventionally because it consists of only those *m* countries which are included in our analysis and not *all* world economies. As a result, the 'world' benchmark w_j we use is not the real world industry share but rather the share referring to its part consisting of *m* economies.

[11] For the complete study on the inequality measurement see Cowell (1995).

positively related to the degree of overall specialization – the bigger the value of an index, the more specialized the economic structure of a country.

Table 2. Specialization measures

Specialization measure	*Formula*	*Lower/upper limit*
Herfindahl index	$H_j = \sum_i \left(s_{ij}^{\ 2}\right)$	$H_j \in \left\langle 0, \frac{1}{n} \right\rangle$
Absolute Gini index	$AbsG_j = \left(\frac{2}{n^2 \overline{E}_j}\right) \sum_i \left[\left(i - \frac{n+1}{2}\right) E_{ij}\right]$	$AbsG_j \in <0,1>$
Coefficient of variation	*CV=standard deviation/mean*	$CV_j \in <0, \infty>$
Absolute Theil entrophy[12] *index*	$AbsT_j = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{E_{ij}}{\overline{E}_j} \cdot \ln \frac{E_{ij}}{\overline{E}_j}\right)$	$AbsT_j \in <0, \ln(n$
Dissimilarity index	$DI_j = \sum_i \left\lvert s_{ij} - w_i \right\rvert$	$DI_j \in \langle 0,2 \rangle$
Relative Gini index	see Amiti(1999)	$\mathrm{Re}\,lG_j \in \langle 0,1 \rangle$
Relative Theil entrophy index	$\mathrm{Re}\,lTheil_j = \sum_{i=1}^{n} \left(s_{ij} \cdot \ln \frac{s_{ij}}{w_i}\right)$	$\mathrm{Re}\,lT_j \in \langle 0, \ln(n) \rangle$
Median of Balassa RCA[13]	$MeBI_j = median_i \left[\frac{E_{ij} / \sum_i E_{ij}}{\sum_j E_{ij} / \sum_i \sum_j E_{ij}}\right]$	$MeBI_j \in <0, \infty>$

Now we present the approach related to the methodological setting and measurement issues.

Methodological approach and reorganisation of the dataset

In order to perform as wide analysis as possible, as well as to assure the full comparability of the results obtained with various data (employment and export) and different specialization measures, we have chosen to work on various levels. The summary of the approach is synthetically presented in Table 3. As far as the sectoral

[12] *Entrophy* is a technical name meaning the 'degree of disorder' (Cowell,1995: 48).

[13] The index has no upper bound and the lower limit is 0. If the value of is equal to 1 for a given sector *i* in a given country *j*, the percentage share of that sector is identical with the benchmark average. If BI is above 1, the country is said to be specialised in sector *i* (or, equivalently, sector *j* is characterised by revealed comparative advantages); BI between 0 and 1 reveals a comparative disadvantage in sector *i*. The result of calculations is a series of Balassa indices – we have *n BI* for every country (for each year). In order to make comparisons between countries, it would be necessary to pass to the synthetic measure, summarizing the level of overall country specialization. In case of distributions with strongly pronounced skewness – like the *BI* - the arithmetic mean is a poor synthetic indicator and the correct move from sectoral to macroeconomic dimension is possible thanks to the use of alternative synthetic indicator: *median* of *BI* (de Benedictis *et al.*, 2006).

division of employment data is concerned, we follow two procedures (A and B). We have decided to do so in order to check if changes in sectoral composition influence the results. In case of several countries the data for certain industries is not available, thus we eliminate these sectors (on country-by country basis) from the sample - procedure *A* maintains the same set of sectors for each country through time but these sectors vary across countries.[14] Instead, procedure *B* adopts the same identical sectoral disaggregation for all countries and for all years, thus allows us to make direct comparisons between results based on two types of specialization measures (relative and absolute), as well as between the specialization patterns emerging from various data (employment and export statistics).[15] In the end, in the procedure *B* we have 17 manufacturing sectors (Appendix 3)[16] Detailed country information concerning the number of missing values (filled in by interpolation/extrapolation techniques) is included in Appendix 2.

Table 3. Methodological approaches

	Procedure A *(constant set of sectors for each country through time but different across countries)*	***Procedure B*** *(the same set of 17 sectors for all countries and for all years)*
Absolute measures of specialization (*Herf, AbsGini, CV, AbsTheil*)	Employment (1980-2000) Export (1980-2005)	Employment (1980-2000) Export (1980-2005)
Relative measures of specialization *(DI, RelGini, medianBI, RelTheil)*	n.a.	Employment (1980-2000) Export (1980-2005)

Note: n.a. - not applicable

To sum up, the reorganisation of original datasets and the adoption of two aforementioned approaches enable us to make several comparisons: first of all between the results obtained with employment data and export data, secondly between the

[14] One of the problems present in the UNIDO database and making the comparative analysis slightly more complicated is the fact that some countries do not provide separate industrial data for all 28 ISIC rev.2, 3-digit industries but combine some of the sectors into wider categories[14]. Usually these aggregations are not adopted consequently through time. Therefore, in case of procedure *A,* if at any point of time between 1980 and 2000 a given country does not report employment data for all 28 ISIC sectors but, instead, adopts a wider aggregation, we aggregate the series accordingly for all remaining years. In addition, on country–by–country basis we eliminated sectors with too pronounced presence of missing values.

[15] The scope of procedure *B* is to have an homogeneous sectoral dataset including employment and export statistics. Because of the presence of missing data we eliminated two sectors ('Petroleum refineries' and 'Miscellaneous petroleum and coal products' - ISIC codes 353 and 354, respectively). Again, some original ISIC industries have been aggregated in order to have the same combination of sectors for all countries. Note that in case of relative specialization measures it is not possible to follow the procedure *A* because the set of sectors must be retained constant through countries. Instead, relative indices are calculated twice: once (A) for as detailed data as possible (but set of sectors varies between countries) and, later on (B) with more aggregated (but homogeneous for all countries) data reclassified into 17 manufacturing sectors.

[16] Detailed list of sectors and adopted aggregations specific for every country (procedure A) available on request.

conclusions drawn from the use of various indices. Consequently, we can confront what kind of relationship between GDP *per capita* and specialization emerges from the adoption of various methodological and empirical settings. The results are presented in the next section.

3. EMPLOYMENT AND EXPORT SPECIALIZATION PATTERNS – RESULTS

Relevance of the specialisation measure

Following the procedure described in the previous section we have calculated several absolute indices of specialization: Herfindahl Index (*Herf),* absolute Gini index *(AbsGini),* coefficient of variation *(CV),* absolute Theil entrophy index (*AbsTheil*); as well as relative measures of specialization: dissimilarity index (*DI*), relative Gini index (*RelGini*), relative Theil entrophy index (*RelTheil*) and median of Balassa index (*medianBI*). Appendix 4. contains summery statistics for the measures obtained with sectoral employment and export data. However, in the context of 'unifying approach' instead of absolute values of separate specialization indices we are more interested in the sign and the magnitude of correlation between them.

Preliminary analysis of pairwise correlation coefficients permits to reveal if the fact of using various measures of specialization can alter the final conclusions. Table 5. reports the complete matrix of Pearson correlations calculated on a pairwise basis for all aforementioned indices. Suffixes *Empl* and *Export* denote the data (employment or export) which has been used for the calculation of an index in question while _A and _B relate to the procedure summarized in Table 3. In general, all the coefficients of correlation have the expected sign.[17] However, a closer investigation of the table of all pairwise correlations permits us to draw some interesting conclusions about the equivalence of different specialization measures. At first, lets have a look at the five subgroups (located along the diagonal of the table and marked as grey rectangles) enclosing the correlations between indices of the same nature (absolute or relative) and calculated following the same approach (A or B).

[17] Note that negative correlations between the median of Balassa index and the other measures of specialization are correct because on the contrary to all other indices we use, *BImedian* is negatively related to the degree of overall specialization.

Table 5. Correlation matrix for the specialization indices (Pearson correlation coefficients)

	HerfEmpl_A	AbsGiniEmpl_A	CVEmpl_A	AbsTheilEmpl_A	HerfEmpl_B	AbsGiniEmpl_B	CVEmpl_B	AbsTheilEmpl_B	DI_Empl_B	RelGini_Empl_B	medianBIEmpl_B	RelTheilEmpl_B	HerfExport_A	AbsGiniExport_A	CVExport_A	AbsTheilExport_A	HerfExport_B	AbsGiniExport_B	CVExport_B	AbsTheilExport_B	DI_Export_B	RelGini_Export_B	medianBIExport_B	RelTheilExport_B
HerfEmpl_A	1																							
AbsGiniEmpl_A	0.83	1																						
CVEmpl_A	0.96	0.92	1																					
AbsTheilEmpl_A	0.95	0.96	0.98	1																				
HerfEmpl_B	0.92	0.8	0.92	0.89	1																			
AbsGiniEmpl_B	0.77	0.84	0.84	0.83	0.87	1																		
CVEmpl_B	0.86	0.82	0.91	0.87	0.97	0.95	1																	
AbsTheilEmpl_B	0.88	0.85	0.91	0.9	0.98	0.96	0.98	1																
DI_Empl_B	0.73	0.78	0.77	0.79	0.84	0.86	0.87	0.88	1															
RelGini_Empl_B	0.7	0.77	0.76	0.76	0.81	0.85	0.86	0.85	0.99	1														
medianBIEmpl_B	-0.69	-0.71	-0.7	-0.72	-0.71	-0.74	-0.7	-0.75	-0.59	-0.56	1													
RelTheilEmpl_B	0.83	0.8	0.83	0.86	0.91	0.83	0.89	0.92	0.95	0.93	-0.64	1												
HerfExport_A	0.38	0.36	0.4	0.38	0.45	0.41	0.46	0.44	0.39	0.38	-0.23	0.37	1											
AbsGiniExport_A	0.37	0.4	0.4	0.39	0.43	0.43	0.46	0.44	0.4	0.39	-0.25	0.35	0.82	1										
CVExport_A	0.42	0.39	0.44	0.42	0.48	0.43	0.49	0.47	0.42	0.4	-0.25	0.39	0.97	0.9	1									
AbsTheilExport_A	0.4	0.4	0.42	0.4	0.46	0.44	0.48	0.46	0.42	0.4	-0.25	0.38	0.95	0.95	0.98	1								
HerfExport_B	0.51	0.41	0.52	0.47	0.56	0.46	0.56	0.53	0.48	0.48	-0.24	0.49	0.85	0.76	0.86	0.86	1							
AbsGiniExport_B	0.46	0.43	0.47	0.45	0.51	0.48	0.54	0.51	0.47	0.47	-0.28	0.45	0.73	0.92	0.81	0.87	0.83	1						
CVExport_B	0.52	0.44	0.53	0.49	0.58	0.49	0.59	0.55	0.51	0.51	-0.27	0.51	0.84	0.83	0.88	0.88	0.98	0.91	1					
AbsTheilExport_B	0.5	0.44	0.51	0.48	0.56	0.5	0.57	0.54	0.49	0.49	-0.28	0.49	0.82	0.87	0.87	0.9	0.95	0.95	0.98	1				
DI_Export_B	0.51	0.46	0.58	0.5	0.63	0.67	0.71	0.65	0.66	0.68	-0.44	0.59	0.59	0.54	0.6	0.6	0.65	0.58	0.66	0.65	1			
RelGini_Export_B	0.48	0.46	0.56	0.48	0.61	0.68	0.7	0.64	0.67	0.69	-0.45	0.58	0.53	0.51	0.54	0.55	0.59	0.53	0.6	0.59	0.99	1		
medianBIExport_B	-0.37	-0.38	-0.39	-0.38	-0.46	-0.47	-0.48	-0.48	-0.47	-0.46	0.34	-0.44	-0.64	-0.81	-0.7	-0.77	-0.71	-0.86	-0.77	-0.83	-0.57	-0.53	1	
RelTheilExport_B	0.56	0.49	0.61	0.54	0.67	0.66	0.72	0.67	0.65	0.67	-0.44	0.62	0.68	0.6	0.68	0.68	0.77	0.65	0.76	0.74	0.96	0.94	-0.61	1

Note: all pairwise correlations are significant at 5% level

Moving from top left hand corner to bottom right hand corner, we observe strong correlation within the groups of various absolute (*Herf, AbsGini, CV* and *AbsTheil*) indices. The same is true for relative measures, apart from the median of Balassa index (we suspect that at this level of sectoral disaggregation *BImedian* is a rather poor overall specialization measure). Therefore, the study of absolute (relative) specialization patters should not be sensitive to the use of various indices, as long as they belong to the same group. However, the nature of specialization measure can be relevant - weak correlations between *DI, RelGini, medianBI* and *RelTheil* on one side and *Herf, AbsGini, CV* and *AbsTheil* on the other suggest that the passage from absolute to relative measures is likely to modify the outcomes of the specialization analysis. Similar pattern is confirmed by Spearman correlation analysis.[18]

Now we present the evolution of specialization patterns in the countries included into our sample. Having calculated various indices of specialization, we can now compare the evolution of specialization patterns in various countries across time, emerging both from export and employment sectoral manufacturing data.

Emerging patterns of employment and export specialization - evolution through time

Reorganisation of the original datasets and the fact that we have computed a wide spectrum of various specialization measures permits us to provide a thorough comparative analysis. Figure 1 demonstrates the evolution of Absolute Gini index in each of the 32 countries taken into consideration, since 1980 onwards (20 years for employment data and 25 years in case of export statistics). Figure 2 refers to relative specialization where in order to provide complete analogy with Figure 1 we show the evolution of Relative Gini index.[19] The fact of having calculated identical measures for exactly the same level of sectoral division (procedure B - 17 modified ISIC 3-digit rev.2 sectors as in Appendix 3) permits us to make direct comparisons between the evolution of two distinct dimensions of specialization (employment and export) on the country level

[18] For the sake of space limitations the table is not included here, available on request.
[19] For the sake of space limitations we plot here only Gini indexes but the patterns of specialization are very similar for all other measures belonging to the same group (absolute or relative).

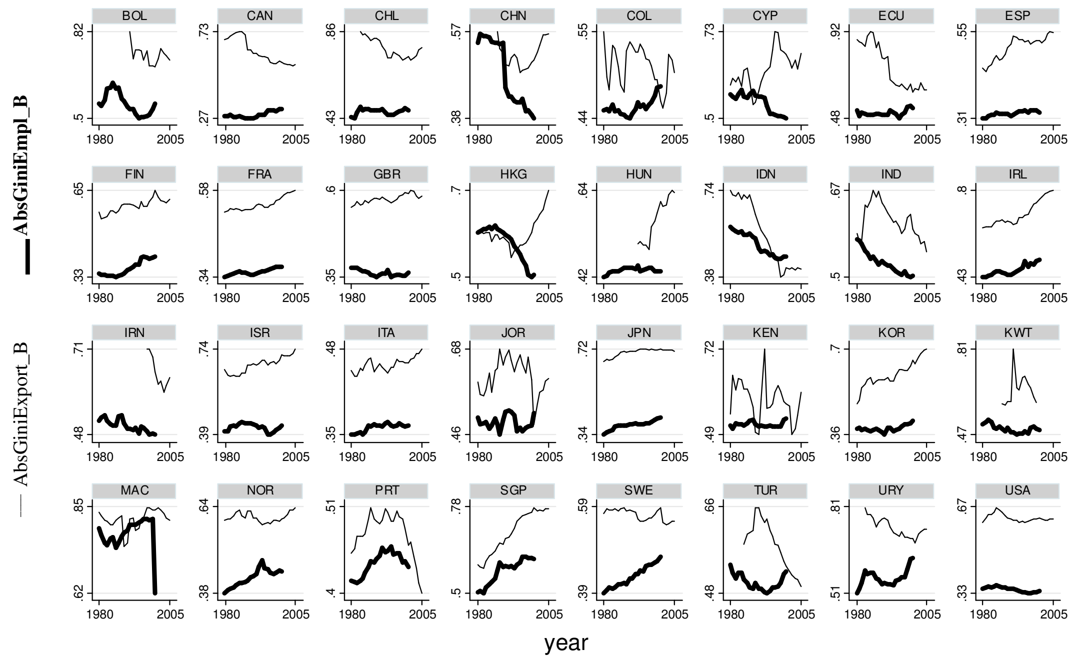

Figure 1. Absolute employment and export specialization – time trends (by country)
Note: indices of specialization refer to 17 manufacturing industries as in the procedure B(explanations in text)

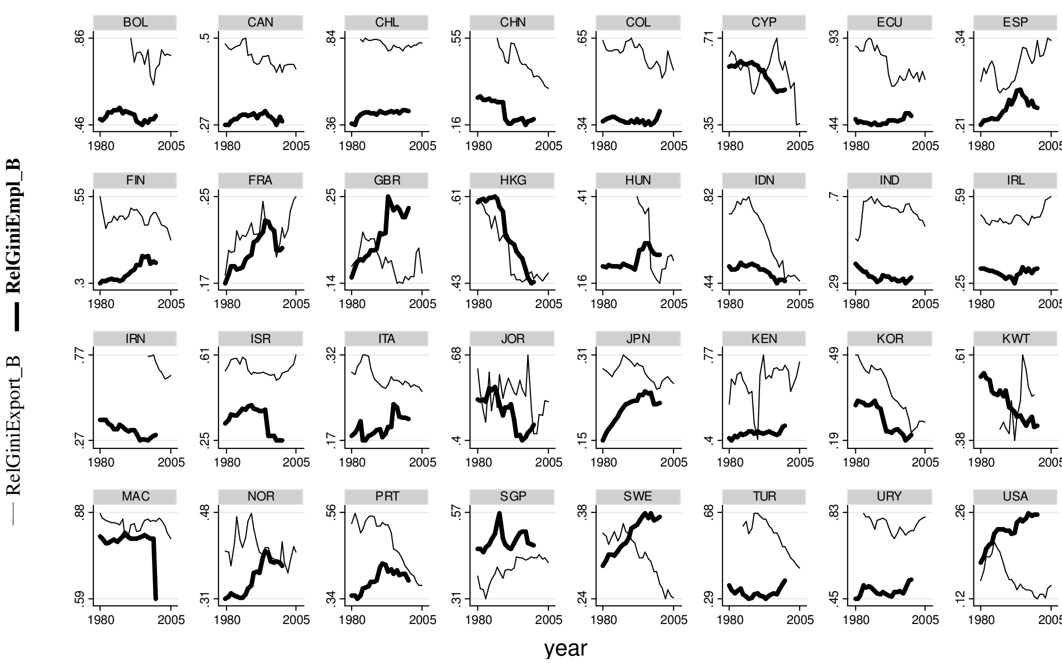

Figure 2. Relative employment and export specialization – time trends (by country)
Note: indices of specialization refer to 17 manufacturing industries as in the procedure B (explanations in text)

Let's start with absolute specialization - the investigation of the graphs makes it clear that employment and export specialization are not necessarily two sides of the same coin. We can note that in absolute terms, export specialization is more pronounced (higher values of Gini indexes) and more volatile than employment sectoral diversification. However, the performance varies considerably across countries. For instance, there are reporters like Finland (FIN), Ireland (IRL), Japan (JPN) or Singapore (SGP) which show clear increasing trend of both employment and export specialization. On the other hand, we have cases of decreasing specialization (in both dimensions) as in Indonesia (IDN). Portugal (PRT) is an example of a curious inverted-U shape of both trade and employment absolute specialization which increased in the 1980s and decreased afterwards. A lot of countries show a very mixed picture - well pronounced increase in absolute employment specialization does not have to be accompanied by an analogous trend in export specialization (as in Sweden – SWE). Increase in export specialization has not been followed by a similar trend in employment structure in Spain (ESP) or Korea (KOR). Similarly, absolute employment *de*specialization may remain not reflected in the trade data - as in case of Canada (CAN), Chile (CHL) or Ecuador (ECU). Particularly interesting cases are those of China (CHN) and Hong Kong (HKG) where absolute export and employment specialization patterns evolve in opposite directions – export specialization first decreases and then increases while employment measures fall down through time. Turkey is characterised by an U shaped evolution of employment specialization but at the same time export specialization follows an *inverted*-U path. India (IND) follows inverted U export specialization curve accompanied by well pronounced employment despecialization. To sum up –we have great variability of specialization trends across countries and, on top of that, employment and export specialization patterns are not always evolving in parallel.

As far as relative specialization is taken into account (Figure 2) again we observe great cross country heterogeneity. We would like to draw attention to these cases, where relative specialization pattern differ from its absolute counterpart. When measured in absolute terms, China (CHN) demonstrates U shaped path of sectoral division of exports but when we refer its export specialization to the world benchmark, we can observe clearly decreasing trade specialization. Opposite trends of increasing absolute and decreasing relative export specialization are evident in manufacturing trade structure of Hong Kong (HKG). Similar differences in the evolution of absolute and relative specialization can be found in Hungary (HUN), Korea (KOR), Sweden (SWE) and USA. This is a clear sign that absolute and relative specialization indices are two distinct groups of measure which quantify two phenomena probably guided by different determinants.[20]

All of the aforementioned considerations are valid also when other measures of specialization are taken into account. In conclusion, we confirm our preliminary hypothesis formulated on the base of pairwise correlations between various specialization indices. First of all, specialization analysis does not seem to be very sensitive to the use of a particular index, as long as it belongs to the same group (absolute/relative) and refers to the same type of data (employment/export). It seems that what really counts is the way of looking at of specialization – so far it is clear that the evolution of manufacturing employment and trade specialization observed since 1980s in many countries has not gone in the same direction. We have also detected differences in absolute and relative specialization. In a few words – our unifying approach demonstrates that methodological setting is crucial. We can therefore expect that in the next section where we link various types of employment and export specialization with corresponding countries' GDP *per capita* performance, we are likely to obtain relationships of a different nature.

4. SPECIALIZATION AND GDP *PER CAPITA* DEVELOPMENT PATH

Having seen that methodology counts, in this section we go forward and explore the link between manufacturing specialization and GDP *per capita* performance. We are particularly interested in the evolution of specialization pattern as countries develop - by analyzing the behaviour of economies at different stages of economic development: in our dataset we have countries with a spectrum of GDP *per capita* ranging from 1267 constant (2000) US$ in Kenya to 34365 constant (2000) US$ in USA.

Now we try to find out if economic growth is associated with increasing concentration of economic activity in limited number of sectors or, on the contrary, if

[20] The explanation of specific determinants of specialization goes beyond the scope of this paper as here we aim mainly at demonstrating the relevance of the nature of a specialization measure used in the analysis. However, it is clear that the fact of referring employment or trade structure to the common 'benchmark' (being ' world specialization' included in the construction of relative measures) is crucial. Consequently, absolute and relative indices measure different things.

there is a tendency towards despecialization. The fact of having a considerable number of observations for both employment and export manufacturing specialization for 32 countries and more than 20 years permits us to do so. In order to plot the 'specialization curve' (GDP per capita on horizontal axis and specialization measure on the vertical axis) we first apply non linear modelling, then turn towards parametric and semi parametric estimations. In particular, GAM (generalised additive models) technique allows controlling the nonparametric shape of specialization-GDP *per capita* relationship for the importance of other (potentially important) determinants of specialization. Fixed effects estimations, taking into account the presence of non specified country characteristics permit us to interpret the specialization curve as a specialization path followed by a 'representative' country along the process of economic development. Additionally, we explore the relevance of the use of particular measures of specialization, as well as compare absolute and relative specialization patterns.

Nonlinear relationship between GDP per capita and specialization

The relationship between sectoral specialization and output *per capita* does not necessarily have to be linear and monotonically stable. In fact, there is some empirical assessment confirming that economies may undergo different stages of specialization as their income *per capita* grows (Imbs and Wacziarg, 2003; Koren and Tenreyro, 2004). Other contribution states that countries tend to diversify their export structures along the development path (de Benedictis *et al.*, 2006). However, to our knowledge no systematic comparison between nonlinear relationship between GDP *per capita* development path and *various* dimensions of specialization has been done so far.

Among all statistical tools, linear modelling is probably most widely used in economics, mainly because it is well developed and allows for thorough checking of the assumptions involved. In the simplest case, it is assumed that the mean of dependent variable Y is a linear function of predictor X:

$$E(Y|X) = \alpha + X\beta \qquad (3)$$

However, in case of built-in (or suspected) nonlinearity present in the data, nonparametric regression techniques[21] provide very useful tools for modelling and exploring such data. Therefore, instead of (3) we consider a nonparametric model:

$$E(Y|X) = f(X) \tag{4}$$

where $f(.)$ is an arbitrary unspecified function. A *smoother* is a nonparametric tool used for estimating the trend and the estimate of $f(.)$ produced by the smoother is known as *smooth.* In particular, we implement locally-weighted smoother (also known as lowess) as suggested by Cleveland (1979).[22] Scatterplot smoothing is characterised by so-called 'bias and variance trade-off' which is governed by the smoothing parameter. Increasing k decreases the variance but increases the bias and consequently larger spans produce smoother but flatter curves. Figure 3 demonstrates the sensitivity of the results depending on the magnitude of the smoothing parameter chosen.

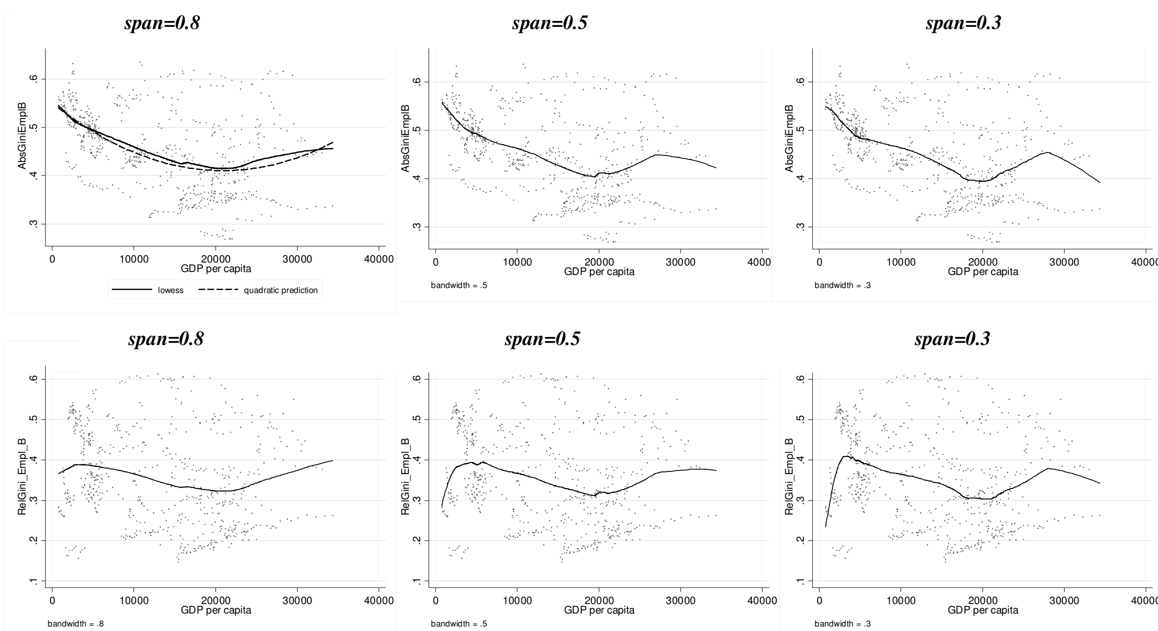

Figure 3. Sensitivity of the results on the value of smoothing parameter (span)

Note: higher panel – Absolute Gini index versus GDP *per capita* (constant US$, 2000), lower panel –Relative Gini index versus GDP *per capita* (constant US$, 2000). Both measures of specialization have been calculated for employment data, modified ISIC Rev.2 3 digit division (procedure B - 17 manufacturing sectors), 32 countries, 1980-2000.

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[21] See Pagan and Ullah (1999) for a detailed formal description of nonparametric econometric methods.

[22] It is computed in the following steps (Hastie and Tibshirani, 1990: 30). Smooth $s(x_0)$ uses k nearest neighbours (closest points to x_o) denoted by $N(x_0)$ which are identified at the beginning. The number of nearest neighbours, usually expressed as a percentage of the data points (*span*) is the smoothing parameter. Next, $\Delta x_0 = max_{N(x_0)} |x_0 - x_i|$, the distance of the furthest near-neighbour from x_o, is computed. Weights w_i are given to each point in $N(x_0)$ using the tri-cube weight function: $W\left[\left(|x_0 - x_i|\right)/\Delta x_0\right]$), where $W[u]=(1- u^3)^3$ for $0 \leq u < 1$ and 0 otherwise. Such weighting scheme provides decreasing weights (and less relative importance) on observations which are more distant from x_0. Finally, $s(x_0)$ is a fitted value at x_0 coming from the weighted least squares fit of Y to X confined to $N(x_0)$. The procedure is repeated for each observation (the number of regressions is equal to the number of observations)[22] and the fitted values are used for the construction of the non parametric curve representing the relationship between Y and X.

Lowess procedure has been performed for one of the absolute and relative measures of employment specialization (Absolute Gini index and Relative Gini index, respectively), as well as for various span levels (0.3, 0.5 and 0.8). Apart from the fact that as span decreases we obtain less smooth curves, the nature of the relationship between a particular type of specialization and GDP *per capita* development path changes substantially. For the highest span (0.8) we obtain U shape curve of absolute employment specialization (higher panel) - very similar to the pattern shown by quadratic prediction. This is the result obtained by Imbs and Wacziarg (2003). However, we have a kind of 'lying S' curve as the span decreases - as GDP *per capita* grows, employment specialization first decreases, then increases and decreases again. In case of relative employment specialization (lower panel), pending tails of U curve can be detected only for lower values of span. Hence, it is clear that the choice of span value is crucial and instead of making an arbitrary choice[23] we need to apply a valid criterion of choosing the correct smoothing parameter. Following Bowman and Azzalini (1997) we choose the optimal smoothing parameter by *cross validation* (*CV*) – a procedure which defines a suitable level of smoothing by finding the compromise between bias and variance (the former increases while the latter decreases as span grows). In practise, optimal value of span (s_{opt}) is defined as this very value of s which minimises the value of *Mean Integrated Square Error*[24].

Figure 4. plots non parametric lowess curves (with the value of span determined by cross validation) approximating the pattern of absolute employment specialization along GDP *per capita* development path. Figure 5. shows analogical plots for relative manufacturing specialization. Thanks to the adoption of the same disaggregation scheme export and employment graphs can be confronted directly.

What emerges is that as GDP *per capita* grows we have some kind of a U shaped curve of absolute employment specialization and constant trend for export specialization. The noticeable characteristic is that these results hold for all four measures of absolute specialization. Moreover, apart from the height of the lines (reflecting differences in the values of indices) there is no difference between the results obtained with the two procedures A and B. It means that in case of absolute

[23] Imbs and Wacziarg (2003) apply 0.8 smooth.
[24] For details see Hastie and Tibshirani (1990): 42-43.

specialization changes in sectoral division we have done, do non have an influence on the shape of the revealed specialization curve.

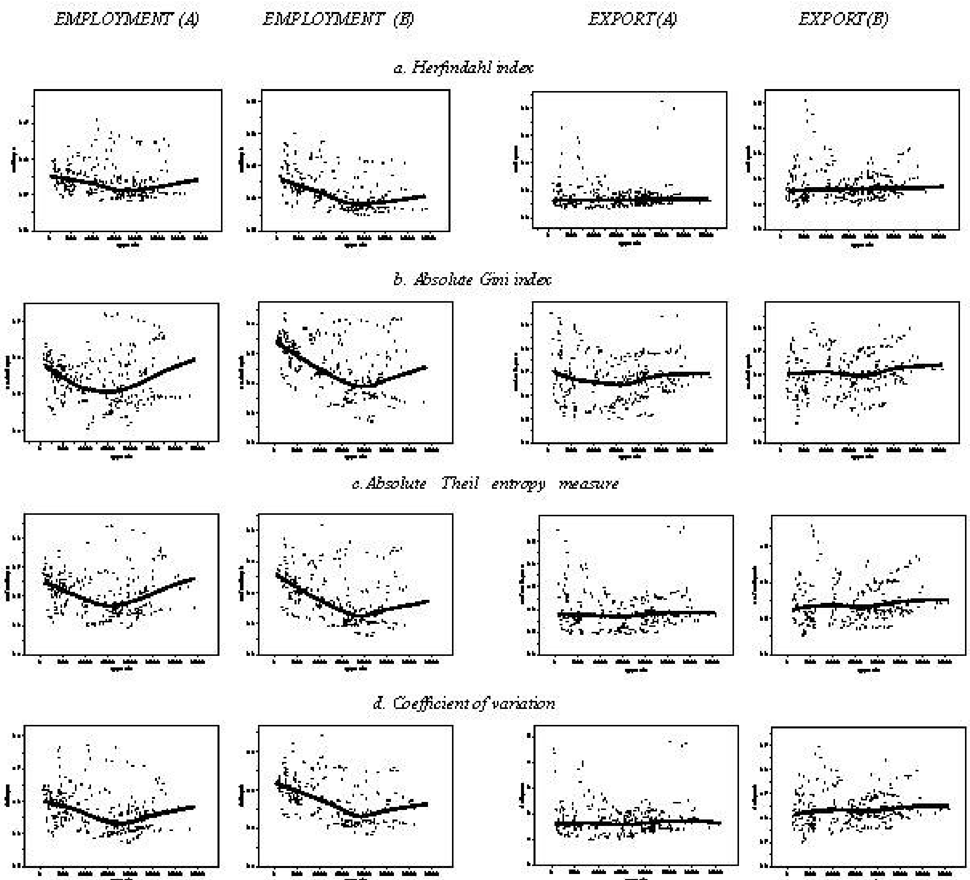

Figure 4. Absolute manufacturing specialization and GDP *per capita* – estimated nonparametric lowess curve for employment and export data (procedures A* and B)**

Note: horizontal axis: GDP *per capita* (const US$, 2000), vertical axis: specialization measure
Single plots refer to distinct data (export or employment –in columns) and diverse specialization measures (in rows), A and B denote the procedures followed: *A: constant number of sectors for each country through time but different across countries, **B: the same set of 17 sectors for all countries and for all years; horizontal axis: GDP *per capita* in constant 2000 US$; Kenya and Macao removed from employment sample Kenya ,Macao and Ecuador removed from export sample (outliers), optimal value of span obtained with cross validation.

However, relative specialization patterns (Figure 5) do not reflect exactly the same picture as absolute ones. We still obtain U curve for employment sectoral data with decreasing relative manufacturing specialization at initial phases of economic development and increasing trend afterwards. Contrastingly, lowess estimations obtained with trade data point towards clearly decreasing tendency for relative export specialization along GDP *per capita* development path. Hence, we reveal different behaviour for absolute and relative export specialization patterns. It is quite a surprising result, not detected in existing empirical literature.[25] Various explanations can be found – remember that lowess estimations do not take into account other factors which may influence manufacturing specialization. In other words, benchmarking with 'world' export specialization patterns is relevant. Moreover, it is also possible that for our sample of countries we observe full U curve for employment data but only a left side of a U curve for export specialization – it could happen if the export turning point occurred so late in the development path that it was impossible to detect it (we will go back to that point when we estimate parametrically the U curve).

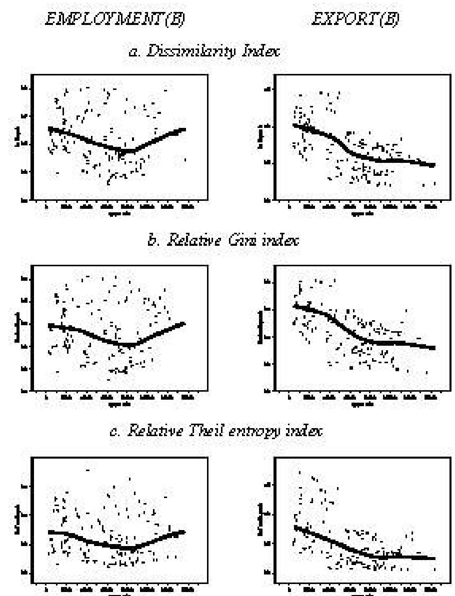

Figure 5. Relative manufacturing specialization and GDP *per capita* - estimated nonparametric lowess curve for employment and export data (procedure B)**
Note: horizontal axis: GDP *per capita* (const US$, 2000), vertical axis: specialization measure; single plots refer to distinct data (export or employment –in columns) and diverse specialization measures (in rows), ** the same set of 17 sectors for all countries and for all years; horizontal axis: Kenya and Macao removed from employment sample; Kenya, Macao and Ecuador removed from export sample (outliers), optimal value of span obtained by cross validation

Non parametric representation based on pooled data hides great variety of country-specific patterns of specialization –output *per capita* nexus. In other words, we have many country - specific 'specialization curves'. It can be seen in Figure 6 where we show countries' lowess estimations of the relationship between export and employment specialization versus their corresponding GDP *per capita* development

[25] In this paper we aim at presenting a unifying approach concerning mainly the way of estimating the link between specialization and GDP *per capita*. Therefore, the main weight is given here on the statistical and computational matters but we are aware of the fact that absolute and relative indices in reality measure slightly different specialization–type phenomena, guided by various determinants and country characteristics. Following research will analyse this problem in detail.

paths.[26] Sectoral disaggregation refers to the procedure B, which means than both for employment and export data we have relative measures of specialization calculated for 17 identical manufacturing sectors.

The fact that different countries show different (that is, increasing or decreasing) trends of specialization along their development paths is intuitive, as it means that they find themselves on distinct (upward or downward pending) sides of the U curve. In fact, poor countries usually (it is not a rule) demonstrate the negative relationship between Gini index and their *per capita* GDP while the opposite is true for the rich reporters. For almost all European countries in our sample (apart from Ireland and Portugal – countries which started at relatively low levels of GDP *per capita*) absolute specialization has decreased along with growing output *per capita*– in absolute terms their manufacturing structures became less concentrated as they developed. However, relative specialization (Figure 7) often demonstrates slightly different pattern which means that the way we measure specialization matters for the ultimate conclusions relating to the 'specialization curve'.

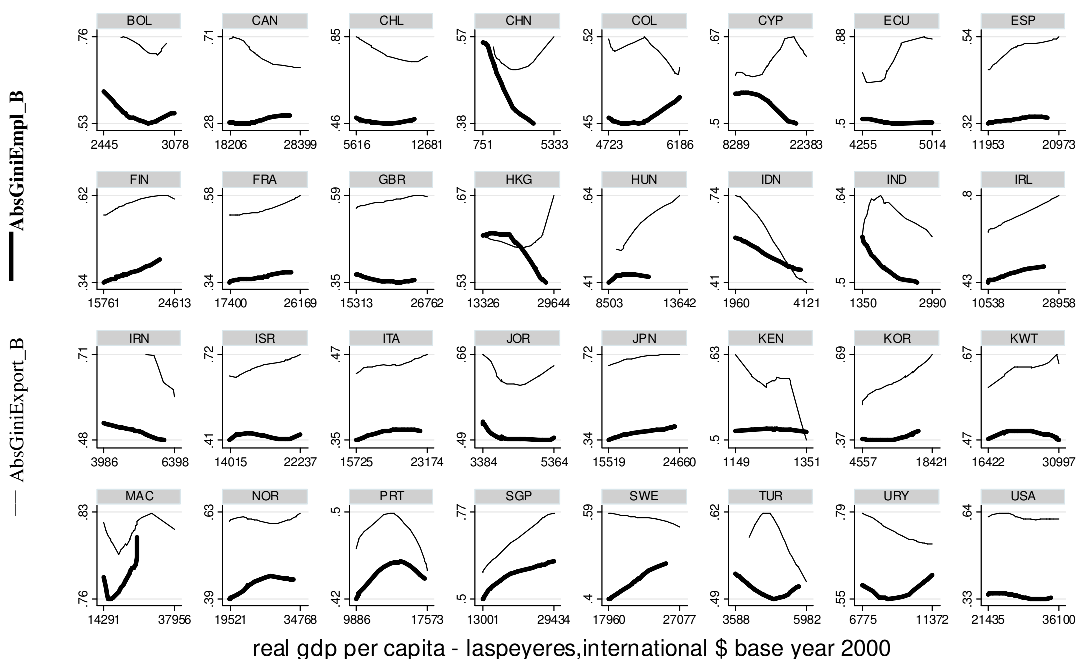

Figure 6 Absolute employment and export specialization versus GDP *per capita* (lowess by country)
Note: horizontal axis: GDP per capita order from lowest to highest level in the whole time period (1980-2000 for employment, 1980-2004 for export); indices of specialization refer to 17 manufacturing industries as in the procedure B(see explanations in text); bandwidth=0.8

[26] For the sake of simplicity and space limitations we have plotted graphs for one measure only – Gini index (in its absolute and relative version). Results referring to alternative measures of specialization available on request.

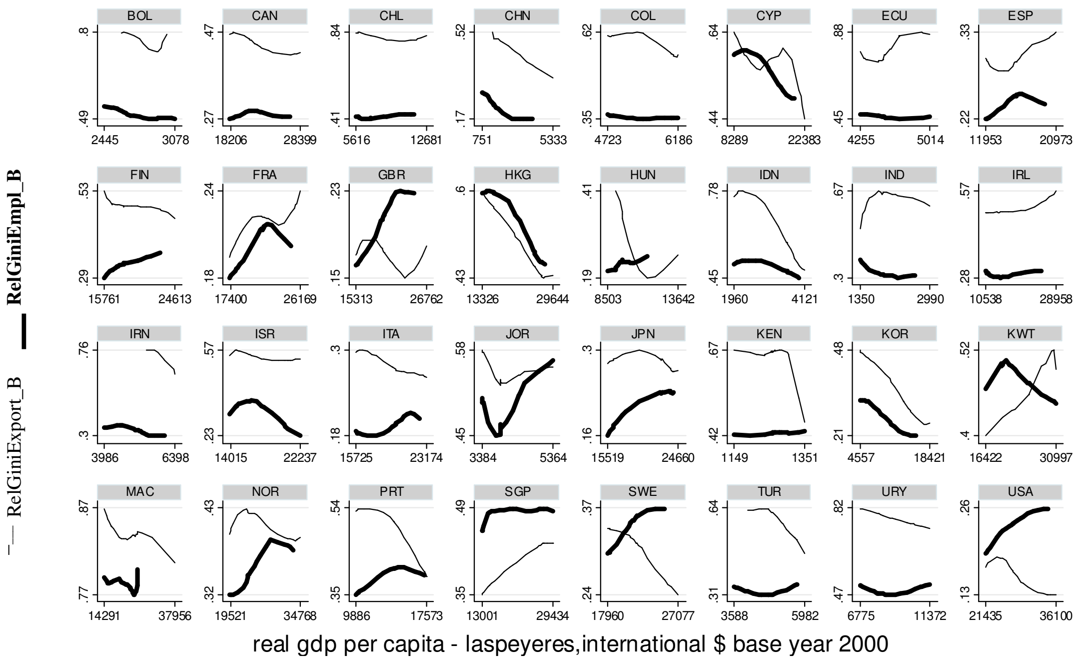

Figure 7. Relative employment and export specialization versus GDP *per capita* (lowess by country)
Note: horizontal axis: GDP per capita order from lowest to highest level in the whole time period (1980-2000 for employment, 1980-2004 for export); indices of specialization refer to 17 manufacturing industries as in the procedure B (see explanations in text); bandwidth=0.8

Thus, can we state that along the development path countries first despecialize and then specialise again (or, eventually, remain at the same level of manufacturing specialization)? So far, the evidence we have is not perfectly conclusive. Again, even at the country level it emerges that the evolution of employment specialization does not necessarily go hand in hand with its export counterpart. Moreover, the trend of absolute specialization versus GDP *per capita* is not always the same as the tendency demonstrated by the analogical relative specialization measure (Figure 7).

Let's have a closer look at a few noticeable examples. China's spectrum of GDP *per capita* extends from 751 US$ to 5333US$ (in constant 2000 prices); the corresponding evolution of specialization demonstrates decreasing (but only slightly decreasing if relative measure is taken into account) trend of absolute employment specialization, decreasing relative export specialization but U shaped pattern of absolute export specialization. In case of Hong Kong the relationship between *per capita* output and corresponding absolute export specialization (measured by *AbsGiniExportB*) is well described by the U curve but analogical relative measure (*RelGiniExportB*) is clearly decreasing along the development path. Absolute export specialization in Hungary increases as its GDP *per capita* grows but when Gini index is measured in relative terms, we find U shaped curve with first strongly decreasing and only later on increasing relative export specialization. In case of United States, trends of absolute specialization are more or less constant while relative measure shows rising employment specialization and decreasing export specialization.

The heterogeneity of behaviours which can be observed across countries (and within them) is the thing which we aim to control for in the following sections. So far, we can state that the simple change of the measurement index or the perspective of looking at the specialization (absolute versus relative, employment versus trade data) can completely modify the conclusions concerning the evolution of specialization along the GDP *per capita* development path.

Parametric estimation of the U curve

Given the previous considerations, we are interested in examining the relationship between specialization and the level of economic development (GDP *per capita*) in more systematic way. As non parametric modelling points towards the non linear U-shaped relationship between the level of employment manufacturing specialization and income *per capita* level, we are particularly interested where the turning point occurs. We turn to a regression analysis and apply quadratic specification including among the explanatory variables the square of *per capita* income:

$$SPEC_{it} = \beta_0 + \beta_1(pcGDP_{it}) + \beta_2(pcGDP_{it})^2 + u_{it} \qquad (5)$$

We estimate the above simple models for all previously calculated measures of specialization (results are included in Appendixes 5-6). Even though we have not found an evident U curve for export relative specialization, we apply the quadratic formulation to trade statistics for the sake of completeness.

Drawing on the parametric regression and lowess results we can now estimate the turning point[27] which will be associated with this very level of *per capita* GDP where countries reach maximum level of the dispersion of economic activity across manufacturing sectors (minimum of the U curve) and start specialising again.

[27] Turning point is calculated as this level of GDP *per capita* for which the first derivative of the estimated equation (5) equals to zero.

As it can be seen it Table 9. such point occurs rather late in the development path – according to the measure of specialization and the method of estimation it varies but its medium value is 15913 and 19054 constant US$ (2000) for absolute employment specialisation (A and B, respectively) and 22441 constant US$ (2000) for employment relative specialisation. Roughly speaking, these three values correspond to the level of *per capita* GDP reached by Italy in 1982, France in 1986 and UK in 1997.Even though so far we have not found convincing evidence for the U shaped export specialization curve, we have repeated the same turning point estimation on the base of quadratic regression, obtaining the mean values of 14304 US$ (2000) for absolute export specialization and 29711 US$ (2000) for relative export specialization. These results are in line with findings of Imbs and Wacziarg (2003) who detect U curve for value added and employment data and conclude that the turning point occurs late in the process of development.

Table. 9 Estimated turning point (US$, 2000), employment specialization, 1980-2000

	Employment A			***Employment B***		
	Lowess	***Quadratic Formulation***		***Lowess***	***Quadratic Formulation***	
		POLS	***FE***		***POLS***	***FE***
Absolute specialization						
Herf	18230	18116	17438	19028	15217	10250
AbsGini	18230	15740	6358	20833	20091	16054
AbsTheil	17970	17128	15139	19775	21830	18755
CV	18129	17029	11458	19775	24912	22132
Relative specialization						
DI	n.a.	n.a.	n.a.	20106	20046	23351
RelGini	n.a.	n.a.	n.a.	19647	20643	22266
RelTheil	n.a.	n.a.	n.a.	19028	25894	30989

Note: turning point in quadratic formulation has been calculated as $\frac{-\beta_1}{2\beta_2}$ *and based on estimated parameters* $\hat{\beta}_1$ *and* $\hat{\beta}_2$ *of equation (5). Detailed regressions' results in Appendixes 5 and 6; n.a. = not applicable; A and B refer to procedures followed (explanations in text).*

However, it seems to us that finishing the analysis here and not taking into account any other factors influencing specialization pattern evolution can be rather misleading. So far we have controlled the country-specific characteristics only by means of FE estimations ahich, however, impose a particular form of a relationship between specialization and GDP *per capita*. We would prefer not to do this, thus we turn to semiparametric estimation techniques. In order to be able to interpret the evolution pastern of specialization as a behaviour of a 'typical' country along the GDP *per capita* development path, we have to account for the importance of other factors. Hence, in the next section, we apply semiparametric estimation procedure in order to control the robustness of the results obtained so far for the inclusion of country specific effects.

Semiparametric approach – despecialization at initial phases of development

In order to complete the analysis, we consider country specific effects which may be, apart from GDP *per capita*, important determinants of the trend of overall manufacturing specialization along the development path. Given the heterogeneity of 'specialization curves' observable between countries we want to control the shape of the general non parametric specialization curve (lowess) for the importance of undefined country fixed effects[28]. We apply semiparametric estimation in form of a Generalised Additive Model (GAM). Additive models introduced by Friedman and Stuetzle (1981) and developed by Hastie and Tibshirani (1990) extend the usual form of a linear regression and allow components of a model to take on nonparametric forms.[29] In particular, GAM specification permits us to apply a mixture of linear and nonlinear components. Hence, instead of estimating linear model of the form:

$$SPEC_{jt} = \beta(pcGDP_{jt}) + \mathbf{X}_{jt}\gamma + u_{jt} \tag{6}$$

where j refers to country, t to time and $\mathbf{X}_{jt}$ is a vector of control variables (country dummies), we apply the following GAM specification:

$$SPEC_{jt} = s(pcGDP_{it}) + \mathbf{X}_{jt}\gamma + u_{jt}\ . \tag{7}$$

The difference with respect to the regression (6) is that in (7) GDP *per capita* does not enter the equation linearly. It means that we do not impose any functional form on the relationship between overall specialization and the level of economic development.

[28] We have also checked for the importance of more specific additional variables such as the degree of openness or proxies for the country size (population and total GDP) including them as parametric components of GAM estimations. The nature of non parametric relationship between the degree of specialization and GDP per capita level remains very similar to that when only country specific effects are taken into account.

[29]Given the standard linear regression model which assumes a linear relationship of the following shape: $E(Y) = \beta_0 + \beta_1 X_1 + ... + \beta_p X_p$ where the estimates of parameters are (usually) obtained by the least square method, GAM specification generalises the linear model by representing the expected value of dependent variable Y as: $E(Y) = s_0 + s_1(X_1) + ... + s_p(X_p)$ where $s_i(X_i)$, $i=1, ...p$ denote smooth functions which shapes are unrestricted. The very difference is that in case of GAM the function s(.) is unspecified which means that we do not impose any particular structure (in particular, linear, as in case of OLS models) on the shape of the relationship. Unknown function *s*(.) is estimated from the data through a back-fitting procedure (Hastie and Tibshirani, 1990)

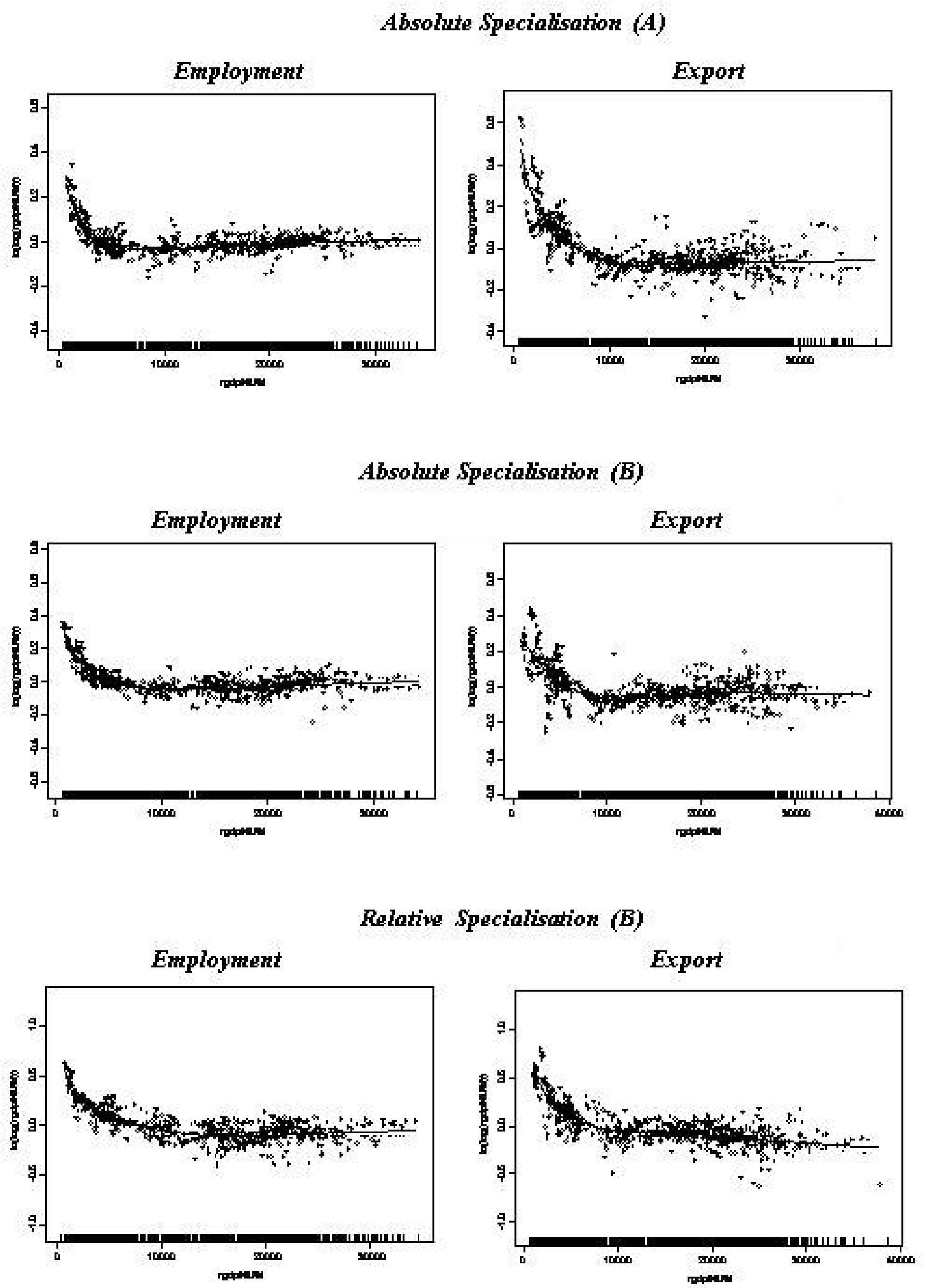

Figure 8.GAM estimations of nonlinear specialization curve along the GDP *per capita* development path

Note: Plots refer to GAM estimations with included country specific effects and Gini index as a measure of specialization (vertical axis) upper and middle line: AbsGini, lower line: RelGini), non parametric span=0.5, GDP *per capita* (horizontal axis) in constant US$ 2000. Analogical results obtained with all other measures of specialization in Appendix 7.

Taking into account country specific effects - not captured by previous standard lowess estimations, we now obtain a very clear result which holds for all types of specialization and for all measures –countries diversify at the initial phase of economic development (Figure 8). Separate plots correspond to single GAM estimations performed for both export and employment specialization measured in absolute and relative terms. Scatterplots of partial residuals[30] against predictor variables help in the interpretation of the non-linear effect of the dependent variable of interest (here: *per capita* GDP) in the overall model. It permits us to evaluate the nature of the relationship between the GDP *per capita* and the adjusted values of a specialization measure after having controlled for country specific effects

Therefore, in the version of GAM model with country fixed effects we detect despecialization trend in manufacturing. Note that this result holds for various methodological settings reflected in disaggregation schemes (A and B), different specialization measures and two types of basic data (employment and export statistics) – see Appendix 7 where we include the statistical significance of non parametric component and plots of partial residuals for all measures used throughout the analysis.. Even though there are some (little) differences between the specialization curves obtained with various measures[31], the general result is robust: in the initial phase of GDP *per capita* growth, countries tend to despecialize.

To sum up, both employment and export specialisation decrease at the initial phases of economic development. The nations initially produce and export 'a bit of everything' but after having reached higher stage of economic development, tend to stabilize their manufacturing structures. In other words, as GDP *per capita* grows a 'typical country' tends to decrease the degree of overall specialisation. In initial phases it concentrates resources (labor force) and exports in a few sectors but as output *per capita* grows this tendency weakens. Employment specialization decreases sharply and then remains rather stable as GDP *per capita* grows, export structures may follow a kind of a U curve of overall trade specialization.

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[30] In a model with n predictors, the partial residuals for a predictor j are computed by removing from the dependent variable values the effects of all predictors i = 1, ... , n, $i \neq j$. Partial residuals are the residuals after controlling for the effect of all other predictor variables.

[31] What happens afterwards, tends to depend on the type of specialization (as far as employment structure is concerned, the distribution of activity remains rather stable, while there might be some kind of a U shaped pattern in case of export specialization): detailed results are presented in Appendix 7.

5. CONCLUSIONS

The aim of this study was to contribute to the existing empirical evidence on specialization-GDP *per capita* nexus by adopting a unifying approach. Two dimensions of specialization have been analysed in parallel – the first one emerging from employment data and the other described by changes in countries' export structures. The results obtained for employment and trade specialization are directly comparable thanks to the thorough reorganisation of the original datasets, the maintenance of the same set of countries and sectors as well as the application of a unique classification scheme (ISIC rev.2, 3 digit). We have adopted a wide range of specialization measures, allowing for distinguishing between relative and absolute specialization, as well as controlling for the importance of changes in the sectoral division of the data.

We have been particularly interested in the evolution of specialization patterns along the development path of GDP *per capita*. In order to avoid imposing the nature of a relationship between the two variables we have chosen to apply non parametric lowess procedure as well as semi parametric GAM estimation. We find a support for nonlinear relationship between manufacturing specialization and GDP *per capita* level, with an evident tendency towards despecialization at the initial phases of economic development. We have demonstrated that the measurement of manufacturing specialization is in general sensitive to the methodological setting. However, when taking into account country specific heterogeneity we find the general tendency of decreasing specialization at the beginning of the development process. The result holds for various measures of specialization, estimation techniques, levels of disaggregation and is confirmed after the inclusion of country specific effects.

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Appendix 1. ISIC Rev.2 manufacturing sectors' codes and names

300 Total manufacturing
311 Food products
313 Beverages
314 Tabacco
321 Textiles
322 Wearing apparel, except footwear
323 Leather products
324 Footwear, except rubber or plastic
331 Wood products, except furniture
332 Furniture, except metal
341 Paper and products
342 Printing and publishing
351 Industrial chemicals
352 Other chemicals
353 Petroleum refineries
354 Misc. petroleum and coal products
355 Rubber products
356 Plastic products
361 Pottery, china, earthenware
362 Glass and products
369 Other non-metallic mineral products
371 Iron and steel
372 Non-ferrous metals
381 Fabricated metal products
382 Machinery, except electrical
383 Machinery, electric
384 Transport equipment
385 Professional & scientific equipment
390 Other manufactured products

Appendix 2. Number of sectoral observations and missing values by procedure

	Procedure A		***Procedure B***		**TOTAL**
	Empl	***Export***	***Empl***	***Export***	
Number of observations	18375	21884	11424	12971	64654
Number of missing values	173	413	141	181	908
% of missing values	0.94	1.89	1.2	1.39	1.4

Appendix 3. List of aggregated sectors – procedure B

LIST OF MANUFACTURING SECTORS – *PROCEDURE B*	*Corresponding ISIC rev. 2, 3-digit codes and names (adopted aggregations)*
1. FOOD, BEVERAGES AND TOBACCO (311B)	311 Food products + 313 Beverages + 314 Tobacco
2. TEXTILES (321)	321 Textiles
3. CLOTHES, LEATHER PRODUCTS AND FOOTWEAR (322B)	322 Wearing apparel, except footwear + 323 Leather products +324 Footwear, except rubber or plastic
4. WOOD PRODUCTS, EXCEPT FURNITURE (331)	331 Wood products, except furniture
5. FURNITURE, EXCEPT METAL (332)	332 Furniture, except metal
6. PAPER AND PRODUCTS (341)	341 Paper and products
7. PRINTING AND PUBLISHING (342)	342 Printing and publishing
8. CHEMICALS (351A)	351 Industrial chemicals + 352 Other chemicals
9. RUBBER PRODUCTS (355)	355 Rubber products
10. PLASTIC PRODUCTS (356)	356 Plastic products
11. POTTERY, CHINA, EARTHERWARE, GLASS AND OTHER SIMILAR PRODUCTS (361B)	361 Pottery, china, earthenware + 362 Glass and products +369 Other non-metallic mineral products
12. IRON, STEEL AND NON FERROUS METALS (371A)	371 Iron and steel + 372 Non-ferrous metals
13. FABRICATED METAL PRODUCTS (381)	381 Fabricated metal products
14. MACHINERY (EXCEPT ELECTRICAL), PROFESSIONAL AND SCIENTIFIC EQUIPMENT (382F)	382 Machinery, except electrical + 385 Professional and scientific equipment
15. MACHINERY, ELECTRIC (383)	383 Machinery, electric
16. TRANSPORT EQUIPMENT (384)	384 Transport equipment
17. OTHER MANUFACTURING (390)	390 Other manufacturing products

Appendix 4. Summary statistics for the specialization indices

	EMPLOYMENT SPECIALIZATION(1980-2000) UNIDO, ISIC rev.2 3-digit							
	Procedure A				***Procedure B***			
	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max
Absolute measures (672 obs)								
Herf	0.100	0.057	0.060	0.476	0.122	0.056	0.072	0.477
AbsGini	0.547	0.083	0.402	0.862	0.463	0.099	0.267	0.816
CV	1.236	0.405	0.774	3.369	1.007	0.365	0.497	2.749
AbsTheil	0.561	0.257	0.280	1.916	0.402	0.227	0.117	1.573
Relative measures (672 obs)								
DI	n.a.	n.a.	n.a.	n.a.	0.558	0.226	0.212	1.395
RelGini	n.a.	n.a.	n.a.	n.a.	0.369	0.137	0.147	0.812
medianBI	n.a.	n.a.	n.a.	n.a.	0.887	0.202	0.136	1.531
RelTheil	n.a.	n.a.	n.a.	n.a.	0.278	0.259	0.036	1.586

	EXPORT SPECIALIZATION (1980-2005) UN COMTRADE (WITS), ISIC rev.2, 3-digit							
	Procedure A				***Procedure B***			
	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max
Absolute measures (761 obs)								
Herf	0.169	0.121	0.060	0.902	0.191	0.103	0.085	0.903
AbsGini	0.684	0.101	0.456	0.950	0.618	0.100	0.376	0.924
CV	1.825	0.678	0.832	4.925	1.466	0.484	0.692	3.904
AbsTheil	0.981	0.441	0.366	2.993	0.754	0.336	0.249	2.541
Relative measures (784 obs)								
DI	n.a.	n.a.	n.a.	n.a.	0.783	0.361	0.183	1.805
RelGini	n.a.	n.a.	n.a.	n.a.	0.491	0.197	0.123	0.928
medianBI	n.a.	n.a.	n.a.	n.a.	0.745	0.308	0.020	1.622
RelTheil	n.a.	n.a.	n.a.	n.a.	0.587	0.493	0.035	2.591

Note: Mean, minimum and maximum values, as well as standard deviations refer to the results obtained for all 32 countries; as specified in the previous section the number of observations varies because we have slightly longer time span in case of trade specialization and, in addition, we do not report export specialization results for some countries and for some years.

Appendix 5. Regression results – employment specialization versus GDP per capita, quadratic specification

EMPLOYMENT SPECIALIZATION 1980-2000								
	Dependent variable (SPEC): absolute employment specialization A							
	Herf		***AbsGini***		***AbsTheil***		***CV***	
	POLS	FE	POLS	FE	POLS	FE	POLS	FE
(pcGDP)	-0.0140* (-3.69)	-0.0046 (-0.84)	-0.0869* (-7.31)	-0.0024 (-0.17)	-0.1771* (-6.50)	-0.1989 (-0.62)	-0.2517* (-6.50)	-0.0868 (-1.54)
(pcGDP)^2	0.0035* (2.65)	0.0005 (0.36)	0.0295* (6.8)	0.0040 (1.2)	0.5541* (5.84)	0.0087 (1.15)	0.0628* (4.66)	0.0169 (1.26)
R-squared	0.031		0.094		0.067		0.093	
Obs	630	630	630	630	630	630	630	630
F p>F	13.81 (0.0000)	1.7 (0.1829)	27.64 (0.0000)	9.59 (0.0001)	23.02 (0.0000)	2.51 (0.082)	42.46 (0.0000)	1.66 (0.1902)
	Dependent variable (SPEC): absolute employment specialization B							
	Herf		*AbsGini*		*AbsTheil*		*CV*	
	POLS	FE	POLS	FE	POLS	FE	POLS	FE
(pcGDP)	-0.0338* (-7.33)	-0.0159** (-2.50)	-0.1343* (-9.84)	-0.0411* (-2.65)	-0.217* (-9.06)	-0.0904* (-3.11)	-0.3398* (-8.47)	-0.1474* (-2.97)
(pcGDP)^2	0.0065* (4.15)	0.0032** (2.16)	0.0321* (6.35)	0.0128* (3.37)	0.0497* (5.75)	0.0241* (3.47)	0.0682* (4.92)	0.0333* (2.83)
R-squared	0.19		0.24		0.22		0.23	
Obs	630	630	630	630	630	630	630	630
F p>F	94.09 (0.0000)	3.56 (0.029)	136.28 (0.0000)	7.68 (0.0005)	115.15 (0.0000)	6.28 (0.002)	120.34 (0.0000)	4.40 (0.0126)

	Dependent variable (SPEC): relative employment specialization B					
	DI		*RelGini*		*RelTheil*	
	POLS	FE	POLS	FE	POLS	FE
(pcGDP)	-0.1720* (-5.21)	-0.1261* (-4.29)	-0.0962* (-4.46)	-0.0953* (-5.42)	-0.0984* (-3.10)	-0.1128* (-3.94)
(pcGDP)^2	0.0429* (-3.89)	0.0270* (3.61)	0.0233* (3.27)	0.0214* (4.92)	0.019** (1.99)	0.0182* (2.58)
R-squared	0.073		0.059		0.038	
Obs	630	630	630	630	630	630
F p>F	24.98 (0.0000)	10.04 (0.0001)	19.79 (0.0000)	14.90 (0.0000)	14.12 (0.0000)	12.45 (0.0000)

Note: *per capita* GDP (*pcGDP*) in 10000 intUS$(year2000) from PWT; all measures of specialization – own calculation with UNIDO ISIC Rev.2 3digit manufacturing data; A and B refer to the procedures followed (explanations in text); constants included – not reported; robust standard errors, * significant at 1% level, **significant at 5% level, *** **significant at 10% level ; t-statistics in parenthesis, 30 countries (China Macao and Kenya excluded as outliers)

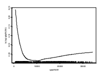
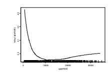
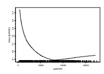
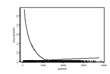
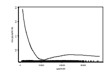
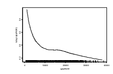
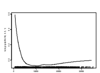
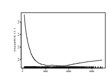
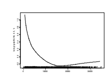
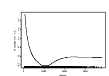
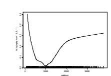
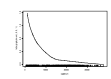
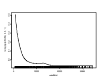
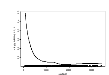
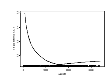
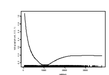
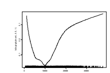
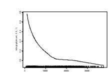
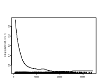
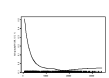
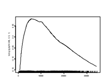
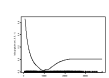
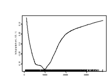
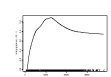
Appendix 6. Regression results –export specialization versus GDP per capita, quadratic specification

EXPORT SPECIALIZATION 1980-2004								
	Dependent variable (SPEC): absolute export specialization A							
	Herf		***AbsGini***		***AbsTheil***		***CV***	
	POLS	FE	POLS	FE	POLS	FE	POLS	FE
(pcGDP)	-0.075* (-3.83)	-0.0715 (-1.75)	-0.0765* (-4.92)	-0.0103 (-0.36)	-0.3006* (-4.31)	-0.2174 (-1.60)	-0.3256* (-3.15)	-0.1595 (-0.78)
(pcGDP)^2	0.0207* (3.57)	0.0205 (1.25)	0.0243* (5.23)	0.0081 (1.24)	0.0895* (4.31)	0.0718** (2.19)	0.0956* (3.08)	0.0696 (1.42)
R-squared	0.032		0.035		0.032		0.017	
Obs	673	673	673	673	673	673	673	673
F p>F	7.39 (0.0007)	3.40 (0.0339)	13.80 (0.0000)	12.31 (0.0000)	9.47 (0.0001)	6.92 (0.001)	4.99 (0.0071)	6.56 (0000)
	Dependent variable (SPEC): absolute export specialization B							
	Herf		*AbsGini*		*AbsTheil*		*CV*	
	POLS	FE	POLS	FE	POLS	FE	POLS	FE
(pcGDP)	-0.007 (-0.85)	0.0082 (0.44)	-0.0281** (-2.07)	0.0328 (1.49)	-0.073** (-1.96)	0.0441 (0.64)	-0.0304 (-0.61)	-0.06 (1.66)
(pcGDP)^2	0.0023 (0.94)	0.004 (0.94)	0.0117* (2.97)	0.0004	0.0269** (2.44)	0.0165 (1.02)	0.0155 (1.06)	0.001 (-0.03)
R-squared	0.01		0.014		0.003		0.003	
Obs	650	650	650	650	650	650	650	650
F p>F	0.45 (0.637)	20.48 (0.0000)	8.16 (0.0003)	25.24 (0.0000)	3.56 (0.028)	23.56 (0.0000)	1.30 (0.273)	27.21 (0.0000)

	Dependent variable (SPEC): relative export specialization B					
	DI		*RelGini*		*RelTheil*	
	POLS	FE	POLS	FE	POLS	FE
(pcGDP)	0.416* (-10.43)	-0.393* (-9.00)	-0.2234* (-9.62)	-0.2122* (-9.31)	-0.454* (-8.84)	-0.50* (-9.40)
(pcGDP)^2	0.0603* (4.73)	0.0818* (7.68)	0.0306* (3.99)	0.0425* (7.81)	0.065* (4.38)	0.107* (8.79)
R-squared	0.39		0.39		0.32	
Obs	650	650	650	650	650	650
F p>F	236.21 (0.0000)	46.28 (0.0000)	250.41 (0.0000)	50.75 (0.0000)	164.77 (0.0000)	42.25 (0.0000)

Note: *per capita* GDP (*pcGDP*) in 10000 int US$(year2000) from PWT; all measures of specialization – own calculation with WITS trade statistics reclassified into ISIC Rev.2 3digit manufacturing division; A and B refer to the procedures followed; constants included – not reported; robust standard errors, * significant at 1% level, **significant at 5% level, *** **significant at 10% level ; t-statistics in parenthesis, 29 countries (China Macao, Ecuador and Kenya excluded as outliers)

Appendix 7.GAM estimations –specialization versus GDP *per capita*

	EMPLOYMENT SPECIALIZATION			***EXPORT SPECIALIZATION***		
	AbsGiniEmplA	***AbsGiniEmplB***	***RelGiniEmplB***	***AbsGiniExportA***	***AbsGiniExportB***	***RelGiniExportB***
Parametric component	Country specific effects	Country specific effects	Country specific effects	Country specific effects	Country specific effects	Country specific effects
Non parametric component	GDP *per capita* 	GDP *per capita* 	GDP *per capita* 	GDP *per capita* 	GDP *per capita* 	GDP *per capita* 
NparF p(F)	81.06 (0.0000)	75.49 (0.0000)	24.14 (0.0000)	47.94 (0.0000)	28.12 (0.0000)	10.52 (0.0000)
Obs	672	672	672	747	724	724
	AbsTheilEmplA	***AbsTheilEmplB***	***RelTheilEmplB***	***AbsTheilExportA***	***AbsTheilExportB***	***RelTheilExportB***
Parametric component	Country specific effects	Country specific effects	Country specific effects	Country specific effects	Country specific effects	Country specific effects
Non parametric component	GDP *per capita* 	GDP *per capita* 	GDP *per capita* 	GDP *per capita* 	GDP *per capita* 	GDP *per capita* 
NparF p(F)	66.38 (0.0000)	72.68 (0.0000)	23.75 (0.0000)	65.63 (0.0000)	35.84 (0.0000)	13.96 (0.0000)
Obs	672	672	672	747	724	724
	HerfEmplA	***HerfiEmplB***	***DIEmplB***	***HerfExportA***	***HerfExportB***	***DIExportB***
Parametric component	Country specific effects	Country specific effects	Country specific effects	Country specific effects	Country specific effects	Country specific effects
Non parametric component	GDP *per capita* 	GDP *per capita* 	GDP *per capita* 	GDP *per capita* 	GDP *per capita* 	GDP *per capita* 
NparF p(F)	26.55 (0.0000)	41.18 (0.0000)	24.70 (0.0000)	50.66 (0.0000)	28.73 (0.0000)	13.24 (0.0000)
Obs	672	672	672	747	724	724
	CVEmplA	***CVEmplB***	***BIMedEmplB***	***CVExportA***	***CVExportB***	***BIMedExportB***
Parametric component	Country specific effects	Country specific effects	Country specific effects	Country specific effects	Country specific effects	Country specific effects
Non parametric component	GDP *per capita* 	GDP *per capita* 	GDP *per capita* 	GDP *per capita* 	GDP *per capita* 	GDP *per capita* 
NparF p(F)	38.82 (0.0000)	54.11 (0.0000)	24.35 (0.0000)	51.17 (0.0000)	31.34 (0.0000)	21.84 (0.0000)
Obs	672	672	672	747	724	724

Note: variables in natural logs, nonparametric span=0.5