Common trends in trade: the impact of vertical specialization

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Abstract

This paper shows that vertical specialization (i.e international fragmentation of productive processes) in developed countries is key to understand trade dynamics. Factor models with different common factors explain the export intensity structures for developed and less developed countries. For developed countries, we identify the most important common factor, which is not stationary, as the degree of vertical specialization. However, the intensity of exports for less developed countries is driven by country-specific features rather than global events. Our results are in line with recent theoretical developments.

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1 Introduction and Motivation

One of the most striking changes in today's world economy is the increased international fragmentation of the productive processes. International sequential productive processes are generalized and have originated an enormous growth in world trade. Since the 1970's, trade intensity has risen worldwide which is, in part, explained by the international fragmentation of production. The emergence of these global supply chains has been considered an opportunity for less developed countries to join international trade, since it requires being competitive in only producing certain intermediate inputs rather than the whole product. However, although these global supply chains are widespread and both DC and LDC participate, their roles in the process seem to be quite different[1].

This paper tests the impact of the increased international fragmentation of productive processes on trade dynamics. We estimate a factor model to explain the different structure of the cross-section dependence of export intensity (i.e. shares of exports to GDP) for two panels of DC and LDC. The countries are grouped together by degree of development. Our analysis studies the common and idiosyncratic unobservable components of these factor models separately. Common factors capture the features shared by all the countries in the sample (non-stationary common factors are interpreted as global stochastic trends and the stationary ones as common shocks) and idiosyncratic components represent the country-specific features.

The estimated empirical factor model that represents the intensity of exports is different for DC and LDC. For LDC, cross-section dependence is very weak, a fact corroborated by the idiosyncratic components clearly driving the variation in the export shares. Consequently, the first estimated common factor has negligible importance for most of the countries. Contrarily, for DC, the cross-section dependence is strong and can be modelled

[1] This phenomenon also increases dependence among developed countries in the sense of larger business cycles synchronization, as shown in Frankel and Rose (1997, 1998), Fatás (1997) and Clark and van Wincoop (2001). However, Calderón *et al.* (2007) also find a significant effect of gains in trade intensity on cycle synchronization among less developed countries(LDC hereafter), although weaker than that found for the developed countries (DC hereafter) group.

with a non-stationary common factor. This difference in the factor structure of DC and LDC leads us to look for some economic meaning in the factor model useful for policy makers. Our intuition is that the non-stationary common factor might be reflecting the general involvement of DC in the global supply chains. If this were the case, given that exports and imports are gross valued in the official statistics, the advance of vertical specialization should leave a deep print in the trade intensity ratios of DC.

We take one step further to get into de economic interpretation of our findings. Firstly, we build a variable (GLOBAL) based on the measure of vertical specialization developed by Hummels *et al.* (2001). Vertical specialization captures the use of imported inputs in producing goods that are exported. Our variable GLOBAL represents the part of international trade which is reflecting the impact of the international fragmentation of production on exports for DC. Afterwards, we identify the single non-stationary factor as the degree of vertical specialization captured by the GLOBAL variable. In other words, we provide evidence suggesting the general involvement of DC in the process of international productive fragmentation. The lack a non-stationary common component in the factor structure of LDC, along with the stronger weight of idiosyncrasy in explaining their export share variability, may suggest that important trade frictions still exist for these countries. These frictions may deviate trade from LDC to DC.

The vertical specialization phenomenon has attracted a lot of attention in the literature to investigate how the fragmentation of the supply chains across borders may affect the volume, pattern and consequences of international trade. On the empirical side, the relevance of international supply chains or, in other words, the relevance of vertical specialization, in explaining the recent expansion of international trade started with the seminal works of Feenstra and Hanson (1996), Hummels *et al.* (1998, 2001), followed by those of Hanson *et al.* (2005), Miroudot and Ragoussis (2008), Bergin *et al.* (2009) and Johnson and Nogera (2012), among others. On the theoretical side, this topic has been studied by, for example, Dixit and Grossman (1982), Yi (2003, 2010), Harms *et al.* (2009), Antras and

Rossi-Hansberg (2009), Baldwin and Venables (2010) and Costinot *et al.* (2011).

Our paper is related to several strands of the literature. First, on the empirical side, we show similar quantitative results to the ones found by Hummels *et al.* (2001) regarding the impact of vertical specialization on world trade intensity. On the theoretical side, our general results also corroborate the results of assignment and matching models that study the relationship between countries and stages of production and that predict the matching between more productive countries and later stages of production. In this line, the recent contributions in Costinot *et al.* (2011) show how vertical specialization, understood as the foreign value added content in domestic exports, shapes international trade and the interdependence of nations. This model predicts different positions for DC and LCD in the global supply chains. The authors develop an elementary general equilibrium model of global supply chains in which production is sequential, subject to mistakes and where, if a mistake occurs, the intermediate good is entirely lost. This leads countries with lower probabilities of making mistakes at all stages (DC) to specialize in the final stages, while those with higher probabilities of making mistakes (LDC) specialize in the first stages and in those labour intensive. Consequently, if countries with similar levels of development specialize in nearby regions of the supply chain, the model posits that richer countries will tend to trade relatively more with other rich countries, while poor countries will tend to trade with other poor countries. Moreover, if the goods produced in the final stages contain higher amounts of imported intermediate inputs and labour, the rich countries, according to Costinot *et al.* (2011), will tend to import and export goods with higher unit values.

Our paper provides evidence consistent with the pattern of trade for DC predicted in this theoretical model. On the one hand, the important cross-section dependence found for DC is a necessary but not sufficient condition to support the position of DC in the value chain proposed by Costinot *et al.* (2011). Moreover, the weak cross-section dependence among LDC also reflects some inconsistency with the pattern of trade predicted for these countries in their free-trade baseline model. This is in line with the extensions of the model that allows for the presence of coordination costs, which are higher for LDC. The unimportance of the common factor might reflect the presence of higher trade frictions in LDC, which according to Costinot *et al.* (2011), result in a complete specialization in a subset of stages. Thus, part of the trade among LDC might be deviated to DC which are outside the sub-sample. None of these papers, however, investigates the relevance of international fragmentation of productive processes for shaping export dynamics. This is the main focus of our analysis.

The rest of the paper is structured as follows. Section 2 analyses dependence among the countries. Section 3 presents the factor model and analyses the structure of the cross-section dependence. Section 4 identifies the estimated factors with observable macroeconomic variables and Section 5 concludes.

2 Dependence structure of export shares

In this section, we first present the methodology used to test for independence in the panel of export shares. Second, we discuss our data and report the empirical results starting with the presentation of the data structure through graphic and descriptive analyses. Then, we formally test the hypothesis of independence by using the tests described below.

2.1 Analysis of cross-section dependence

To study the cross-section dependence among the countries in a panel we choose independence among individuals as our null hypothesis. There are several tests available in the literature. The tests propose by Pesarn (2004) to check for cross-section dependence are applicable to a variety of panel data models, including stationary and unit root dynamic heterogeneous panels. These tests are based on the average of pair-wise correlation coefficients of OLS residuals from the individual regressions in the panel. The null hypothesis of cross-section independence is considered against the alternative of dependence by means of the following test statistic:

$$DC(p) = \sqrt{\frac{2T}{p(2N-p-1)}}\left(\sum_{s=1}^{p}\sum_{i=s+1}^{N}\widehat{\rho}_{i,i-s}\right) = \sqrt{\frac{2T}{p(2N-p-1)}}\left(\sum_{s=1}^{p}\sum_{i=1}^{N-s}\widehat{\rho}_{i,i+s}\right) \longrightarrow N(0,1) \tag{1}$$

where i index the cross-section dimension and $p = 1, 2, ..., N-1$. $\widehat{\rho}_{i,}$ is the cross-section pair-wise Pearsan's correlation of the errors in the ADF (p) regression equations. It is convenient to order the cross-section units by their topological position, so that the p^{th} order neighbours of the i^{th} cross-section unit are the $i+p$ and the $i-p$ cross-section units[2].

However, since we are also interested in the severity of the correlations among the countries, we also use the test proposed by Ng (2006) that not only aims to test the null hypothesis of independence but also gives a compelling view about the strength and extent of cross-section correlation.

The test is carried out in two steps. First, we estimate an AR model to isolate cross-section dependence from serial correlation. For each pair of countries, we compute the absolute value of the Pearson's correlations of the estimated residuals from country-ADF-type regression. Let these Pearson's correlations be denoted by:

$$\overline{\mathbf{p}} = (|\widehat{p}_1|, |\widehat{p}_2|, |\widehat{p}_3|, ..., |\widehat{p}_n|), \tag{2}$$

where $n = N(N-1)/2$ [3].

Second, we order $\overline{\mathbf{p}}$ ascendantly and we split the sample into groups of small (S) and large (L) correlations to test whether the small correlations are different from zero.

Let define $\overline{\phi}_j = \Phi(\sqrt{T}\overline{p}_{[j:n]})$ where $j = 1, ..., n$ and Φ is the cumulative distribution function of the standard normal distribution. Since $\overline{p}_{[j:n]}$ is ordered, $\overline{\phi} = (\overline{\phi}_1, \overline{\phi}_2, ..., \overline{\phi}_n)'$ is also ordered. So, the spacings are $\Delta\overline{\phi}_j = \overline{\phi}_j - \overline{\phi}_{j-1}$ and we split the sample at $\mu = \frac{n_1}{n} \in$

[2]Note that $CD(N-1)$ reduces to the CD statistic. Local dependence makes sense only for values of $p < N-1$.

[3]Taking absolute values is important in order to ensure that large negative correlations are treated symmetrically as large positive correlations.

$(0, 1)$.

The mean of the spacings for each group is defined as follows:

$$\overline{\Delta}_S(\mu) = \frac{1}{[\mu n]} \sum_{j=1}^{[\mu n]} \Delta\overline{\phi}_j \text{ and } \overline{\Delta}_L(\mu) = \frac{1}{[n(1-\mu)]} \sum_{j=[\mu n]+1}^{n} \Delta\overline{\phi}_j, \tag{3}$$

where $[\mu n]$ is the integer part of μn.

To consistently estimate μ, we minimize the sum of the squared residuals evaluated at $\mu \in (0,1)$[4]:

$$\widehat{\mu} = \arg \min_{\mu \in [\underline{\mu}, \overline{\mu}]} Q_n(\mu) = \sum_{j=1}^{[\mu n]} (\Delta\overline{\phi}_j - \overline{\Delta}_S(\mu))^2 + \sum_{j=[\mu n]+1}^{n} (\Delta\overline{\phi}_j - \overline{\Delta}_L(\mu))^2 \tag{4}$$

Once the sample has been divided into two sub-samples at $\widehat{n}_1 = [\widehat{\mu} n]$, it is possible to test the hypothesis of whether the smaller $\widehat{n}_1$ correlations are different from zero. It is worth noting that, if we reject the null hypothesis for the small correlations, then the large correlations in $\mathrm{L}(n - \widehat{n}_1)$ must be different from zero as well.

The standardise Spacing Variance Ratio, $svr(\eta)$ tests the null hypothesis of independence across individuals with the standardized

$$svr(\mu) = \frac{\sqrt{\mu} SVR(\mu)}{\sqrt{\omega_q^2}} \tag{5}$$

where $\eta = \widehat{n}_1$. $SVR(\eta) = \frac{\widehat{\sigma}_q^2}{\widehat{\sigma}_1^2} - 1$ and $\omega_q^2 = \frac{2(2q-1)(q-1)}{3q}$. Under the null hypothesis, the standardized statistic $svr\ (\eta)$ is distributed, in large samples, as a standard normal [5].

[4]This analysis is designed for cases where a subset of correlations are non-zero. We should note that, if we cannot reject the null hypothesis of $p_j = 0$, for all j, then $\overline{\Delta}_S(\mu) \approx \overline{\Delta}_L(\mu) \approx \frac{1}{2(n+1)}$ for all μ. Equally, when all the correlations are close to unity, there is no variation in $\overline{\phi}_j$. Thus, there would be no mean shift in $\Delta\overline{\phi}_j$.

[5]This test, based on spacings, can be applied to any subset of the spacings between adjacent order statistics since spacings are exchangeable.

2.2 Data and Empirical Results

We study a panel of 48 countries, made up of 22 DC and 26 LDC, for the period 1956-2007[6] (see Appendix I for the list of countries). Our variable of interest is the annual ratio of exports normalized by GDP, (X/GDP). The variables used to construct this ratios are nominal terms of GDP, merchandise exports FOB and either official exchange rate or market exchange rate, depending on the availability of data. These series are taken from the International Financial Statistics provided by the International Monetary Fund. Figure 1 plots the data.

We start by computing the pairs of contemporaneous correlations among the 48 countries. Figure 2 plots the pair correlation probability density function for pure and mixed pairs of countries. We observe that the densities for DC show a quite important concentration of pairs around high correlations, while densities for LDC and mixed pairs groups concentrate around 0 and lower correlations. The differences in the correlation densities between pure pairs of DC and LDC suggest that the dependence pattern of export shares may differ substantially depending on the degree of development of the country.

Dividing the correlation matrix into quantiles provides further evidence of the different patterns of correlation between DC and LDC. We observe that the highest quantile, the one with the 10% highest correlations, mainly contains pairs of DC (72%), quite smaller number of mixed correlations (24%) and only 4% of the correlations for pure pairs of LDC. By contrast, in the lowest quantile, the one with the 10% lowest correlations, we find more than 50% of mixed pairs, 29% of LDC pairs and 20% of DC pairs.

Although the previous descriptive analyses are merely suggestive, they are very informative because they show the different structure of the data for DC and LDC. From this, we conclude that the analysis of the joint samples of DC and LDC might be misleading. So, we focus the analysis on two sub-panels, one for DC and the other for LDC, separately.

[6]We should note that while missing values force us to stop in 2004 for the whole panel and the panel of LDC, for the 22 DC we have data covering the period 1956-2007. We decided to stop the analysis in 2007 to avoid the recent crisis .

Next, we formally test for dependence among countries by using the statistics described in Section 2.1. The CD statistics for LDC and DC are 9.96 and 32.70 respectively. Thus, we reject the null hypothesis of independence for the two sub-panels at the conventional significance levels, concluding that there is cross-section dependence in the two panels.

Before presenting the results of Ng's (2006) test, the spacings q-q plots of reveal information about the extent of cross-correlation in the data by showing the cumulative distribution function of the spacings. The more prevalent and the stronger the correlation, the further away $\overline{\phi}_j$ are from the straight line with slope $1/2(n+1)$. Figures 3(a) and 3(b) clearly show that the factor structure is stronger for DC than for LDC. DC have small idiosyncratic errors and LDC have large ones. For LDC, most of the $\overline{\phi}_j$ lie along a straight line and the quantile function does not exhibit any abrupt change in slope indicating an apparent substantial homogeneity among low correlations. Conversely, for DC, we observe that $\overline{\phi}_j$ no longer evolves around the straight line with slope $1/2(n+1)$. The correlations are heterogeneous and most of them are above high, 0.8.

Regarding the test statistic, for the panel of DC, the test statistics for the S group and for the L group are -1.04 and 6.116, respectively. The estimated point to split the whole sample of spacings, $\widehat{\mu}$, is 0.18. Evidence against independence across individuals is compelling since the null hypothesis of independence can be rejected for 82% of the correlation pairs. Conversely, for LDC, the statistics are -0.08 for the S group and 0.4 for the L group. Thus, the null hypothesis of independence cannot be rejected at the traditional significance levels and it can be concluded that the countries in this panel are independent.

The analyses reveal that cross-section dependence is stronger for DC than for LDC. Consequently, in order to further investigate this pattern, a factor model appears to be a suitable characterization of the export shares given that common factors capture cross-section dependence among units.

3 Factor model analysis

This section studies the factor structure for the panels of DC and LDC[7]. We use factor analysis, which is based on principal components, to model the cross-section dependence and investigate the nature of this dependence in the export shares. We proceed in two steps. In the first step, we analyse the factor structure. This entails estimating the total number of common factors and determining their stochastic properties. The second step involves gauging the relative importance of the common factors with respect to the idiosyncratic components.

Once we have detected the number of factors, the PANIC methodology (Analysis of non-stationarity in the idiosyncratic and common components) developed by Bai and Ng (2004) enriches these results in two ways. It consistently estimates the common and the idiosyncratic component and allows us to identify whether the source of non-stationarity is general or country-specific by testing for unit roots in common factors and idiosyncratic components separately. Moreover, once we have a consistent estimation of the common and idiosyncratic components, we are able to better understand the co-movement of the export shares, which are contemporaneously related, by assessing the relevance of the different components. As said before, unobserved factors are either common or idiosyncratic. The common components are features shared by all the countries in the panel while idiosyncratic components are country-specific features that the individual does not share with the rest of the countries in the panel. We associate the idiosyncratic component with the individual features of each country that determine its exports, namely, internal barriers such as infrastructure quality, bureaucracy, TFP and relationships with countries that dot no belong to the panel. We associate the common components with global supply chains,

[7] Taking the joint sample, we order the 1128 spacings to look for the composition of the S and L group. For the correlations in the S group, only 9% of them are pairs of DC, while 35% are pairs of LDC and the rest, 56%, corresponds to mixed pairs of LDC and DC. Regarding the L group of correlations, 37% of them are between DC, 20% between LDC and 43% are mixed pairs of countries. The three largest correlations are between Austria-France, Austria-Germany and France-Netherlands, while the three lowest correlations are between El Salvador-Jamaica, Greece-New Zealand and Costa Rica-Ireland.

trade agreements, global technology spillovers and common shocks in general.

The first subsection discusses our methodology and the second reports our empirical results.

3.1 Methodology

Factor modelling assumes that any series can be decomposed into two unobservable components: one of them is idiosyncratic (specific for each individual country) and the other is a common component strongly correlated with the rest of the individuals in the panel.

The factor model, with N individuals, will have N idiosyncratic components but a small number of factors. We consider the decomposition of the export shares according to the following factor analytic model:

$$x_{it} = D_{it} + \lambda_i' F_t + e_{it}, \tag{6}$$

where D_{it} is a p-order polynomial trend function which contains the deterministic components, a constant and a linear trend in our particular case. F_t is the $(r \times 1)$ vector of common factors, λ_i is the vector of loadings and e_{it} is the error term, which is largely idiosyncratic.

In practice, the number of common factors it is unknown and we need to estimate it. Ng and Bai (2002) develop procedures that can consistently estimate the total number of common factors. The information criteria proposed by these authors, to be applied to factors estimated by principal components on first differences ($\Delta x_{it} = \lambda_i' F_t + \Delta e_{it}$), requires to minimize the following expression:

$$\begin{aligned} IC_{p1}(k) &= \ln(V(k) + k\left(\frac{N+T}{NT}\right)\ln\left(\frac{NT}{N+T}\right), & (7)\\ IC_{p2}(k) &= \ln(V(k) + k\left(\frac{N+T}{NT}\right)\ln(\min\{N,T\}), & (8)\\ IC_{p3}(k) &= \ln(V(k) + k\left(\frac{\ln(\min\{N,T\})}{\min\{N,T\}}\right), & (9)\end{aligned}$$

where k is the number of factors included in the model and $V(k)$ is the variance of the estimated idiosyncratic components $\widehat{e}_{it} = x_{it} - \widehat{D}_{it} + \widehat{\lambda}_i' \widehat{F}_t$

Simulations showed that when N and T are large, the number of factors can be estimated precisely. However, the number of factors can be overestimated when T or N is small (say, less or equal to 20). These authors show evidence that, in those cases, suggest using the modified criteria BIC_3.

$$BIC_3 = (V(k) + k\widehat{\sigma}^2 \left(\frac{(N+T-k)\ln(NT)}{NT} \right). \tag{10}$$

The case of determining only the number of non-stationary factors is also interesting for the analysis. Bai (2004) proposes new information criteria (IPC) to apply to the factor model of the series in levels.

$$\begin{aligned} IPC_1(k) &= V(k) + kV(k_{\max})\alpha_T \left(\frac{N+T}{NT} \right) \log \left(\frac{NT}{N+T} \right), & (11) \\ IPC_2(k) &= V(k) + kV(k_{\max})\alpha_T \left(\frac{N+T}{NT} \right) \log(\min\{N,T\}), & (12) \\ IPC_3(k) &= V(k) + kV(k_{\max})\alpha_T \left(\frac{N+T-k}{NT} \right) \log(NT), & (13) \end{aligned}$$

where $\alpha_T = [T/4 \log\log(T)]^8$.

Second, to formally check the integration order of both common factors and idiosyncratic components we use the PANIC approach. This methodology permits to test the integration order of the unobservable components separately instead of the observed data. The key feature of PANIC is the analysis of the non-stationarity in idiosyncratic and common components separately consistently estimated by using the method of principal components. It allow us to determine whether the non-stationarity is pervasive, country-specific or both. It is important to notice that, since we are isolating the common component from the idiosyncratic one, the latter is assumed to be independent between countries which

[8] $V(k_{\max})$ is equal to $\left(\Sigma_{i=i}^{N}\Sigma_{t=i}^{T}E(e_{it})^2\right)/NT$, which in practice, is equal to $V(k)$.

allows to use a panel unit root test. The procedure consists of taking first differences in the model to estimate F by applying principal components. Then we need to run the ADF equation on the two components separately[9].

$$\Delta\widehat{F}_t = c + \varphi_0 \widehat{F}_{t-1} + \sum_{j=1}^{M} \varphi_j \Delta\widehat{F}_{t-j} + u_t \tag{14}$$

$$\Delta\widehat{e}_{it} = c + \psi_0 \widehat{e}_{it-1} + \sum_{j=1}^{M} \psi_j \Delta\widehat{e}_{it-j} + \varepsilon_{it} \tag{15}$$

The statistic does not depend on the behaviour of the common stochastic trends. If the common factor is non-stationary, the unit root test can be performed on the estimated residual of the model in levels. However, these individual tests cannot be pooled.

Once we have filtered the co-movements via common factor identification, we perform the pool test on the idiosyncratic components to check their integration order.

The unit root test for the idiosyncratic components is constructed by pooling the p-values since they are independent across countries. The statistic follows asymptotically a standard normal distribution:

$$Pooled - t = \frac{-2\sum_{i=1}^{N} \log p^{\tau}(i) - 2N}{\sqrt{4N}} \sim^{as} N(0,1)$$

3.2 Factor model: estimation and behaviour

The analysis starts by determining how many common factors are necessary to capture the cross-sectional correlation and what their stochastic properties are. Regarding the number of common factors, first, we detect the total number with the IC and BIC_3 criteria, Eq. (5) to (8). Given the number of countries in the two panels we consider a maximum number of common factors equals to four. As observed in Table 1, for DC the results with IC criteria are inconclusive. The first two criteria, IPC_1 and IPC_2, always reach the

[9] Demeaning is not necessary since the mean of the standardised differenced data must be 0.

maximum number of factors allowed and IPC_3 does not detect any common factor in this panel. The lack of at least one common factor in this panel is contradictory to the results in the previous section which document an important cross-section dependence. For LDC, even though IPC_1 and IPC_2, always reach the maximum number of factors permitted, IPC_3 suggest one common factor.

However, as we explained before, these information criteria presents problems if T and N are relatively small since it is well-known that that tend to over estimate the true number of factors. In those cases, Bai and Ng (2002) recommend using BIC_3 to alleviate the problem. For DC, this criterion suggests four factors if allow for a maximum of four factors allowed . If we set $kmax = 3$ it suggest two factors. Finally if we set either $kmax = 2$ or $kmax = 1$ the criterion yields a single factor. For the panel of LDC, there is strong evidence in favour of a single common factor.

Once we have determine the total number of factors, our next tasks is to determine how many of these factor are non-stationary. We apply the criteria proposed in Bai (2004), Eq. (9) to (11), to factors on levels. Table 2 reports our results. For DC, there is evidence of a single stochastic factor, regardless of the maximum number of factors allowed. For LDC, it seems that there is no stochastic common trends since IPC_3, which is known to lead to the most parsimonious specification, persistently suggests zero stochastic factors if we set a $kmax$ equal to 3, 2, or 1, besides for $kmax = 1$ all three criteria yield zero stochastic factors.

From these information, the evidence in favour a single non-stationary factor for LDC is compelling. Moreover, the absence of non-stationary common factors suggest that the single factor detected must be stationary. For the panel of DC, we conclude that there is a single non-stationary factor. However, the possibility of a second stationary factor still uncertain.

Next, in addition to this information criteria, we formally test the characteristics of the common factors and the idiosyncratic components with the PANIC methodology. Table 3 reports the results of the tests. We start by estimating a factor model with a single common factor for DC. This factor represents a 31% of the total variation for this panel. The ADF test cannot reject the null hypothesis of a unit root, confirming the results of IPC[10]. If we estimate a second factor, we reject the unit root hypothesis at 1% of significance for this second factor. The two factors together explain more than 50% of the variation in the export shares. Considering one factor for the sub-panel of LDC we reject the null hypothesis and conclude that this factor is stationary. It confirms the IPC's suggestion about the integration order of this single factor. For robustness issues, we also allow up to 4 factors in the two sub-panels. We observe that results do not change and all the additional factors are stationary. These factors explain a negligible part of the total variation in the sub-panels for DC and LDC[11].

Regarding the integration order of the idiosyncratic components, we applied the pool test proposed in Bai and Ng (2004). As mentioned before, pooling the idiosyncratic components is valid since once we estimate the common factors, the idiosyncratic components are free of the cross-section dependence. We provide evidence that suggests that this condition is, in fact, met in our data by testing for the cross-section dependence among the idiosyncratic components with the *svr* test. The null hypothesis of independence is not rejected even for the S group in any of the two sub-panels. The test statistic is 0.55 for the S group of DC, which contains 70% of the country pairs, for the case of a single factor (for the case of two factors, the test statistic is 0.44 with $\widehat{\mu} = 0.73$). For the LDC, $\widehat{\mu}$ is 0.50 and the value of the test statistics for the S and L groups are -1.42 and 1.56, respectively. So, a single factor is enough to get rid of the cross-section dependence among the individuals for the two sub-panels.

The last column of Table 3 shows that, for the case of a single factor, we do not reject the null hypothesis of a unit root in the idiosyncratic components. However, we do reject

[10]We include a maximum number of 4 lags. Since we are working with the standardized data in first differences, we include a constant but not a trend.

[11]We do not include these results to save space. They are available upon request.

the existence of a unit root for the idiosyncratic components, at a significance level of 10%, when estimating two factors. For LDC, we cannot reject the null hypothesis of a unit root in the idiosyncratic residuals. These results hold regardless of the number of factors considered[12]. To conclude, we find evidence for the non-rejection of the null hypothesis of a unit root for DC and LDC. However, the source of the non-stationarity is different for these two groups of countries. In the panel of DC, non-stationarity is pervasive, due to a common stochastic trend and, only for the case of a single common factor, country-specific characteristics contribute to strengthen the non-stationary behaviour of openness by adding to the effect of the global stochastic trend. Conversely, the analysis reveals that, for LDC, the non-stationarity comes only from some countries. Global shocks have a transitory effect on the openness ratios and only deviate temporarily from their long-run growth path. Country-specific shocks, by contrast, have a permanent effect on the export shares of some countries. In any case, the non-stationarity for this panel is not pervasive.

Table 4 reports an analysis by countries to illustrate the individual importance of the co-movement of the contemporaneously related export shares. Columns 2 and 5 of this table shows the importance of the idiosyncratic components relative to the total variation of the export shares and columns 3 and 6 show the importance of the common factor relative to the idiosyncratic components. For DC, we observe in column 2, that the variance of the common factor is large relative to the total variation in export shares. The common components explain more than 50% of the total variation in the export shares for France, the Netherlands, New Zealand and Norway. It is slightly less than 50% for the UK. For the rest of the countries in the panel, the variability explained by the idiosyncratic component of the export shares dominates the common component. The relative variability of the idiosyncratic factor appears to be slightly more important for Germany and Portugal

[12]This non-stationarity of the idiosyncratic components might be induced by the presence of structural changes that affect the countries at different time and intensity. The seminal work of Perron (1989) demonstrates that, if a structural break is present, it can be quite perilous to ignore since it could mislead the results of unit root tests. Taking into account structural changes and cross-section dependence, the panel test developed by Carrion *et al.* (2005) suggests that this panel is stationary with breaks. This means that country-specific shocks are endowed with no infinite memory for LDC.

and substantially more important for countries like Korea, Iceland and Greece, where the idiosyncratic component is strongly driving the movements of the export shares. For these three countries, the common factor explains less than 10% of the total export shares variation. In general, the contribution of the factors to explain the variation in export shares is heterogeneous among countries. For the extreme case of Korea, the export shares are barely affected by the common features of DC. This does not mean that Korean exports are just under the influence of domestic variables but the variables that explain the 98% of fluctuations in its exports are not related to the export shares of DC in our sample. Issues underlying the idiosyncratic components might be the trade links with partners not included in this panel such as countries of South-East Asia.

Although there are some exceptions, the common component still drives most of the export shares for DC. The third column of Table 4 shows an alternative way of assessing the variation of the common factors relative to that of the idiosyncratic components. We observe that the common factors are more relevant than the idiosyncratic component in Australia, the Netherlands, New Zealand, Norway, Portugal and the UK. However this relative variation is low in countries like Canada or Ireland and the lowest, only 11%, in Korea. It also confirms the heterogeneity observed in the previous analysis. Appendix C shows that the results when considering two factors in the model barely change except for Iceland that they are opposite. For LDC, the results are much more homogeneous. As can be seen in the last two columns of Table 4, for all the countries but Venezuela and Trinidad and Tobago, country-specific events, which also include trade relationships with other countries outside this panel, are driving the variation in export shares. For 16 out of the 26 countries, the idiosyncratic component accounts for at least 90% of the total variation in the export shares.

The results in this section support our priors about the grater importance of common factors than country-specific circumstances in driving the variation in the export shares for DC. This intensity of exports is modelled with a global component which includes one or two common factors (a stochastic trend and might be a global shock) and a component which is idiosyncratic. As can be seen in Table 3, the stochastic common trend and the global shock together explain more than half of the total variation in the data, more than 30% and 20%, respectively. However, the intensity of trade in LDC is mainly driven by country-specific features rather than common shocks. The factor model structure for these countries is quite different since it consists of a global shock which plays a smaller role in the total export share variation, 27%, and country-specific variables with a great importance in explaining the variation in the countries' export intensities. It is in line with Costinot 's et al. (2011) suggestions about the existence coordination costs. Trading frictions (customs, infrastructure, bureaucracy, etc), which continue to be more relevant in LDC, might result in a complete specialization in a subset of stages, thus deviating the trade with other countries in the same sub-panel.

4 Inference on estimated factors

So far, we have analysed the unobservable factor model structure of export shares. However, the importance of the common component to explain the trade share variations, especially for DC, leads us to focus on the economic interpretation of this common trend. Building on the previous results, we work on the identification of the underlying stochastic factors with observable macroeconomic variables. We examine the relationship between the estimated common stochastic factor and the international fragmentation by using the methodology proposed by Bai (2004). In particular, the consistent estimation of the underlying factor derived from the unobservable factor model in (4) allow us to check whether the unobservable factor model is consistent with an empirical factor model.

To define the candidate observable variable to be the underlying factor, we combine the theoretical evidence about the patterns of trade in DC and LDC and the information from our analysis about the nature of export shares. The candidate variable may fit in the interpretation of a global stochastic trend so, it must hold two conditions. First, to affect all the countries in the panel. Second, to deviate the export shares from their long-run equilibrium permanently. The first condition is easily hold by the international fragmentation since, as it is well-known, fragmentation is one of the major changes in the world economy affecting most countries. Regarding the second one, international fragmentation has changed the traditional paradigm of international trade. In the past, First wave of Globalization, international trade was horizontally specialized since trade costs, technology available and current communication and service developments made international fragmentation uneconomic, hence, good were produce from the beginning to the end in the same location and even in the same country. In the last decades, the specialization in stages of the production process means a permanent shock for export shares since the exports of a country are not bounded any more by its GDP (domestic value added) but countries have the possibility of exporting not only domestic value added but also foreign value added. Thus, shocks that affect international fragmentation phenomenon may deviate export shares from the long-run equilibrium growth permanently. Similar arguments have been suggest by several authors for the controversial topic of GDP stochastic properties. These authors point technology shocks as events that deviate GDP from its long run growth, hence, they endow GDP with a non-stationary behaviour.

However, in addition to the our intuition, it would be interesting to provide empirical evidence to support this prior. In order to test the hypothesis of whether international fragmentation phenomenon might be the underlying common stochastic factor in the panel for DC, we construct an indicator to capture the importance of this phenomenon on international trade. The indicator is based on the measure of vertical specialization (VS henceforth) originally defined by Hummels *et al.* (2001). The key idea behind fragmentation is that countries link sequentially to produce goods by carrying out different tasks of the productive process. goods. The approach to constructing the VS measure focuses on one feature of this sequential linkage which is the imported intermediate goods embodied in the domestic exports of a particular country. In other words, VS measures the amount of imported intermediate goods used by a country to make goods or goods in process which are, in turn, exported to another country[13],

$$VS_{kti} = \sum_i \left(\frac{IIM_{kti}}{gross\ output_{kti}} \right) \cdot X_{kti}, \tag{16}$$

where IIM_{kti} denotes the value of imported intermediate inputs in sector i in country k and X_{kti} represents the merchandise exports. The simple aggregation of this measure across all i-sectors gives us the VS for country k at time t, $VS_{kt} = \sum_i VS_{kti}$, which represents the foreign value added embodied in exports for a particular country.

Let GLOBAL be our candidate to identify the factor. It is constructed as a ratio of the sum of the VS for the different countries at time t and the sum of the GDP for the different countries at time t:

$$GLOBAL_t = \frac{\sum\limits_{k=1}^{K} VS_{kt}}{\sum\limits_{k=1}^{K} GDP_{kt}}, \tag{17}$$

where K is the number of countries. Input-output tables provide industry-level data on imported intermediates, gross output and exports to construct VS[14]. The data source used to calculate VS are the OECD input-output tables, except for Ireland and Korea whose tables are provided by their national statistical agencies or Central Banks. Input-output tables facilitate the measurement of the indirect import content of exports. VS concentrates on the manufacturing sector since service exports do not contain foreign value added so they are not a good variable for capturing the fragmentation phenomenon. Exports of services are registered in the official statistics at value added instead of gross value, as occur in manufacture exports.

The countries for which we have information about VS, for several years between

[13]For a more detailed description of the measure, see Hummels *et al* (2001).
[14]The output is divided into 35 sectors, including 22 manufacturing sectors.

1968 and 1998, are Australia, Canada,Denmark, France, Germany, Ireland, Japan, Korea, Netherlands, Spain the UK and the US. Hummels *et al.* (2001) provide data on VS for all the 12 countries but Spain. For the latter Minondo and Ruber (2002) provide this information. Chen *et al.*(2005) and Miroudot and Ragoussis (2008) update the VS measure for 2000 and 2005, respectively. Given the input-output temporal coverage, we need to interpolate the available data to generate the yearly country foreign value added export series. The GLOBAL measure is computed yearly over 1968-2007. Interpolations are based on cubic spline polynomials, which are the approximating functions of choice when a smooth function is to be approximated locally[15].

As long as these countries are representative of DC, we expect GLOBAL to be an accurate measure for capturing the fragmentation phenomenon. In 2007, the merchandise exports for these 12 countries accounted for 82% of the advanced economies' merchandise exports and for more than 83% of the aggregated GDP for this group. Taking the world as a reference, these 12 countries account for almost 50% of the world GDP and around 70% of world trade. Therefore, the information contained in this sample is quite representative and should provide enough insight to analyse the consequences of the international fragmentation of production on the stochastic properties of the export shares.

The distribution theory developed in Bai (2004) allows us to check whether the variable GLOBAL is the underlying stochastic factor. Let us define the empirical model as follows:

$$\left(\frac{X}{GDP}\right)_{it} = \alpha + \lambda_i' GLOBAL_t + e_{it}, \tag{18}$$

[15]This interpolation method is preferable to the method of truncated Taylor series. The general idea of any interpolation method is to compute the values of $f(x)$ in the interval $[a, b]$ knowing $f(a)$ and $f(b)$. The truncated Taylor series provides a satisfactory approximation for the series at each point x if its path is sufficiently smooth and the interpolation point is sufficiently close to a or b. But, if a function is to be approximated on a larger interval, the degree of the approximating polynomial may have to be chosen unacceptably large. The alternative is to subdivide the interval $[a, b]$ of approximation into sufficiently small intervals $[\zeta_j, ..., \zeta_{j+1}]$, with $a = \zeta_1 < ... < \zeta_{j+1} = b$, so that, on each of them, a polynomial P_j of a relatively low degree can provide a good approximation to the time series. This can even be done in such a way that the polynomial pieces blend smoothly, so that the resulting patched or composite function $s(x)$ that equals $P_j(x)$ for $x \in [\zeta_j, ..., \zeta_{j+1}]$, and all j, has several continuous derivatives. Any such smooth piecewise polynomial function is called a spline.

where $i = 1, ..., N$, is the index for countries and $t = 1, ...T$, for time. λ_i' is the vector of loadings and e_{it} represents a group of country-specific characteristics that are largely idiosyncratic.

We take the consistent estimation of the factor to examine the relationship between the common factor and observable macroeconomic variables. To test whether GLOBAL is the true underlying factor, we rotate the unobservable stochastic common factor toward GLOBAL through the following OLS estimation:

$$GLOBAL_t = \alpha + \gamma' \widetilde{F}_t + \upsilon_t \tag{19}$$

where $\widetilde{F}_t$ is the estimated factor and υ_t is an error term.

Then, we construct the 95% confidence intervals for the estimated stochastic factor. If GLOBAL is the underlying factor, we expect this variable to lie inside the confidence intervals most of the time.

For the case of a single common factor the explanatory power of the model, measured by the adjusted R-squared is 93%. Figure 4 (a) plots the 95% confidence intervals for the estimated stochastic common factor (dotted line) and the observable variable GLOBAL (solid line). GLOBAL lies inside the confidence intervals most of the times. More precisely, we do not reject the null hypothesis that the estimates stochastic factor and GLOBAL are equal in 85% of the times and conclude that GLOBAL is the underlying common factor. For robustness, a second factor is included in the estimations. For this regression, the explanatory power of the model is also very high, 94%, and, as shown in Figure 4 (b), 75% of the GLOBAL observations are inside the limits of the confident band. In addition, results remain the same when working with different constructions of GLOBAL variable.

To conclude, we suggest a simpler representation of the trade openness, more efficient estimation and a direct economic interpretation of the global stochastic trend. In the light of the results, export intensity across DC can be well explained by a non-stationary factor and non-stationary idiosyncratic components. We find strong evidence suggesting that, international fragmentation (vertical specialization) is the underlying common factor. Using a different methodology, Hummels *et al.* (2001), similarly estimate that VS accounts for 30% of the total variation in the world exports. Given the lack of representative foreign value added in the exports shares for LDC, it is sensible to assume that this figure may depict, mainly, the relevance of international fragmentation for DC.

Further evidence about how this factor affects the individual countries in the panel come from the loadings. Once conclude that international fragmentation can proxy for our single non-stationary factor, we present its contribution to the variation of the export shares for each individual DC. As can be seen, in Figure 5, the largest contributions of the stochastic common factor are for the Netherlands and Ireland which are the countries that export the highest shares of foreign value added. Conversely, the US, Japan and Australia which are large and more geographically isolated than the former, are the ones for which vertical specialisation has less impact in their export shares, together with Greece and Spain. For the rest of the countries, the global trend has a similar impact[16]. After controlling for traditional variables, i.e. distance, trade agreements and size, the cases of Greece and Spain, which are the less developed economies in the group of DC, might reflect the positive relationship between the degree of development and the importance of vertical specialization on export share variation suggested in this paper.

5 Conclusions

The international fragmentation of productive processes is re-shaping the traditional way of thinking about trade and the borders of production. This paper shows the different structure of export intensity for DC and LDC. Our finding might reflect the consequences of participating in global supply chains in terms of the dependence structure of export intensity across countries. One of our main contributions is the identification, through a

[16]France, Italy and Portugal show the global trade impacts on export intensities below the average

dynamic factor model analysis, of the fragmentation phenomenon as a common stochastic trend that may explain changes the international trade dynamics of DC. For LDC, we show that, rather than common shocks, country-specific characteristics drive trade dynamics. These countries face relatively high coordination costs and tend to specialize in a subset of production stages at the bottom of global supply chains, providing developed countries with parts and components. Thus, the imported intermediates content in exports for less developed countries is still comparatively low. Our results are in line with recent theoretical models that show how fragmentation shapes the trade interdependence among nations.

These results corroborate several predictions of recent theoretical models such as Costinot *et al.* (2011). The different positions of DC and LDC in the global supply chains, together with trade frictions, may determine the international trade dynamics for the different groups of countries. On the one hand, the analysis suggest that DC tend to be involved in the later stages of global supply chains, which endows these countries with a stochastic global trend. On the other hand, for LDC, the importance of the idiosyncratic components and the lack of a non-stationary common factor reflect some inconsistency with the pattern of trade predicted for these countries in Costinot's *et al.* (2011) free-trade baseline model. The presence of trade frictions may lead to a complete specialization in a subset of stages rather than the carrying out of sequential stages of the global supply chains. As a result, LDC tend to focus on certain stages of production in order to export the intermediate good to any DC. Thus, part of the trade among LDC might be deviated to DC which are outside the sub-sample. Regarding the absence of the non-stationary common factor, we can argue that international fragmentation changes the traditional paradigm of international trade only for DC. In this scenario, LDC may simply join in international trade under more favourable conditions but without exporting representative amounts of foreign value added.

Appendices

A Countries

TABLE AI
Countries

Less developed countries	Developed countries
Barbados	Australia
Colombia	Austria
Costa Rica	Canada
Cyprus	Denmark
Dominica Republic	Finland
Egypt	France
El Salvador	Germany
Fiji	Greece
Guatemala	Iceland
Guyana	Ireland
Honduras	Italy
India	Japan
Jamaica	Korea
Malta	Netherlands
Mauritius	New Zealand
Mexico	Norway
Morocco	Portugal
Nigeria	Spain
Pakistan	Sweden
Panama	Switzerland
Philippines	United Kingdom
South Africa	United States
Sri Lanka	
Thailand	
Trinidad and Tobago	
Venezuela	

Notes: Countries classified according to the World Bank criteria.

B Robustness check: relative importance of common factors (two factors)

TABLE C

Exports' structure by countries

Developed countries

	$\frac{VAR\Delta(\widehat{e}_{0it})}{VAR\Delta(X_i)}$	$\frac{\sigma(\widehat{\lambda}_i'\widehat{F}_t)}{\sigma(\widehat{e}_{0it})}$
AU	0.59	1.45
AT	0.65	0.37
CA	0.78	0.33
DK	0.64	0.76
FI	0.67	0.69
FR	0.47	0.69
GE	0.60	0.58
GR	0.93	0.41
IC	0.02	3.90
IR	0.82	0.33
IT	0.75	0.52
JP	0.67	0.93
KO	0.98	0.11
NL	0.36	2.42
NZ	0.42	1.18
NO	0.36	2.51
PO	0.60	1.12
SP	0.58	0.39
SW	0.66	0.57
SZ	0.66	0.60
UK	0.52	1.03
US	0.84	0.42

Notes: Factor model structure includes two common factors for DC and LDC

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Tables

TABLE I

Number of common factors				
Developed countries				
k_max	1	2	3	4
IC_1(k)	1	2	3	4
IC_2(k)	1	2	3	4
IC_3(k)	0	0	0	0
BIC_3(k)	1	1	2	4
Less Developed countries				
k_max	1	2	3	4
IC_1(k)	1	2	3	4
IC_2(k)	1	2	3	3
IC_3(k)	1	1	0	1
BIC_3(k)	1	1	1	1

TABLE II

Number of common stochastic trends				
Developed countries				
k_max	1	2	3	4
IPC_1(k)	1	1	1	1
IPC_2(k)	1	1	1	1
IPC_3(k)	0	1	1	1
Less developed countries				
k_max	1	2	3	4
IPC_1(k)	0	1	1	1
IPC_2(k)	0	1	1	1
IPC_3(k)	0	0	0	1

TABLE III

Panic Analysis					
	nf	$ADF_F^C(1)$	% variance explained	Pooled test P_x	Pooled test $P\widehat{e}_{0it}$
Developed countries				-1.216	
	1	-0.617	31.32		-1.300
	2	-3.26***	21.36		-1.722*
Less developed countries				0.948	
	1	-2.731*	27.22		0.800

Notes: ADF tests include a maximum of 4 lags. P_x *represents the unit root test results of the observable series*

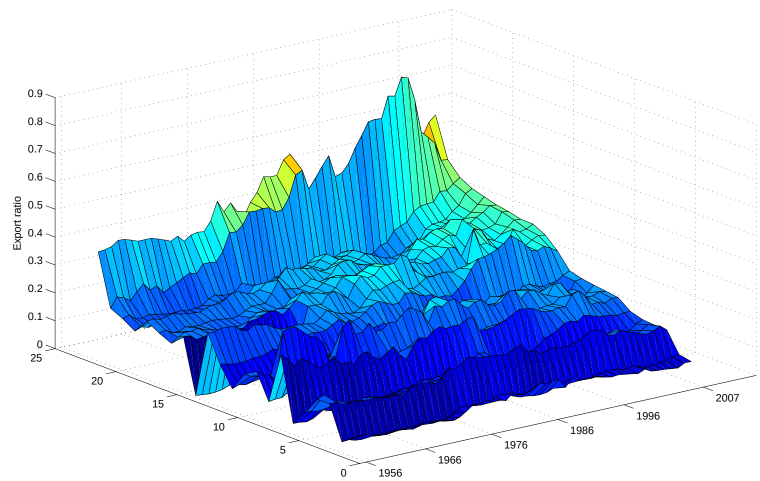
TABLE IV

Export structure by countries

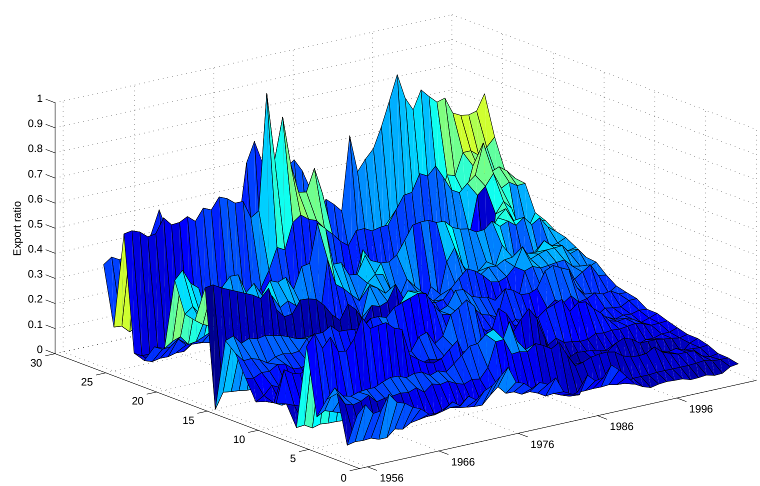
Developed countries			Less developed countries		
	$\frac{VAR\Delta(\widehat{e}_{0it})}{VAR\Delta(X_i)}$	$\frac{\sigma(\widehat{\lambda}_i'\widehat{F}_t)}{\sigma(\widehat{e}_{0it})}$		$\frac{VAR\Delta(\widehat{e}_{0it})}{VAR\Delta(X_i)}$	$\frac{\sigma(\widehat{\lambda}_i'\widehat{F}_t)}{\sigma(\widehat{e}_{0it})}$
AU	0.69	1.29	**BA**	0.99	0.03
AT	0.66	0.38	**CO**	0.98	0.07
CA	0.78	0.33	**CR**	0.99	0.04
DK	0.64	0.75	**CY**	1.00	0.02
FI	0.68	0.69	**DR**	0.94	0.10
FR	0.48	0.70	**EG**	0.90	0.17
GE	0.63	0.55	**ES**	0.99	0.04
GR	0.93	0.40	**FJ**	0.76	0.24
IC	0.97	0.37	**GU**	0.93	0.16
IR	0.82	0.33	**GY**	0.78	0.26
IT	0.75	0.52	**HO**	0.99	0.04
JP	0.71	0.88	**IN**	0.94	0.06
KO	0.98	0.11	**JA**	0.80	0.31
NL	0.37	2.39	**ML**	0.87	0.09
NZ	0.42	1.18	**MA**	0.74	0.49
NO	0.37	2.40	**MX**	1.00	0.01
PO	0.62	1.11	**MO**	0.61	0.53
SP	0.67	0.40	**NI**	0.76	0.37
SW	0.68	0.58	**PK**	1.00	0.03
SZ	0.67	0.62	**PA**	0.93	0.13
UK	0.52	1.04	**PH**	0.99	0.02
US	0.84	0.42	**SA**	0.89	0.20
			SL	0.99	0.05
			TH	0.97	0.03
			TR	0.47	0.60
			VE	0.19	1.89

Notes: Factor model structure includes a single common factors for DC and LDC

Figures



(a) Developed countries arranged in ascending order according to their 2007 values



(b) Less developed countries arranged in ascending order according to their 2004 values

Figure 1: The intensity of exports across countries

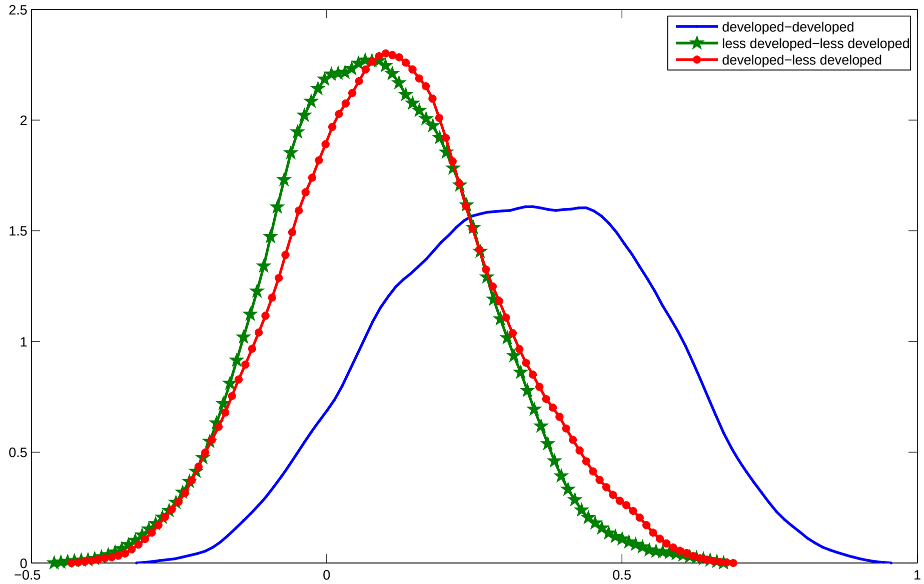
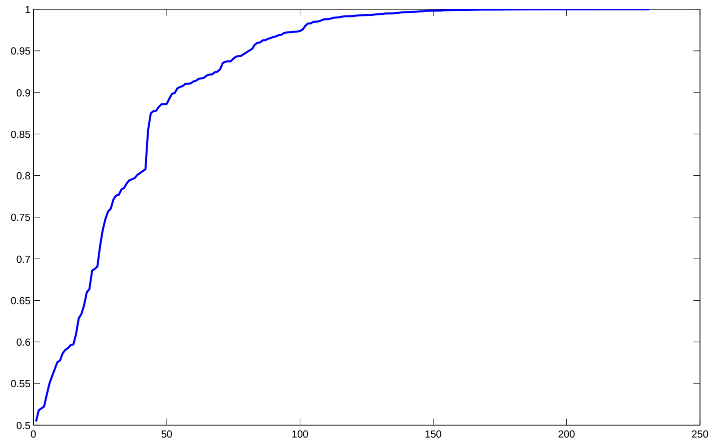
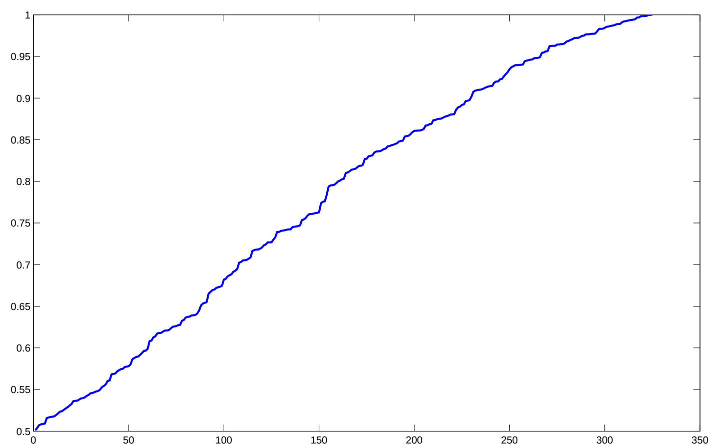


Figure 2: Densities

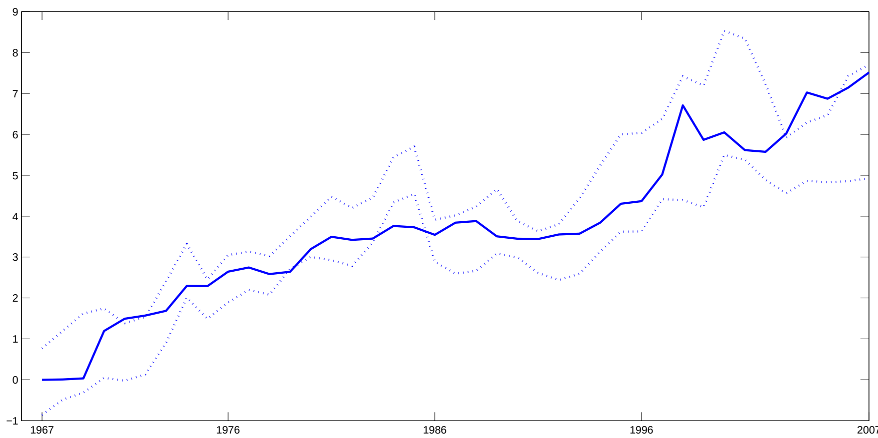


(a) Spacings: Developed Countries

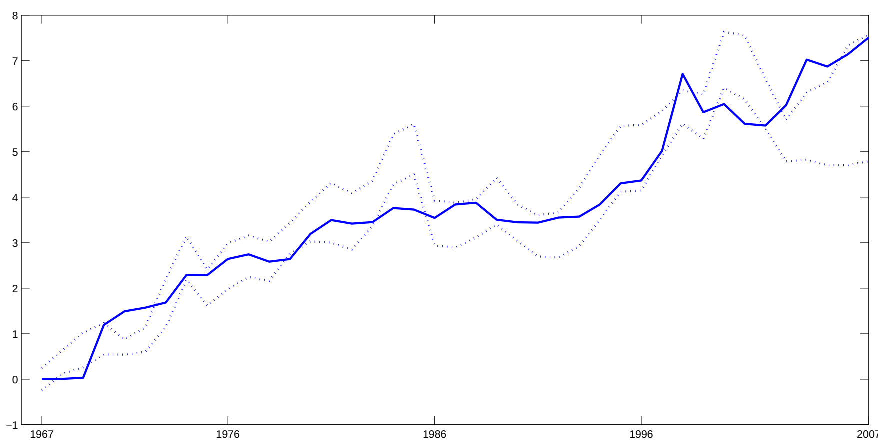


(b) Spacings: Less Developed Countries

Figure 3: Spacings



(a) One factor



(b) Two factors

Figure 4: Confidence intervals (dotted line) for testing GLOBAL measure (solid line) as a factor

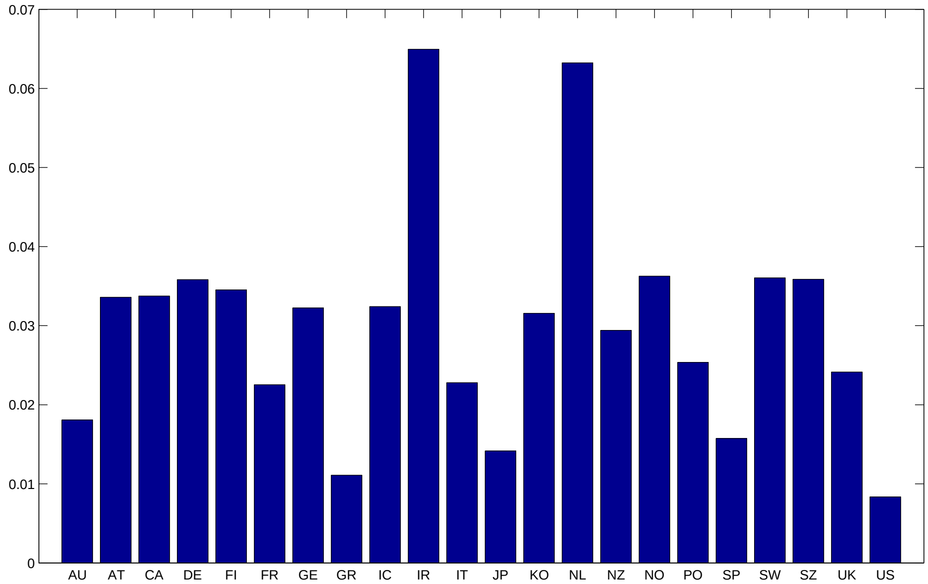


Figure 5: Loadings