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The Network Origins of Economic Growth

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Abstract

In this paper, we propose a new approach to represent a country's outward orientation. Prior work mostly uses indicators of aggregate trade intensity, trade policy or trade restrictiveness. Our approach offers a broader perspective as it measures a country's level of integration not only by its set of direct trade connections with the rest of the world but also through the full architecture of its second, third, and all other higher-order connections. We apply our methodology to a sample of 167 countries spanning the period from 1962 to 2009 and perform a Bayesian model-averaging analysis on the determinants of growth. We find a prominent positive effect of integration on a country's level of per capita income, while the aforementioned traditional measures of outward orientation display only a secondary, largely insignificant, weight. This, we argue, highlights the network basis of economic growth and adds a novel perspective to the notion of economic openness. We also perform several sensitivity checks and conclude that our baseline findings are extremely robust to different data input and alternative assumptions about the computation of country integration.

JEL classification: C11, D85, F15, F63, O40
Keywords: Globalization, Trade Integration, Economic Growth, Network Analysis, Dynamic Panel Model, Bayesian Model Averaging

1 Introduction

A long-standing theme in the empirical literature on economic growth concerns the identification of growth determinants. Inspired by early work of Baumol (1986) and Barro (1991), numerous studies were designed to establish whether a given variable does or does not help explain cross-country growth differences. The variable which has attracted considerable research interest for decades is a country's openness to international trade. Despite countless efforts to identify its effect on growth, the debate has proven inconclusive. By the late 1990s, the so-called *Washington Consensus* had emerged, saying that greater openness to international trade leads to faster growth and higher standards of living for a country. This view was based on the influential work by Dollar (1992), Sachs and Warner (1995), and Frankel and Romer (1999)[1]. However, a thorough re-investigation of existing evidence undertaken by Rodríguez and Rodrik (2001) turned the consensus quite on its head. Specifically, these authors argue that the results are not reliable because of two broad reasons. The first is a number of econometric difficulties such as endogeneity or the high sensitivity of results to new data-sets and to small modifications of the empirical model. The second reason concerns misgivings as to whether existing indicators of a country's outward-orientation in fact measure what they are supposed to measure, in the sense that they do not seem well suited to capture the particular dimensions of a country's openness which are potentially relevant for its economic performance[2].

In this paper, we jointly address both points of the critique. On the one hand, we propose a novel approach to represent a country's outward orientation that is based on the architecture of connections each country entertains with the rest of the world. More specifically, we interpret the bilateral trade flows between countries as a (weighted) network and evaluate the degree of integration of an economy into the global network structure not only by the number of direct connections an economy has (and the way they are distributed) but also by its second and all other higher-order connections. The theoretical motivation for our approach derives from the theory developed by Duernecker and Vega-Redondo (2012) to study the phenomenon of economic globalization. Their analysis suggests that the characteristic of a country's outward orientation that matters for its economic performance is related to the country's network centrality – i.e. the extent to which the country is economically "close" to others in the network, either directly or indirectly. This is the notion of "closeness" that provides the conceptual basis for our approach and also induces the operational measure for a country's integration into the world economy that will be used in this paper.

[1]It is also the position supported by more recent studies such as Dollar and Kraay (2003), Alcala and Ciccone (2004), Romalis (2007) and Feyrer (2009)

[2]For a review of recent work see Winters (2004), Rodríguez (2007) and Estevadeordal and Taylor (2013).

On the other hand, we use a dynamic panel framework to revisit the empirical debate of whether a country's outward orientation does have a significant impact on its economic growth performance. The main concern of our analysis is to assess the extent to which our new measure of outward-orientation – what we call "integration" – really matters for explaining cross-country growth differences. And to carry out this assessment, we do not simply estimate a single growth equation but, instead, we perform a comprehensive Bayesian model averaging analysis. This allows us to solve the traditional problem of model uncertainty originating in the question of which regressors to include into the statistical model.

In much of the existing empirical work, a country's outward orientation was measured either by indicators of the aggregate trade intensity (such as the trade share of a country) or by indicators of trade policy and trade restrictiveness (for instance, the Sachs-Warner index, average tariffs, or Leamer's intervention index)[3]. Our approach offers a broader, and also qualitative different, perspective on the phenomenon. As explained, it adopts a global approach to measuring economic integration that takes into account the architecture of *both* direct and indirect connections that each country has with the rest of the world. Our empirical analysis shows that the customary "local" approach (based e.g. on the volume of trade of a country with its direct partners) misses much of the high explanatory power that trade connections do possess for explaining inter-country differences in growth performance.

We apply our methodology to a sample of 167 countries spanning the period from 1962 to 2009[4]. A preliminary analysis of the data already reveals a number of interesting patterns. One of them is that, along the period considered, the world as a whole has become more integrated but also more unequal. In particular, we find that while the group of most integrated countries shows a persistent tendency to increase their integration, the majority of less integrated countries displays an opposite trend towards lower integration. For countries lying in the middle integration range, on the other hand, we observe that there is a significant heterogeneity in the evolution of their integration over time and a substantial change in the ranking of many of them.

An additional interesting finding gathered from our initial descriptive analysis is that our measure of country integration is essentially uncorrelated with the classical trade-share variable for openness used by the literature. This observation provides some preliminary but stark evidence in support of one of our main points in the paper, namely, that a network perspective to understanding outward orientation is qualitatively distinct from the local one customarily pursued in the economic analysis and policy discussion.

[3]Durlauf et al. (2005) provides a tabular listing of the set of indicators.
[4]The resulting data-set can be downloaded from the authors' websites.

Then, in addressing the problem systematically, we conduct an extensive exercise of model selection based on Bayesian model-averaging techniques. The essential conclusion derived from it is that trade integration is a robust and economically important determinant of cross-country differences in growth performance. Specifically, the results establish a positive and very significant effect of more integration on a country's level of per capita income. Furthermore, when we include two of the conventional indicators for outward orientation in the analysis, we find that both are only marginally important. This result sheds some light on why the aforementioned debate around the validity of the *Washington Consensus* has largely undermined it. In particular, it confirms Rodriguez and Rodrik's (2001) view that the traditional measures of outward-orientation do not measure the particular dimensions of a country's openness that are truly important for economic performance.

To conclude the paper, we perform a number of sensitivity checks and find that our baseline findings are extremely robust to different data input and alternative assumptions about the computation of country integration. In one of these modifications, we consider trade in selected categories of goods instead of aggregate trade flows to derive a country's connectedness. Interestingly, this exercise lends support to the notion that a country's connectedness to the global trade in investment goods is particularly important for its growth performance, whereas the connectedness to trade in commodities and processed raw materials is only *marginally* relevant. These results are in line with the theories developed by Alvarez *et al.* (2013) and Chaney (2014). In the first paper, Alvarez *et al.* (2013), the engine of growth is the flow of ideas through the global trade network. More specifically, their model assumes that ideas are embodied in technologies and their diffusion occurs through interpersonal contacts mediated by trade. More trade leads to a selection effect – the replacement of inefficient domestic producers with more efficient foreign producers – which enhances the quality of ideas of domestic producers and therefore increases productivity and accelerates economic growth. In the second paper, Chaney (2014), the focus is on how firms expand their contacts and thus gain access to new consumers by relying on their existing contacts. As in our paper, better connected firms use their higher access to opportunities to grow faster – however, an important difference with our paper is that, as explained, in our case the notion of connectedness is global and thus, even for a given firm, it pertains to the whole social network.

The remainder of this paper is structured as follows. Section 2 introduces the new measure of country integration and explains the details of its operationalization and its connection to related proposals found in the literature. Section 3 contains the empirical analysis of the role of country integration for explaining cross-national income and growth differences. Section 5 presents the results of this analysis, Section 6 discusses various robustness tests and Section 7 concludes. An Appendix contains supplementary materials.

2 Network measure of economic integration

Underlying theory: a brief outline and its operationalization

The model proposed by Duernecker and Vega-Redondo (2012) (hereafter referred to as DV) has provided the conceptual basis to formulate the problem precisely. In Appendix A, the reader can find an extended, yet informal, account of the model studied in DV and its main conclusions. At this point, therefore, we choose to provide just a brief outline of the key features and conclusions that are relevant for our purposes.

The model studied by DV is a model of network formation, where the agents are given recurrently the opportunity to form new links (conceived as fresh valuable economic opportunities) while pre-existing links decay at a constant exogenous rate. The performance of the economy is identified with its ability to organize itself so that it can maintain a high density of connections – in a nutshell, this entails the need to create links at a rate that is fast enough to offset link decay, which will be large if existing links are numerous. In the model, agents are distributed uniformly over some underlying "physical space" and create links when they meet others who can complement their own skills. But, in the end, whether such possibilities do in fact fructify requires that the two agents involved be close, either geographically or, more commonly, socially (i.e. in terms of the current social network). One of the key insights of the model is that, in order for the economy to achieve in the long run a dense network of partnerships, it must become globalized. This, in essence, means that the social (network) distance between agents is typically short. Dense connections and globalization are, in other words, two sides of the same coin.

More specifically, a direct prediction of the model is that, *ceteris paribus*, a node/agent is able to grow faster (i.e. maintain a higher number of active links) the closer it is to others in the social network. This is the starting point from where we proceed to formulate our empirical setup. Important adaptations, however, are needed. First, we identify nodes with countries and their measure of economic performance with the classical one used in the empirical analysis of growth across countries, i.e. their GDP. Links, on the other hand, conceived as a reflection of interaction between countries, can no longer be suitably defined as binary entities (0/1), since this would be too coarse a representation of country interaction. Instead, we focus on trade as a continuous measure of country bilateral interaction. This implies, in particular, that the relevant social network is a weighted one, i.e. the links have a real-valued (non-negative) weight associated to them.

In this paper, for the sake of focus, we measure economic interaction through the magnitude of trade flows across countries. But, in general, one could also consider other forms of interaction such as investment flows (FDI), financial transfers, or population movements.

Formally, the pattern of trade flows prevailing at a certain point in time will be usually described by a corresponding square matrix of a dimension equal to the number of countries considered. In what follows, we explain how our measure of country integration is constructed from these data. This is then complemented by Appendix C, where we describe an efficient algorithm for computing the integration measure.

Let n be the set of countries and denote by x_{ij} the trade flow from any given country i to some other country j. Thus x_{ij} stands for the exports from i to j while x_{ji} corresponds to the imports from j to i. The matrix of all such bilateral flows is denoted by $X \equiv (x_{ij})_{i,j=1}^n$, with $x_{ii} = 0$ for all elements of the main diagonal. Starting from such matrix X of trade flows, we now normalize its entries to account for inter-country asymmetries that would otherwise distort the respective magnitudes. This normalization is geared to capture the following two important features of these flows:

(i) the true openness of each country, as measured by the magnitude of its trade flows *relative* to both its size and the size of the rest of the world;

(ii) the relative weight of each partner in the overall trade flows of every given country.

To account for (i), denote by y_i the GDP of country i and by β_i the fraction of country i's GDP in world economy, i.e. $\beta_i \equiv \frac{y_i}{\sum_{j=1}^n y_{ij}}$. Then, we follow Arribas et al. (2009) and identify the *openness* of a country i with the value $\theta_i \equiv \frac{\sum_{j \neq i} x_{ij}}{(1-\beta_i)y_i}$. This normalizes the aggregate exports of the country by its own size (as captured by its GDP) and the size of the of the "rest of the world" with which trade is conducted.[5] To account for (ii), on the other hand, we simply normalize the export flows of each country i by their aggregate volume, so that the induced magnitudes $\tilde{x}_{ij} \equiv \frac{x_{ij}}{\sum_{j \neq i} x_{ij}}$ satisfy $\sum_{j \neq i} \tilde{x}_{ij} = 1$. Then, we construct a matrix of interaction $A = (a_{ij})_{i,j=1}^n$ as follows:

- $\forall i = 1, 2, ...n, a_{ii} = 1 - \theta_i$
- $\forall i = 1, 2, ..., n, i \neq j, a_{ij} = \theta_i \tilde{x}_{ij}$

Provided $0 \leq \theta_i \leq 1$, the matrix A defined as above is a row-stochastic matrix, i.e. $\sum_{i,j=1}^n a_{ij} = 1$. This allows us to view this matrix as the adjacency matrix of a *weighted directed network* where the aggregate level of interaction flowing from each node is normalized to unity. Equivalently, of course, we can also regard the entries of the matrix A as the transition probabilities of a Markov chain where each of the n agents is associated to a distinct state.

[5]This normalization requires, for example, that if either the size of the country or the rest of the world increases, exports should increase in the same proportion if the country is to be judged as equally open.

Building upon the latter interpretation, it is natural to define the proximity of two agents/nodes, i and j, as the expected number of steps it takes i to reach j. We compute the expected number of steps that, according to such induced Markov chain, the process would take to move from each country i to every other country $j \neq i$. This defines, for each country i a vector of distances to all other countries j, $(\varphi_{ji})_{j \neq i}$.

In the Appendix, we explain in detail how such distance measure can be easily computed from the matrix A. To understand it conceptually, let us interpret any given a_{ij} in this matrix as the fraction of links of a typical individual in country i that connect to agents in country j. Then, that entry may be also identified with the *probability* that there is an indirect connection to country j mediated through some randomly selected individual of country i. It is in this sense that we argue that our (continuum) notion of distance represents a natural counterpart of the network distance defined in our theoretical model for a (discrete) binary network.

To assess the degree of global integration of any given country i, we construct an index that is given by a weighted average of the different φ_{ji} for every other $j \neq i$, where the weight associated to each country j is equal to its share β_j in world GDP (see above for the definition). This weighting scheme reflects the idea that any access obtained to a particular country has to be evaluated in terms of the "value" (i.e. GDP) generated in that country. Thus, the integration ϕ_i of each country $i = 1, 2, ..., n$ is given by

$$\phi_i \equiv \sum_{j \neq i} \beta_j \varphi_{ij}$$

Then, the "closeness" of country i to the rest of the world is identified with the inverse of such weighted distance, i.e. $1/\phi_i$. And, since this magnitude is compressed close to zero for countries whose weighted distance to large countries is high, it is useful to consider the logarithmic transformation given by $\log(1/\phi_i) = -\log \phi_i$ and then simply focus on the absolute magnitude $\varsigma_i \equiv |-\log \phi_i| = \log \phi_i$ as our measure of integration of country i. Note that lower values for ς_i correspond to countries i that are better integrated in the world economy. Heuristically, therefore, a country is regarded as highly integrated if it is quite central to the network of world trade. That is, when economic interaction is measured by the relative intensity of trading conducted by each country (relative to its GDP), an integrated country is one where the suitably weighted number steps required to access a large fraction of world GDP is relatively low.

An approach related to ours is conducted by Garlaschelli and Loffredo (2005) to study the properties of the world trade network and its evolution over time. The main difference to our approach is that these authors use a binary system to represent the relation between countries. We consider the weighted network approach more suited for the analysis because it allows us to capture the intensity of the interaction between countries. A binary network, in other words, seem to embody too coarse information to be really useful (see more on this below). These authors, in any case, do not aim at using the properties of the trade network to explain the economic performance of the different countries.

The study closest to ours is Kali and Reyes (2007). These authors use trade data for 192 countries and for the years 1992 and 1998 to compute a number of different network-based measures of each country's participation and influence in the global trade network. They also run a cross-country growth regression and find that a country's position in the network (measured by degree centrality) has significant implications for economic growth. There are two main differences between their analysis and ours. First, in Kali and Reyes (2007) the interaction between countries is described by binary variables, similar to (but slightly more sophisticated than) the approach pursued by Garlaschelli and Loffredo (2005). As mentioned before, we consider this representation of country interaction as too coarse because it ignores the intensity of the bilateral exchange relations between two countries. And, intuitively, it seems clear that the intensity margin is what reflects the strength of a country's ties to the global network. Therefore, if all trade flows are treated equally, a substantial amount of variation in true countries' connectedness will be ignored. Indeed, when we apply the binary approach to our sample of countries, we find that the standard deviation of the resulting integration indicator is less than a fifth of the standard deviation of our benchmark measure. The second difference concerns the econometric approach used to analyze the importance of a country's connectedness for its economic growth. Kali and Reyes (2007) use a cross-sectional approach and estimate only a small number of models. This approach runs into many of the econometric problems that will be discussed in detail in Section 3, e.g. omitted variable bias or potential endogeneity. Instead, our dynamic-panel approach is much more effective in tackling these difficulties, and also addresses (through the use of Bayesian model averaging) the problem of model selection – by now, understood to be a key concern in empirical growth analysis.[6]

Data sources and descriptive statistics

Our trade data is taken from the United Nations Commodity Trade Statistics Database (UN Comtrade) and it covers 167 countries on an annual basis over a period from 1962 - 2009.[7] Table 7 reports the complete list of countries in our sample. For each year,

[6]More work on the network structure of international trade was done by Kali et al. (2007), Arribas et al. (2009) and Fagiolo et al. (2010). Most of these studies provide only a descriptive analysis, and also use smaller samples or shorter time intervals.

[7]This data base is freely accessible at http://comtrade.un.org/. In our benchmark calculation, we use the raw export data from the UN Comtrade. There exists, however, a National Bureau of Economic Research (NBER) project lead by Robert Feenstra that has taken the UN Comtrade data and systematically cleaned it from a number of inconsistencies. As a robustness check, we also use this data instead of the

$t = 1962, ..., 2009$ and for every pair of countries ij, we have the total value of exports, measured in current USD. The indices i and j respectively denote the country of origin and the country of destination. Table 1 provides an example to illustrate the structure of the data – it depicts the bilateral export flows in the year 2000 among three countries: Germany, China and the USA.

The export flows for the countries used in the sample cover, on average, 96% of the total yearly world export flows over the period from 1962-2009. Likewise, the GDP coverage ratio in our sample is also high and very stable over time, with an average of 98% of world GDP. Such a high and stable coverage ratio, both in terms of trade flows and GDP, suggests that our GDP-weighted data provides a good description of the world trade network[8].

		Destination		
		China	Germany	USA
	China	-	9,277,789,992	52,156,428,118
Origin	Germany	8,472,113,000	-	55,389,893,000
	USA	16,249,167,650	29,219,631,160	-

Table 1: Export flows in 2000, in current USD

Based on this data, it is useful to present an illustrative account of the evolution of our measure of integration over time for a collection of selected countries. The outcome of this exercise is displayed in Table 2 for the period 1965-2005. We find that, among the group of most integrated countries, there has been a persistent tendency to increase their integration and a quite stable preservation of its ranking (with the important exception of China). Such ranking stability is also observed among the less integrated countries but in this case the majority of them show a tendency towards lower integration. In contrast, within the larger set of countries whose integration is in the middle range, we observe that there is a significant heterogeneity in the evolution of their integration over time and a substantial change in their ranking.

Figure 1 elaborates further on how the measure of integration has evolved over time across the different countries and compares it with the traditional measure of openness used in the literature. First, in Figure 1(a), we provide a more detailed description of the time evolution of integration for a set of four selected countries displaying very different characteristics and contrasting experience in this respect. A general account of the situation

raw data to compute our integration indicator (see Section 6).

[8]To cope with missing values, we use the observed import flows from country j to country i to impute the missing export flow from i to j. On average, 6.4% of the yearly export flows are imputed. Relatedly, an important issue is the treatment given to the former Soviet Union, former Yugoslavia, former Czechoslovakia and Germany. In all these cases, we choose to disregard all trade flows among the constituting subunits and treat all of them as a single country (e.g. as a unified Czechoslovakia after 1993 or a unified Germany before 1990).

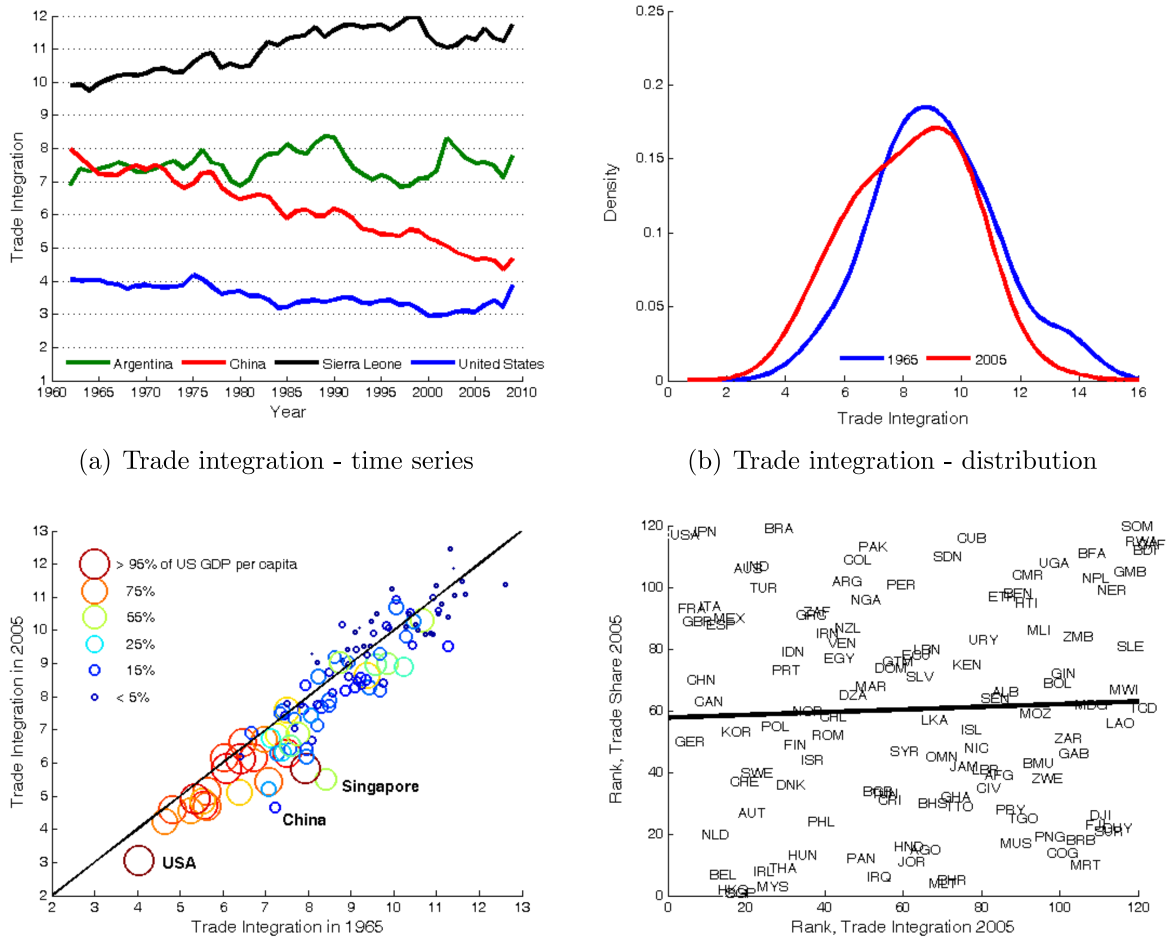
is then presented in Figure 1(b). There we observe that, along the period considered, there has been a general shift towards more integration at the world level in the sense that its distribution has experienced an unambiguous first-order dominance shift in this direction. Next, Figure 1(c) shows that, with a few (important) exceptions, the ranking of countries in terms of integration has remained rather stable and, generally speaking, the richest countries show higher integration than poorer ones.

	Trade integration			Δ	rank			rank_{TS}	SW
	1965	1985	2005	65-05	1965	1985	2005	2005	1985
United States	4.0	3.2	3.1	-0.9	1	1	1	127	1
Germany	4.7	4.4	4.2	-0.3	2	2	2	54	1
France	5.2	4.7	4.6	-0.4	4	4	3	103	1
United Kingdom	4.8	4.8	4.6	-0.2	3	5	4	98	1
China	7.2	5.9	4.7	-2.5	25	11	5	75	0
Mexico	7.1	6.3	5.2	-1.9	21	17	12	100	0
Korea	8.4	6.3	5.5	-2.9	56	19	14	57	1
India	6.4	6.6	6.2	-0.2	15	22	21	117	0
Malaysia	7.3	7.0	6.3	-1.0	26	32	24	3	1
Brazil	7.6	6.8	6.4	-1.2	37	26	27	129	0
Argentina	7.4	8.1	7.6	0.2	29	57	46	112	0
Nigeria	7.8	7.6	7.8	0.0	41	46	51	102	0
Peru	7.9	8.9	8.3	0.4	43	68	61	107	0
Sri Lanka	8.5	8.8	8.8	0.3	59	67	71	61	0
Yemen	12.7	9.0	9.2	-3.5	129	73	82	68	1
Zimbabwe	9.2	9.9	10.1	0.9	76	96	102	40	0
Bolivia	9.8	10.2	10.2	0.4	93	100	105	74	0
Chad	11.6	11.5	11.5	-0.1	126	126	128	65	0
Burundi	11.4	11.6	11.9	0.5	124	127	129	122	0
Central African Rep.	11.3	11.7	12.5	1.2	123	129	130	124	0

rank: ranking of countries based on the trade integration in a given year, $\textbf{rank}_{TS}$: ranking of countries based on the trade share (country with highest trade share is no. 1), **SW**: Sachs-Warner dummy variable - is 1 (0) if country is open (closed) to trade. The underlying data can be obtained from the authors' websites.

Table 2: Trade integration - summary statistics and comparison

Finally, Figure 1(d) bears on a very interesting and somewhat striking fact that is at the heart of our work. It shows that integration is essentially uncorrelated with the classical measure of openness used by the literature, which has sparked the wide and intense debate summarized in Section 1. More precisely, for the year 2005 we compute a very low rank correlation equal to 0.04. This underscores the important point that a network perspective to understanding "openness" is qualitatively distinct from that customarily pursued in the economic analysis and policy discussion. And, as advanced, our key conclusion at the end of the paper will be that such a systemic perspective represents a much more powerful basis to explain the contrasting growth experiences of the different countries, thus also shedding some light of why the aforementioned debate has often proven to be inconclusive.



(a) Trade integration - time series

(b) Trade integration - distribution

(c) Income (in 2005) and change in integration

(d) Trade integration and trade share

Figure 1: Trade integration - time series, distribution, change and comparison

3 Empirical Analysis

In this section, we revisit the debate on the identification of growth determinants and we put our new indicator of trade integration to the test to see if it is a robust determinant of cross-country income differences. Our empirical strategy differs from previous attempts in a number of important respects. First, the empirical analysis is based on a *dynamic panel model*. This class of models allows for a superior identification strategy which avoids the traditional shortcomings of the cross section analysis (such as contemporaneous feedback effects and omitted variables bias). Second, to address the *potential endogeneity* of the right-hand-side variables, we treat all time-varying covariates as predetermined. This assumption requires extending the model to include a process which relates the predetermined variables in a given period to a set of instruments. We follow, Moral-Benito (2013) and choose as instruments all lags of the explained variable, all lags of the predetermined variables, and the time-invariant variables. Third, we estimate the parameters of the model by *limited-information maximum likelihood* (LIML). We refrain from using the first difference GMM and system GMM estimator. Both approaches are often applied in the context of dynamic panel models. However, many of the variables we use are very persistent which means that the first-differenced GMM estimator would suffer from a weak instrument problem. Moreover, it is questionable, whether the key identifying assumption for the system GMM estimator of mean stationarity is satisfied for several of the variables in the sample, which casts doubts on the validity of the moment conditions. And fourth, we perform a *Bayesian model averaging approach* to address the issue of model uncertainty. Model uncertainty arises because it is ex-ante unclear how to specify the statistical framework, that is what explanatory variables to include into the model.

3.1 Empirical Panel Data Model

The empirical analysis is based on a dynamic panel model. Let y_{it} denote the log of GDP per capital of country i in period t. y_{it} is modeled as a linear projection on its own lag and a set of explanatory variables:

$$y_{it} = \alpha y_{it-1} + \boldsymbol{\beta}\mathbf{x}_{it} + \boldsymbol{\delta}\mathbf{z}_i + \eta_i + \zeta_t + v_{it}. \tag{1}$$

$\mathbf{x}$ and $\mathbf{z}$ are vectors of explanatory variables of dimensions $k \times 1$ and $m \times 1$, respectively. The variables in $\mathbf{x}$ are time-varying whereas the variables in $\mathbf{z}$ are constant over time. η_i is a country fixed effect, ζ_t is a time effect that is common across all countries and v_{it} is the random disturbance term which is assumed to satisfy $E[v_{i,s} \cdot v_{j,t}] = 0$ for all i, j, s, t. Empirical growth models such as the one in (1) are known to be plagued by endogeneity problems. Endogeneity may arise from various sources, the most common are reverse causality, measurement error and unobserved country-fixed effects. The consequence of which is that the condition $E[v_{it}|y_{it-1}, \mathbf{x}_{it}, \mathbf{z}_i, \zeta_t, \eta_i] = 0$ fails to hold.

In this paper, we take multiple steps to reduce potential problems of endogeneity. First, we group the data into time intervals and consider period-averages. This step is likely to reduce the measurement error in the set of variables (a detailed description of this step follows below). Also, we use time-invariant country dummies η_i to mitigate problems of unobserved country fixed effects. And to eliminate endogeneity due to contemporaneous feedback effects, we follow Moral-Benito (2013) and relax the assumption of strict exogeneity of all time-varying regressors. In particular, we assume only the time-invariant variables in $\mathbf{z}$ to be strictly exogenous and we treat all variables in $\mathbf{x}$ as potentially predetermined. To complete the model, we augment it by an unrestricted feedback process which relates the predetermined variables in period t, $\mathbf{x}_t$, to all lags of the explained variable y, all lags of the predetermined variables, and the exogenous variables $\mathbf{z}$. The augmented model can be written as follows:

$$
\begin{aligned}
y_{i0} &= \boldsymbol{\delta}_y \mathbf{z}_i + c_y \eta_i + v_{i0} \\
y_{it} &= \alpha y_{it-1} + \boldsymbol{\beta} \mathbf{x}_{it} + \boldsymbol{\delta} \mathbf{z}_i + \eta_i + v_{it} \\
\text{for} \quad t \geq 1 \qquad \mathbf{x}_{it} &= \boldsymbol{\chi}_{t0} y_{i0} + ... + \boldsymbol{\chi}_{tt-1} y_{it-1} + \boldsymbol{\psi}_{t1} \mathbf{x}_{i1} + ... + \boldsymbol{\psi}_{tt-1} \mathbf{x}_{it-1} \\
&\quad + \boldsymbol{\phi}_t \mathbf{z}_i + \mathbf{c}_t \eta_i + \mathbf{u}_{it}
\end{aligned}
\tag{2}
$$

with $\boldsymbol{\psi}_{11}$=0 and $\boldsymbol{\psi}_{10}$=0.

For convenience, we transform the model in (2) to obtain a simultaneous equations representation. This representation has be proven to be useful because it allows to concentrate the parameters of the model's log-likelihood which considerably facilitates the estimation of the model[9]. To arrive at the simultaneous equations representation we first define $\eta_i = \gamma_y y_{i0} + \boldsymbol{\gamma} \mathbf{x}_{i1} + \epsilon_i$, then substitute this expression into the system in (2). For each country i, the model consists of a system of $T + (T-1)k$ equations, where T is the total number of time periods. Using matrix notation, we can express the model compactly as:

$$
A\boldsymbol{R}_i = B\boldsymbol{Z}_i + \boldsymbol{U}_i \tag{3}
$$

where the following definitions are used:

$$
\begin{aligned}
&\boldsymbol{R}_i = (\boldsymbol{y}_i, \mathbf{x}_i)' \qquad && \boldsymbol{y}_i = (y_{i1}, y_{i2}, ..., y_{iT})' \\
& && \mathbf{x}_i = (\mathbf{x}_{i2}, \mathbf{x}_{i3}, ..., \mathbf{x}_{iT})' \qquad \mathbf{x}_{it} = \left(x_{it}^1, x_{it}^2, ..., x_{it}^k\right)' \\
&\boldsymbol{Z}_i = (y_{i0}, \mathbf{x}_{i1}, \mathbf{z}_i)' && \mathbf{z}_i = (z_i^1, z_i^2, ..., z_i^m)' \\
&\boldsymbol{U}_i = (\epsilon_i + \mathbf{v}_i, \boldsymbol{\xi}_i)' && \mathbf{v}_i = (v_{i1}, v_{i2}, ..., v_{iT})' \\
& && \boldsymbol{\xi}_i = (\boldsymbol{\xi}_{i2}, \boldsymbol{\xi}_{i3}, ..., \boldsymbol{\xi}_{iT})' \qquad \boldsymbol{\xi}_{it} = \left(\xi_{it}^1, \xi_{it}^2, ..., \xi_{it}^k\right)'
\end{aligned}
$$

$$
A = \begin{pmatrix} A_{11} & A_{12} \\ 0 & \mathbf{I} \end{pmatrix} \quad
A_{11} = \begin{pmatrix} 1 & 0 & 0 & \cdots & 0 \\ -\alpha & 1 & 0 & \cdots & 0 \\ 0 & -\alpha & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & -\alpha & 1 \end{pmatrix} \quad
A_{12} = \begin{pmatrix} 0 & 0 & \cdots & 0 \\ -\boldsymbol{\beta} & 0 & \cdots & 0 \\ 0 & -\boldsymbol{\beta} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & -\boldsymbol{\beta} \end{pmatrix}
$$

[9] For an explanation of the technical details behind this transformation, see Moral-Benito (2013).

$\mathbf{I}$ is an identity matrix of dimension $(T-1)k \times (T-1)k$.

$$B = \begin{pmatrix} B_1 \\ B_2 \end{pmatrix} \qquad B_1 = \begin{pmatrix} \alpha + \gamma_y & \boldsymbol{\beta} + \boldsymbol{\gamma} & \boldsymbol{\delta} \\ \gamma_y & \boldsymbol{\gamma} & \boldsymbol{\delta} \\ \vdots & \vdots & \vdots \\ \gamma_y & \boldsymbol{\gamma} & \boldsymbol{\delta} \end{pmatrix} \qquad B_2 = \begin{pmatrix} \boldsymbol{\pi}_{2y} & \boldsymbol{\pi}_{2x} & \boldsymbol{\pi}_{2z} \\ \boldsymbol{\pi}_{3y} & \boldsymbol{\pi}_{3x} & \boldsymbol{\pi}_{3z} \\ \vdots & \vdots & \vdots \\ \boldsymbol{\pi}_{Ty} & \boldsymbol{\pi}_{Tx} & \boldsymbol{\pi}_{Tz} \end{pmatrix}$$

$$\boldsymbol{\beta} = \left(\beta^1, \beta^2, ..., \beta^k\right) \qquad \boldsymbol{\gamma} = \left(\gamma^1, \gamma^2, ..., \gamma^k\right) \qquad \boldsymbol{\delta} = \left(\delta^1, \delta^2, ..., \delta^m\right)$$

$$\boldsymbol{\pi}_{ty} = \begin{pmatrix} \pi_{ty}^1 \\ \pi_{ty}^2 \\ \vdots \\ \pi_{ty}^k \end{pmatrix} \qquad \boldsymbol{\pi}_{tx} = \begin{pmatrix} \pi_{tx}^{11} & \pi_{tx}^{12} & \dots & \pi_{tx}^{1k} \\ \pi_{tx}^{21} & \pi_{tx}^{22} & \dots & \pi_{tx}^{2k} \\ \vdots & \vdots & & \vdots \\ \pi_{tx}^{k1} & \pi_{tx}^{k2} & \dots & \pi_{tx}^{kk} \end{pmatrix} \qquad \boldsymbol{\pi}_{tz} = \begin{pmatrix} \pi_{tz}^{11} & \pi_{tz}^{12} & \dots & \pi_{tz}^{1m} \\ \pi_{tz}^{21} & \pi_{tz}^{22} & \dots & \pi_{tz}^{2m} \\ \vdots & \vdots & & \vdots \\ \pi_{tz}^{k1} & \pi_{tz}^{k2} & \dots & \pi_{tz}^{km} \end{pmatrix}$$

Under normality of the random disturbances, the model in (3) gives rise to the following log-likelihood function:

$$\mathcal{L}(\mathbf{y}, \mathbf{X}|\mathbf{Z}, \boldsymbol{\theta}) \propto -\frac{N}{2} \log |\boldsymbol{\Omega}| - \frac{1}{2} tr\left(\boldsymbol{\Omega}^{-1}\mathbf{U}\mathbf{U}'\right) \tag{4}$$

where $\mathbf{y}$, $\mathbf{X}$ and $\mathbf{Z}$ are the observations on $\mathbf{y}_i$, $\mathbf{x}_i$ and $\mathbf{z}_i$ for all N countries in the sample. $\boldsymbol{\theta}$ is the vector of model parameters and $\mathbf{U} = [\mathbf{U}_1, \mathbf{U}_2, ..., \mathbf{U}_N]$. Moreover, $\boldsymbol{\Omega}$ is the variance-covariance matrix of $\mathbf{U}$ and tr denotes the trace of a matrix. Notice that the following simplification was made $\sum_{n=1}^{N} \mathbf{U}_n' \boldsymbol{\Omega}^{-1} \mathbf{U}_n = tr(\boldsymbol{\Omega}^{-1}\mathbf{U}\mathbf{U}')$. Also notice that the determinant of A is equal to unity.

3.2 Bayesian Model Averaging

Prior to estimating the model given in (4), one must decide what variables to include in $\mathbf{x}$ and $\mathbf{z}$. The question of how to specify the statistical framework has proven to be one of the key difficulties in estimating empirical growth models. The difficulty of this choice is exacerbated by the lack of guidance from the theoretical literature about what factors ultimately matter for growth. Therefore, it has become the common practice in empirical work to specify the model in a more or less ad-hoc fashion. In addition to a standard set of regressors - which the profession seemed to have agreed upon - every study used to include a number of other explanatory variables. Hence, over the years, a large number of variables has been proposed as drivers of economic growth. Durlauf et al. (2005) conducts a survey of the empirical growth literature and identifies a total of 145 regressors which are found to be statistically significant in at least one study. The large number of candidate determinants for explaining economic growth suggests that there exist potentially very many empirical growth models, each given by a different combination of explanatory variables, and each with some probability of being the "true" model. To resolve the inherent model uncertainty, we follow a relatively recent strand in the literature and apply the Bayesian model averaging approach[10].

Suppose there are K different candidate explanatory variables, implying that there are 2^K possible combinations of regressors each being a different model M_j, with $j = 1, .., 2^K$, where M_j is a given model specification that relates the outcome of interest y to a particular set of explanatory variables. The logic of Bayesian inference suggests that we can use Bayes rule to derive a probability statement about what we do not know (i.e. whether a model is correct or not) conditional on what we do know (i.e. the data). Given a model prior, we calculate the posterior model probability as:

$$P(M_j|\mathbf{y}) = \frac{p(\mathbf{y}|M_j)P(M_j)}{P(\mathbf{y})} \tag{5}$$

where $P(M_j)$ measures how likely we believe M_j to be the correct model before seeing the data; $p(\mathbf{y}|M_j)$ is the marginal (or integrated) likelihood; $P(\mathbf{y})$ is the likelihood of the data and $P(M_j|\mathbf{y})$ quantifies the support a given model M_j receives from the data. The integrated likelihood can be derived as follows:

$$p(\mathbf{y}|M_j) = \int p(\mathbf{y}|M_j, \boldsymbol{\theta}) f(\boldsymbol{\theta}|M_j) d\boldsymbol{\theta} \tag{6}$$

where $p(\mathbf{y}|M_j, \boldsymbol{\theta})$ is the conditional likelihood of the data. The expression in (6) is typically hard to evaluate, but there exists a simple and accurate approximation of it, the so-called BIC approximation which makes use of Laplace's method. A detailed description of the procedure can be found in Appendix D.

What we are ultimately interested in is not so much the probability of a given model. Rather we want to evaluate how important each of the K candidate regressors is for explaining the outcome variable y. To that end, we compute the posterior probability that a particular variable k is included in the statistical model. This measure is given by the sum of the posterior model probabilities for all of the models including the k-th variable:

$$P(k \in \mathbf{M}|\mathbf{y}) = \sum_{k \in M_j} P(M_j|\mathbf{y}) \tag{7}$$

$P(k \in \mathbf{M}|\mathbf{y})$ is also known as the posterior inclusion probability of variable k because it can be interpreted as the probability that the variable belongs in the "true" growth model

[10] Bayesian model averaging is based on work by Raftery (1995) and was first used by Sala-i-Martin et al. (2004) to determine which regressors should be included in linear cross-country growth regressions.

M. Consequently, the variables with high posterior probabilities of being included are considered as robust determinants of economic growth.

Once all of the 2^K different models are estimated, we can obtain parameter point estimates from the posterior distribution of the parameters. This posterior distribution is calculated as a weighted average of all the 2^K model specific posterior distributions. The weights are given by the posterior probability of the model to be the "true" model. For each candidate regressor k, we are interested in the point estimate of the parameter which is obtained from the mean of the posterior distribution of the parameter given the data:

$$E(\theta_k|\mathbf{y}) = \sum_{k \in M_j} P(M_j|\mathbf{y})\hat{\theta}_k^j \tag{8}$$

where $\hat{\theta}_k^j$ is the maximum likelihood estimate of θ_k in model M_j. To evaluate the accuracy of the coefficient estimate, we also compute the posterior variance of the estimate which, according to Leamer (1978), can be written as follows:

$$V(\theta_k|\mathbf{y}) = \sum_{k \in M_j} P(M_j|\mathbf{y})V(\theta_k|\mathbf{y}, M_j) + \sum_{k \in M_j} P(M_j|\mathbf{y}) \left[E(\theta_k|\mathbf{y}, M_j) - E(\theta_k|\mathbf{y})\right]^2$$

The posterior variance has two components. The first term measures how precisely the parameter has been estimated within each given model, whereas the second term measures how dispersed the estimates are across all the models.

The implementation of the Bayesian model averaging requires specifying the model priors $P(M_j)$. We follow Ley and Steel (2009) and use the so-called Binomial-Beta prior structure (named after the implied prior-model size distribution) which has shown to limit the effects of weak priors. As a result, we only need to specify the prior mean model size. In the benchmark case we set it equal to 5, but we also consider alternative values as a robustness check.

3.3 Markov Chain Monte Carlo Model Composition

The logic of Bayesian inference suggests that one should estimate all the different models and average them using appropriate weights. However, implementing Bayesian model averaging can be difficult since the number of models under consideration is often huge. For instance, in our case, we are dealing with 34 potential regressors which leads to $2^{34} = 1.7 \times 10^{10}$ different models to be estimated. Evaluating all of them is unfeasible which prevents an exhaustive computation of the exact probability distribution over the entire model space.

To address this issue, we follow Madigan and York (1995) and apply the Markov-Chain Monte-Carlo Model-Composition (MC^3) method to estimate the posterior model probability distribution. The main idea underlying the MC^3 is that we can compute the posterior probability distribution via simulation of the ergodic distribution of a stochastic process that moves through the model space. The stochastic process is modeled as a first-oder Markov chain that is defined on the (finite, but large) model space and evolves according to the following transition kernel. Given the current state of the chain M_j, a candidate model is sampled from the neighborhood of M_j which consists of the set of models with either one variable more or one variable fewer than M_j. The candidate model, denoted by $M_{j'}$, is then "compared" to M_j and accepted with probability $\min\{1, \frac{P(M_{j'}|\mathbf{y})}{P(M_j|\mathbf{y})}\}$. If the candidate model is accepted then the Markov chain moves to $M_{j'}$, otherwise it stays at M_j. $\frac{P(M_{j'}|\mathbf{y})}{P(M_j|\mathbf{y})}$ is the posterior odds (= prior odds $\times$ Bayes Factor) and it measures how much the data supports one model over the other. The posterior odds for M_j and $M_{j'}$ is given by:

$$\frac{p(M_{j'}|\mathbf{y})}{p(M_j|\mathbf{y})} = \frac{p(\mathbf{y}|M_{j'})}{p(\mathbf{y}|M_j)} \times \frac{p(M_{j'})}{p(M_j)}$$

where $p(\mathbf{y}|M.)$ and $p(M.)$ are the integrated likelihood and the prior probability of a given model. If the Markov chain is simulated for a sufficiently long time, the model-to-model transition probabilities become stationary and the chain has converged its ergodic distribution. To check the mixing and convergence properties of the simulated chain, we compute a number of diagnostic statistics. A description of these measures is in Appendix E.

4 Data

In the Bayesian model averaging (BMA) analysis, we consider a total of 34 different variables as candidate regressors. The set of regressors contains variables covering institutional, geographical, economic and demographic factors. Tables 5-6 list all the variables in the data set. Many of the selected regressors are commonly used in empirical growth studies. We would have liked to consider an even wider range of variables but we were restricted by limited data availability. The dependent variable in all the models under consideration is given by the logarithm of real GDP per capita. Among the candidate regressor variables is also the measure of trade integration we introduced in Section 2. Our primary interest is in the effect of the benchmark measure. However, we also perform several robustness tests with different versions of the indicator or different data-sets and we report these results in Section 6.

To reduce the problem of serial correlation, we group the data into time intervals. That is, for a given time period, the dependent variable is the end-of-period value of per-capital GDP and the regressor variables are related to their within-period values. In our benchmark case, we use 10-year intervals but as a robustness check, we also use 5-year intervals. We follow Caselli et al. (1996) and measure the flow variables (such as population growth) as 10-year averages while for the stock variables (such as life expectancy), we use the value of the variable in the first year of each 10-year period. As an example, consider the period from 1960-1969. In this case, the dependent variable is the value of real per-capita GDP of a given country in 1970; the lagged dependent variable is the 1960-value of GDP; the value of the variable "population growth" is the 1960-1969 average of the country's population growth rate and the value of the variable "life expectancy" is the value of the life expectancy in the year 1960. The second column in Tables 5-6 shows how each of the regressor variables is measured.

We use data from N=82 countries (covering all regions of the world) over the period 1960-2000. Table 7 lists the sample of countries in the data set[11]. We have yearly observations for the dependent variable and all the candidate explanatory variables. Using the 10-year intervals, gives us a balanced panel with T=4 observations for every country. The data we use is taken from a number or sources. In Tables 5-6, we list the data source for each variable and we provide a detailed description of how the raw data has been transformed.

5 Results

Table 3 shows the results of the Bayesian model averaging analysis. The column labeled with $\mathbf{INT}_B$ corresponds to the benchmark scenario in which we include our new integration measure. In the robustness analysis below, we will refer to the remaining columns of Table 3. We have ranked the variables (in descending order) according to their posterior inclusion probability. For each of the candidate regressor variables, we report three statistics. *p-mean* is the the posterior mean of the coefficient, computed as in (8), together with the significance; we report the 1% (***), 5% (**) and 10% (*) level of significance. PIP is the posterior inclusion probability of a variable, computed as in (7), and $\%_{sig}$ is the percentage of models in which the coefficient estimate of a given included variable is significant at the 5% level[12].

In the lower part of the table, we report a number of statistics describing the properties of the simulated Markov chain. *Markov Steps* refers to the total number of steps (in 1000) of the simulated chain. *Posterior model size* refers to the posterior model size. *Models covering* 50% is the number of models with the highest posterior model probability which, in sum, account for 50% of the posterior model probability. *P(max)* is the maximum posterior model probability achieved by a single model. *Visited probability* refers to the estimated fraction of the total posterior probability mass that the Markov Chain has visited.

[11] The countries which are included in the BMA are printed in italic.

[12] For example the variable INT_B is included in x different models, and in 89% of these models, the estimated coefficient of INT_B is significant at the 5% significance level

This number is computed by using the capture-recapture algorithm described in George and McCulloch (1997). The remaining statistics **Corr(Π,Freq)**, **Corr(Bayes,Freq)**, and **Raftery-Lewis** describe the convergence and mixing properties of the simulated chain. A detailed explanation of each of them is in Appendix E.

A number of interesting findings emerge. First, we find that seven variables have a posterior inclusion probability of more than 50%, which is also reflected by the posterior model size equal to 7.6. For our measure of country integration, we obtain a very high inclusion probability of 61%, indicating an important role of this measure for explaining cross-country income differences. Moreover, the posterior mean of the estimated parameter has a negative sign, it is significant at the 5% level, and the estimated model-specific parameters are significant in 89% of all models which include the variable. Recall that a higher value of the measure indicates a lower degree of integration of a given country into the global network. Therefore, the negative sign of the posterior mean implies a positive effect of more integration on a country's level of per capita income. And since we are controlling for the initial level of income, it also implies a positive effect on the GDP growth rate of a country. In the set of candidate regressors, we have also included two of the conventional integration indicators: the trade share and the Sachs-Warner indicator. For both variables, we obtain a very low posterior inclusion probability. This finding lends support to Rodriguez and Rodrik's (2001) conjecture that the traditional indicators of outward-orientation do not capture the particular dimensions of a country's openness which are potentially key for economic performance.

Table 3 reveals another interesting finding, namely the dichotomy between the posterior inclusion probability and the $\%_{sig}$-statistic which applies to a number of variables, including, for instance, the *government share*, the *consumption share* or the *average years of primary schooling*. This dichotomy is reflected by the high value of the $\%_{sig}$-statistic for these variables - meaning that the respective coefficient estimates are significant in a large fraction of the models - and a low PIP indicating that the models which include these variables receive only little support from the data. For instance, the *government share of real GDP* has a PIP of only 4% but the estimated coefficient was significant for 95% of the models. This result underlines the importance of the Bayesian model averaging. It shows very tellingly why the traditional practice of estimating only a single empirical growth model can lead to inconclusive results. If one were to estimate a model with the above mentioned variables, the conclusion would most likely be that all three variables are important growth determinants because of the high significance of the estimated coefficients. The BMA analysis reveals that the contrary is actually the case.

	$\mathbf{INT}_B$			$\mathbf{INT}_F$			$\mathbf{INT}_W$			$\mathbf{INT}_H$		
Description of variable	*p-mean*	*PIP*	$\%_{sig}$	p-mean	PIP	$\%_{sig}$	p-mean	PIP	$\%_{sig}$	p-mean	PIP	$\%_{sig}$
Lagged logarithm of real GDP per capita	0.9438***	100	100	0.8691***	100	99	0.9473***	100	100	0.8280***	100	100
Investment share of real GDP	0.8681**	76	76	0.7101*	77	44	0.8825**	73	76	0.7936***	79	95
1/0 dummy for Sub-Saharan African country	-0.0793*	68	48	-0.0876*	68	56	-0.0784*	64	48	-0.0871*	66	44
Life expectancy at birth	1.2859**	66	77	1.1358*	58	62	1.3021*	71	75	1.3962**	48	78
1/0 dummy for East Asian country	0.0711	65	42	0.0503	64	22	0.0734	68	43	0.0438	48	18
Benchmark integration measure	-1.8528**	61	89	.	.	.	.	.	.	.	.	.
... computed with the Feenstra trade data	.	.	.	-1.9000***	81	92	.	.	.	.	.	.
... under the changing-world assumption	.	.	.	.	.	.	-1.8541**	58	87	.	.	.
... based on trade in high-tech goods	.	.	.	.	.	.	.	.	.	-2.2940***	89	95
Population share in the geographic tropics	-0.0464	60	16	-0.0446	65	10	-0.0451	60	17	-0.0518	69	14
1/0 dummy for armed conflict on own territory	-0.0866	40	12	-0.0601	50	6	-0.0873	35	14	-0.0590	63	3
Land within 100km of nearest navigable water	12.2469	34	89	12.5322	43	89	11.9254	31	89	12.8991	53	90
1/0 dummy for former Spanish colony	-0.0600*	31	38	-0.0542	26	25	-0.0609*	30	39	-0.0527	41	19
1/0 dummy for Latin-American country	-0.0331	29	15	-0.0281	31	9	-0.0330	29	19	-0.0121	47	4
Price level of investment	-0.0533	23	2	-0.0472	22	2	-0.0546	26	3	-0.0697	26	3
Share of land area in the geographic tropics	-0.0108	10	17	-0.0040	8	12	-0.0204	9	22	-0.0141	15	5
Percent of land area in Koeppen-Geiger tropics	0.0583	8	16	0.0644	10	16	0.0549	9	14	0.0722	17	14
Average years of primary schooling	-1.5455**	8	83	-1.4181*	5	69	-1.5410**	8	80	-1.2812*	4	57
Sachs & Warner openness measure	0.1290**	7	68	0.0968	6	42	0.1263**	7	65	0.1008*	6	53
Land area in km^2	-0.1324**	7	61	-0.1452**	10	67	-0.1291*	7	57	-0.1619**	12	68
Population share aged 0-14 years	-1.0843*	6	66	-0.7061	4	54	-1.0896*	6	67	-0.7772	5	41
Average years of secondary schooling	1.0190	5	59	0.2977	4	37	1.0986	5	65	0.3582	5	27
Labor force: Ratio of workers to population	0.7877	5	39	0.5634	3	35	0.8210	5	38	0.6848	5	28
Democracy index, from 0 (lowest) to 1 (highest)	-0.1188	5	19	-0.1273	4	23	-0.1171	4	17	-0.0788	6	4
1/0 dummy for landlocked country	-0.0483	5	19	-0.0410	5	11	-0.0466	6	17	-0.0497	6	15
Air distance to New York, Rotterdam, or Tokyo	-0.0590	5	14	-0.0371	4	9	-0.0619	5	19	-0.0160	4	8
Population density	0.0802	5	1	0.0889	5	1	0.0752	5	1	-0.0061	6	1
Government share of real GDP	-1.7358***	4	95	-1.5412***	3	93	-1.7051***	4	93	-1.3652***	3	89
Annual growth rate of population	-1.8220	4	33	0.3967	5	15	-1.9724	4	35	-3.0119	6	51
1/0 dummy for Western European country	0.0674	4	27	0.0679	6	28	0.0671	5	28	0.0650	6	14
Consumption share of real GDP	-0.5306**	4	76	-0.6157***	6	94	-0.5225**	3	72	-0.6505***	13	96
Urban population	-0.9288**	3	80	-0.9229**	2	75	-0.9337**	3	79	-0.3171	3	45
Total population	0.8238*	3	7	0.8167*	6	20	0.8831*	5	51	0.5245	8	2
Population share aged 65 years and above	2.0169	2	41	-0.3572	1	8	2.6208	3	56	3.6765	2	70
Exports plus imports as a share of GDP	0.0355	2	7	-0.0379	3	5	0.0509	2	7	-0.0000	2	6
1/0 dummy for socialist rule during 1950 to 1995	-0.0304	2	3	-0.0266	2	2	-0.0353	2	2	-0.0338	3	1
Timing of national independence	-0.0126	1	5	-0.0130	1	4	-0.0102	2	5	-0.0028	2	3
Markov steps ($\times 10^3$)			896			1058			1041			961
Posterior model size			7.6			7.9			5.4			8.7
Models covering 50%			163			167			156			165
P(best model)			4.35			3.21			4.05			4.57
Visited probability			96.3			97.3			96.1			97.0
Corr(Π,Freq)			0.989			0.996			0.991			0.994
Corr(Bayes,Freq)			0.983			0.981			0.974			0.989
Raftery-Lewis			3.74			3.46			3.44			3.42

Table 3: **Coefficient estimates, posterior inclusion probability and % of significant inclusions**

6 Robustness

In this section, we test the robustness of our main finding that country integration is an important growth determinant. More specifically, we explore the sensitivity to different data input and alternative assumptions about the computation of country integration.

Raw data vs. cleaned data

In our benchmark calculation, we use the raw trade data from the UN Comtrade to compute the indicator of country integration. There exists, however, a National Bureau of Economic Research project lead by Robert Feenstra that has taken the UN Comtrade data and systematically cleaned it from a number of inconsistencies. The resulting data set is available from the Center for International Data and a detailed description of it is provided in Feenstra et al. (2005). As a first robustness check, we use these data instead of the raw trade data to recompute our integration measure. Then, we perform a BMA analysis where we include this new measure. The column labeled with $\mathbf{INT}_F$ in Table 3 shows the results. The statistics change only marginally for most of the variables. For our measure of country integration, we observe a slight change in the posterior mean as well as a strong increase in the posterior inclusion probability by 20 percentage points to 81%.

Changing world

In the benchmark scenario, we calculate the integration indicator only for the countries for which trade data is available for all years between 1962 and 2009. That is, we study a world-wide trade network spanned by the same set of nodes in every year. In an alternative scenario, we add also those countries for which the data is available for some but not all years. As a result, the total number of countries in our sample increases up to a total of 167. Column $\mathbf{INT}_W$ in Table 3 shows that again the results of the BMA are very similar to those for the baseline case.

High-tech vs low tech goods

So far, we have used aggregate bilateral trade data to characterize the global trade network. That is, we were treating Brazilian coffee exports to Japan, and Japanese computer equipment shipped to Brazil equivalently, conditional on having the same dollar value. However, arguably, not all type of trade is equally important for a country's economic performance. Trade in capital goods seems likely to be a catalyst for the diffusion of ideas and technology. Whereas, trade in low tech goods, such as raw materials, is perhaps less relevant for long-run growth.

To test this conjecture, we calculate the integration indicator based on the trade flows for selected types of goods categories. More specifically, first we consider all trades flows involving the exchange of goods which belong to the following categories: *chemicals and related products*, *manufactured goods*, *machinery and transport equipment* and *miscellaneous manufactured articles*[13]. Then, we run the Bayesian analysis using this high-tech integration indicator. Column $\mathbf{INT}_H$ in Table 3 has the results. The inclusion probability of the indicator increases strongly to 89%. Also the value of the posterior mean is substantially higher and it becomes more significant.

In contrast, the picture changes considerably when we employ an integration indicator based on low tech goods. We compute this low-tech measure by using data on trade in: *food and live animals*, *beverages and tobacco*, *crude materials, inedible, except fuels*, *mineral fuels, lubricants and related materials* and *animal and vegetable oils, fats and waxes*. In Panel (a) of Table 4, we show the corresponding BMA-statistics for this variable. The differences to the baseline scenario and particularly to the high-tech indicator are truly striking. Not only becomes the posterior mean insignificant, but also the posterior inclusion probability drops considerably to 23%. These findings support the notion that a country's connectedness to the global trade in capital goods is particularly important for its growth performance, whereas the connectedness to trade in commodities and processed raw materials seems less important.

UN Comtrade and IMF DOTS

The International Monetary Fund (IMF) publishes the Direction of Trade Statistics (DOTS) which provides detailed data on bilateral trade flows. We recompute our integration indicator and test the robustness of our baseline results to this alternative data source. Panel (c) of Table 4 shows the comparison with other results. If anything, the statistics are stronger than they were in the baseline case. We conclude that the choice of the data source - between UN Comtrade and IMF DOTS - does not seem to play an important role for the outcome.

Penn World Tables

A number of the variables included in the BMA are constructed using data from the Penn World Tables (PWT). Ciccone and Jarocinski (2010) raise an important concern that the results of growth empirics are very sensitive to revisions in the PWT data. We address this concern by testing the robustness of the baseline outcome to older editions of the PWT, including PWT 6.2 and PWT 6.3, as well as the new release, PWT 7.1. Panel (d) of Table 4 compares the results. By and large, our main finding that country integration is a key growth determinant is robust to revisions of the PWT. In fact, the results obtained for the alternative PWT editions seem even somewhat stronger, in terms of the significance and the inclusion probability, than the benchmark results. The 7.1 release provides data until

[13] The data is taken from the UN Comtrade database.

the year 2010. This allows us to extend the time horizon of the BMA analysis and to cover the period from 1960 to 2009. This gives us a total of five observations for each country. We also organize the data into five year time intervals (instead of 10 year intervals) which gives us a total of 10 country observations. The findings for both cases are shown in Panel (d) of Table 4. Again, we do not observe any noteworthy changes in the sign and significance levels of the estimated posterior means.

	p-mean	PIP	$\%_{sig}$
Benchmark	**-1.8428****	**61**	**89**
Panel (a)			
High-tech goods	-2.2940***	89	95
Low-tech goods	-0.9217	23	54
Panel (b)			
Higher-order links	-2.1923**	60	89
Changing world	-1.8541**	58	87
Panel (c)			
Feenstra et al. data	-1.9000***	81	92
IMF DOTS data	-2.0251***	72	92
Panel (d)			
PWT 6.2	-1.9010***	85	95
PWT 6.3	-1.5175***	98	88
PWT 7.1, 60-99	-1.9744***	76	95
PWT 7.1, 60-09	-2.2666***	89	98
PWT 7.1, 5 yrs	-0.7600***	99	98
Panel (e)			
Prior model size = 2	-1.8805**	51	89
Prior model size = 15	-1.8081**	63	86

Table 4: Results of the Robustness Analysis

Prior model size

The implementation of the BMA necessitates specifying the prior for each model. We use the so-called Binomial-Beta prior structure, which requires only the choice of the prior mean model size. In the baseline case, we set this value equal to five. We have checked, however, the robustness of our results to changes in the prior mean model size and considered two alternative prior values, namely 2 and 15. For both cases, the results are very similar to the baseline results, as we can see in Panel (e) of Table 4. Also the posterior model size hardly changes and is equal to 6.8, 7.6 and 8.1 for the prior values of 2, 5, and 15, respectively. In general, the effect of alternative model priors seems very limited.

Higher-order trade connections

Several of the regressors we consider in the BMA, including our integration indicator, are potentially endogenous. Even though we believe to have properly addressed this issue in the empirical analysis, we now discuss a complementary, somewhat more direct, route that we have also explored to address the endogeneity problem of the integration index. This index is potentially endogenous to a country's macroeconomic conditions because economic performance is likely to determine a country's trade pattern with its immediate trading partners. To tackle the issue, we propose a variation of the benchmark measure which is strictly exogenous. Here, we provide just an informal account of how this has been done while a detailed description of the procedure is provided in Appendix C. The main underlying idea is to compute a measure of integration that is based only the higher-order trade connections of a country and disregards the potentially endogenous first-order connections. The computation of this indicator involves the following sequence of steps.

First, define $\varphi_{m,j,-i}$ as the expected number of steps required to reach node j from node $m \neq i$, conditional on **not** utilizing any of the links that involve node i. This concept implies that any path that connects j to m is not allowed to go through i. The connections from and to i are disregarded since these are the ones that may be endogenous to country i's GDP. If we now take the index m to range over i's partners, for each one of them the expected distances $\varphi_{m,\cdot,-i}$ determine its corresponding integration into the world trade network. Then, to determine country i's integration, what we need is an indicator to measure the proximity of country i to each of its (potential) trading partners. In this context, it is essential that such an indicator is exogenous to country i's contemporaneous growth performance. We use the geographical distance, measured in kilometers, between countries. This choice has several advantages: it is strictly exogenous, it is known to be a good proxy for the intensity of bilateral trade, and its measurement is accurate. Let $geo_{i,m} = geo_{m,i}$ denote the geographical distance between countries i and m. We use the inverse of that geographical distance as a measure of proximity – i.e. $\omega_{i,m} = \frac{1}{geo_{i,m}}$ – and rescale these weights $\tilde{\omega}_{i,m} = \frac{\omega_{i,m}}{\sum_{m \neq i} \omega_{i,m}}$ such that $\sum_{m \neq i} \tilde{\omega}_{i,m} = 1$. This allows us to compute the expected number of steps from country j to country i as follows:

$$\tilde{\varphi}_{j,i} = \sum_{m \neq i} \tilde{\omega}_{i,m} \varphi_{j,m,-i}$$

Finally, to construct the *indirect* measure of integration of country i, we use again a weighted average of the form $\sum_j \beta_j \tilde{\varphi}_{j,i}$ where $\tilde{\varphi}_{i,i} = 0$. Figures 2 - 3 in Appendix C provide a graphical illustration of how the benchmark indicator and in the modified version are calculated.

The values of this alternative indicator and the benchmark measure are highly correlated with a correlation coefficient of 0.98. It is therefore not surprising that when we include the indirect integration indicator into the empirical model and perform the BMA analysis, the results hardly change with respect to the benchmark. This can be seen in Panel (b) of Table 4.

7 Conclusion

In this paper, we have proposed a new approach to measuring a country's outward orientation. Previous work mostly uses indicators involving aggregate trade intensity, trade policy, or trade restrictiveness of the country in question. Instead, our approach offers a broader perspective on the phenomenon as it measures a country's level of integration not only through its direct trade connections with the rest of the world but also uses the whole architecture induced by its second and higher-order connections. We have used trade data from the United Nations Commodity Trade Statistics Database and applied our methodology to a sample of 167 countries spanning the period from 1962 to 2009. A first descriptive analysis of the data reveals that trade intensity and integration are largely uncorrelated. It also shows that, along the period considered, the world as a whole has become more integrated but also more unequal. This is because the group of rich and most integrated countries has shown a persistent tendency to increase their integration, while the majority of poor and less integrated countries have been falling behind over time.

The main objective of the paper has been to use our dynamic-panel framework to revisit the long-standing debate in the empirical literature concerning the importance of countries' outward orientation for explaining their income differences. To this end, we have performed a comprehensive Bayesian model-averaging analysis on a sample of 82 countries and a total of 34 different variables as candidate regressor variables. The key finding has been that our measure of trade integration is a robust and economically important determinant of cross-country income differences. More specifically, the results suggest that a country's integration should be part of the model specification with high posterior (inclusion) probability and that its positive effect on per capita income is sizable and significant. We have also found that the integration indicators conventionally used are only marginally important. The latter result sheds some light on why the aforementioned debate concerning the importance of outward orientation on growth has proven to be largely inconclusive. In particular, it provides support for the now widespread viewpoint that existing indicators of outward-orientation do not truly capture the dimensions of a country's openness that are most relevant for economic performance. Finally, we have performed a number of sensitivity checks and found that our baseline findings are extremely robust to different data input and alternative ways of computing trade-based integration.

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Appendix

A Theoretical framework

Here we outline the theoretical approach undertaken in DV (Duernecker and Vega-Redondo (2012)) to study globalization. As explained below, this approach motivates the different measures of globalization (or integration) that are considered in the present paper. The model proposed by DV involves a fixed set of agents, $N = \{1, 2, ..., n\}$, who are uniformly distributed in some (say, physical) space. For simplicity, let us identify this space with a one-dimensional ring and denote by $d(i.j)$ the geographical distance between any two nodes, i and j.

Let $t \geq 0$ be the continuous variable indexing time. At each t, agents are connected by a network $g(t)$ specifying the pair of agents $\{i, j\}$ who are connected by a link at t. Over time, agents establish and destroy the economic links to each other, thus giving rise to the dynamics of the overall social network. To fix ideas, link creation is viewed as the result of "innovation," while link destruction is interpreted as the outcome of "obsolescence". We formulate each of them first, and then turn to motivating them.

Innovation: At each t, every agent $i \in N$ obtains an "idea" for an economically valuable project at rate $\eta > 0$. But to carry out the corresponding project, agent i needs the collaboration of some other agent. *Ex ante*, the probability that any *specific* agent j be the one required for the project is assumed proportional to $d(i, j)^{-\alpha}$. (Thus the probability that any two agents enjoy some new linking/collaboration opportunity decays with their bilateral geodistance at the rate α.)

Consider any pair of agents $\{i, j\}$ who enjoy such a linking opportunity. We assume that the link will indeed materialize if, and only if, the following two conditions are jointly satisfied:

(i) They are not already linked.

(ii) They are either direct neighbors or/and their social distance is not larger than some parameter μ.

Volatility: At each t, every link $\{i, j\} \in g(t)$ becomes "obsolete" and vanishes at the rate $\alpha > 0$.

Our formulation for innovation displays several key features. First, it posits that the underlying space plays an important role in shaping economic opportunities. That is, *ceteris paribus*, opportunities are more likely to arise close-by than far-away. This, for example, could be a reflection of the fact that the more distant agents are the less of a common background they have (language, expectations, norms), which makes it more difficult for them to collaborate fruitfully.[14] The rate at which such space-induced decay occurs is given by α. This parameter captures the important of geography, and can be associated to technological and cultural factors such as the effectiveness of communication technologies or the cross-cultural convergence of habits and social norms, which we take as exogenous to the model. For conciseness, we shall refer to α as the degree of *social cohesion*.

A second feature of the process of link formation is that no pair of players may undertake more than one project at a time. Admittedly, this an extreme assumption but represents a simple way of capturing the idea that profitable opportunities must be exhausted if an agent revisits the same partner repeatedly. As explained, it is the key force leading agents to turn "global" in order to sustain a large number of valuable links/projects.

And thirdly, our formulation of innovation separates the arrival of (non-redundant) opportunities from the actual materialization of those opportunities. For the latter to occur (i.e. a link to be formed), it is required that the two agents involved must be sufficiently close, either physically or/and socially. A natural motivating idea here is that, once the possibility for a new project has arisen between some agents i and j, they must be able to either

(a) learn about each other and their complementary skills,[15] or/and

(b) monitor and trust the partner's behavior in their ongoing collaboration.[16]

The assumption is that, in order for this to happen, the agents must be immediate geographic neighbors (in which case information in every respect should flow readily) or the number of intermediaries in the social structure cannot be too high, i.e. no larger that μ. To fix ideas, we shall think of this parameter as a reflection of (the quality of) *institutions*. The motivation is that, in some contexts, it could capture the readiness of agents to abide by a cooperative norm of behavior, e.g. by relaying valuable information or providing third-party monitoring.

[14]It is sometimes argued that diversity breeds innovation. If we associate diversity to increasing geographical density, such a relationship will indeed be a feature of our model, but an *endogenous* one. That is, agents who collaborate globally (and thus do so with diverse agents) are more innovative, because they are better at escaping the saturation of *fresh* (i.e. not yet exploited) opportunities existing in the geographical vicinity.

[15]See e.g. the survey by Rauch (2001) where he discusses the role of global social networks as a key channel though which business practices, technical know-how, and market opportunities spread and get to be known across distant geographic locations.

[16]The importance of the social network as a basis for monitoring and deterrence of opportunistic behavior was stressed in the classical work of Coleman (1988), while a more recent account of this phenomenon can be found in Karlan, Mobius, Rosenblat, and Szeidl (2009)), both at a theoretical and empirical levels. This line of research highlights that the social network can operate as "social collateral',' thus rendering opportunistic behavior unprofitable. Another interesting illustration of this phenomenon is discussed in the celebrated study of Southern Italy by Banfield (1958), who coined the term *amoral familism*. In essence, this describes a situation where the deviation from a cooperative norm is the concern of third parties only when it involves closely related individuals. In our context, this would amount to a low value of μ.

Our formulation of volatility, on the other hand, is particularly simple.[17] It postulates that all projects eventually become obsolete and vanish, and this process occurs at a constant rate λ. This rate is to be compared with that at which ideas arrive to the system, η, which is a measure of the potential (or innovativeness) of the economy. Naturally, in our continuous-time dynamic system, only the ratio η/λ matters, so we chose to normalize $\lambda = 1$ without loss of generality. In essence, the overall dynamic process is a struggle between link creation and link destruction. If the network connectivity is high, so will be as well the rate at which links are destroyed. Thus, in the long run, *a dense network can be sustained only if such a fast pace of link destruction can be offset with a comparably high rate of link creation.*

Naturally, the aforementioned considerations not only apply to the network as a whole but also at the individual level – i.e. any given agent who succeeds in maintaining many links must be capable of creating many links as well. And since such link-creation ability in turn depends on being sufficiently close (in the social network) to others, the following prediction ensues. Agents who are socially closer to the rest of the population should also display more links. Therefore, if we identify the rate of link/project creation of each node with its rate of growth, the aforementioned prediction can be recast as follows: the average rate of growth of each individual node is proportional to its network proximity to other nodes.

To be more precise, define by $F_i(\delta)$ the fraction of agents that are at less than social distance δ from any given agent i. Clearly, the function $F_i : \mathbb{R} \to [0, 1]$ can be regarded as a cumulative distribution function. Consider now any other agent j with her corresponding function F_j. Then, if both agents are in a fully symmetric situation in every other respect, a sufficient condition for the rate of link creation of agent i to be higher than that of j for *any value of* μ is that F_j first-order stochastically dominates F_i, i.e.

$$F_j(\delta) \le F_i(\delta) \quad \forall \delta \ge 0.$$

But this is such a strong requirement that one can hardly expect it to be relevant for empirical analysis. (In particular, it yields only a very partial ordering across different situations, and hence it is unsuited to construct a useful measure of globalization.) We shall thus rely on a natural proxy for it based on the average magnitudes given by the aforementioned distributions. We shall then say that some agent i is better integrated than some other agent j iff

$$\int \delta \, \mathsf{d}F_i < \int \delta \, \mathsf{d}F_j.$$

[17]Other more elaborate formulations could be contemplated without affecting the gist of our results. For example, it could be postulated that the rate of destruction of any particular link increases in the number of links the two agents involve currently have, or on their social distance. This would not affect the essential gist of our analysis.

In this paper, our objective is to test empirically the prediction that more integrated "agents" perform better, in the sense of growing faster.[18] And, as is common in the theory of growth, we shall conceive of each individual/node in our model as a representative agent of a corresponding country, and use country aggregate data to conduct the analysis. So, as a first step, we need to provide an operational counterpart of the discrete (binary) network model that can be applied to contexts when the intensity of interaction is measured by continuous variables (trade, investment, etc.). This is the objective of the next section, where we propose a measure of globalization that is applied to "nodes" whose flows of interaction are real rather than binary.

B Computing integration

Our starting point is an $(n \times n)$-matrix A, which is row-stochastic, as the one constructed in Section 2. We want to think of it as the adjacency matrix of a weighted directed network over n nodes. Thus each entry a_{ij} is the weight/probability with which node i connects to node j. Then, the directed distance φ_{ij} from i to j is identified as the expected number of steps required to reach j from i when, at every node $k = 1, 2, ..., n$, each possible link $\overrightarrow{kl}$ is chosen with probability a_{kl}. is foll It is To fix ideas, think of a particle lying at i that can move to one of the neighbors of it, say j, with probability a_{ij} (staying at i with probability a_{ii}).

To compute such expected magnitude, it is useful to consider the $(n-1) \times (n-1)$ matrix A_{-j} obtained from A by deleting the jth row and the jth column. (This matrix, of course, is no longer a stochastic matrix.) Then, it can be easily seen that the probability that a path that started at i is at $k \neq j$ after r steps is simply $[(A_{-j})^r]_{ik}$, where $(A_{-j})^r$ is the rth-fold composition of A_j with itself and $[\cdot]_{ik}$ stands for the ik-entry of the matrix $[\cdot]$. Thus, the probability that it visits node j for the first time in step $r+1$ is simply

$$\gamma_{ij}(r+1) = \sum_{k \neq j} [(A_{-j})^r]_{ik} \; a_{kj}.$$

[18]The model studied in DV also predicts, for example, that, if geographical cohesion is not too strong, the transitions to globalization are abrupt, large, and robust. It identifies as well a novel (network-based) source of equilibrium multiplicity that – in contrast with the classical theory of growth – implies that globalized economies are not only richer but also grow faster as environmental conditions improve. Finally, another related implication is that, as geographical cohesion falls (an apparent feature of the modern world economy), the wedge between rich and poor countries would widen, as long as the latter do not make the transition to globalization.

Therefore, the expected number of steps φ_{ij} can be obtained as follows:

$$\begin{aligned}\varphi_{ij} &= \sum_{r=1}^{\infty} r\ \gamma_{ij}(r) = \sum_{r=0}^{\infty}(r+1) \sum_{k\neq j}\left[(A_{-j})^r\right]_{ik}\ a_{kj} \\ &= \sum_{k\neq j}\sum_{r=1}^{\infty} r\left[(A_{-j})^{r-1}\right]_{ik}\ a_{kj} = \left[\left(\sum_{r=1}^{\infty} r\ (A_{-j})^{r-1}\right)_{ik}\right]_{\substack{k=1,2,\dots,n\\k\neq j}}\left(a_{kj}\right)_{\substack{k=1,2,\dots,n\\k\neq j}}\end{aligned} \tag{9}$$

Using now a standard formula from linear algebra we have:

$$\sum_{r=1}^{\infty} r\ (A_{-j})^{r-1} = (I - A_{-j})^{-2}$$

so that, in an integrated matrix form, the (column) vector $\left(\varphi_{ij}\right)_{\substack{i=1,2,\dots,n\\i\neq j}}$ can be written as follows

$$\left(\varphi_{ij}\right)_{\substack{i=1,2,\dots,n\\i\neq j}} = (I - A_{-j})^{-2}\ \left(a_{ij}\right)_{\substack{i=1,2,\dots,n\\i\neq j}}.$$

Finally, note that, because A is a row-stochastic matrix, it follows that

$$a_{ij} = 1 - \sum_{k\neq j} a_{ik}$$

and therefore

$$\left(a_{ij}\right)_{\substack{i=1,2,\dots,n\\i\neq j}} = (I - A_{-j})\ e$$

where e is the column vector $(1, 1, ..., 1)^{\top}$. Hence the vector $\left(\varphi_{ij}\right)_{\substack{i=1,2,\dots,n\\i\neq j}}$ can be computed from the following simple expression:

$$\begin{aligned}\left(\varphi_{ij}\right)_{\substack{i=1,2,\dots,n\\i\neq j}} &= (I - A_{-j})^{-2}(I - A_{-j})\ e \\ &= (I - A_{-j})^{-1}\ e.\end{aligned}$$

C An alternative measure of integration

The computation of the *indirect* measure of integration involves the following steps:

1. Pick country a country $j \neq i$ and determine $\varphi_{m,j,-i}$, that is the expected number of steps required to reach node j from node $m \neq i$, conditional on **not** utilizing any of the links that involve node i. This concept implies that any path that connects j to m is not allowed to go through i. The connections from and to i are disregarded since these are the ones that may be endogenous to country i' GDP. The computation of $\varphi_{m,j,-i}$ largely follows the steps taken to compute the measure $\varphi_{m,j}$ in the benchmark

case.

$$\varphi_{m,j,-i} = \sum_{k\neq i,j} \sum_{r=1}^{\infty} r \left[(A_{-i,-j})^{r-1} \right]_{m,k} a_{k,j} \tag{10}$$

$A_{-i,-j}$ is a $(n-2) \times (n-2)$ matrix that is obtained from A by deleting the ith and the jth column, and the ith and the jth row. $[\cdot]_{m,k}$ indicates the elements of the mth row and the kth column of the array $[\cdot]$. Rearranging equation (10) yields the following expression:

$$\varphi_{m,j,-i} = \left[\left(\sum_{r=1}^{\infty} r \left(A_{-i,-j}\right)^{r-1} \right)_{m,k} \right]_{k=1,2,...,n;k\neq i,j} \left(a_{k,j}\right)_{k=1,2,...,n;k\neq i,j} \tag{11}$$

where $\left(a_{k,j}\right)_{k=1,2,...,n;k\neq i,j}$ is an $(n-2)\times 1$ vector that is obtained from the jth column of matrix A by deleting the ith and the jth element. By using $\sum_{r=1}^{\infty} r \left(A_{-i,-j}\right)^{r-1} = \left(I - A_{-i,-j}\right)^{-2}$ and substituting it into (11), we obtain

$$\varphi_{m,j,-i} = \left[\left(I - A_{-i,-j}\right)^{-2}_{m,k} \right]_{k=1,2,...,n;k\neq i,j} \left(a_{k,j}\right)_{k=1,2,...,n;k\neq i,j} \tag{12}$$

2. In the next step, $\varphi_{m,j,-i}$ is computed for all combinations of (m, j), where $m = 1, 2, ..., n$ and $j = 1, 2, ..., n$, with $m, j \neq i$. This results in the $(n-1) \times (n-1)$ dimensional matrix $\left(\varphi_{m,j,-i}\right)^{n,n}_{m=1,j=1,m,j\neq i}$. An element of which gives us, the expected number of steps from any country j to each of country i's potential trading partners $m = 1, 2, ..., n, m \neq i$. The key difference to the related matrix in the benchmark case, i.e. $\left(\varphi_{m,j}\right)^{n,n}_{m=1,j=1}$, is that here all connections from and to country i are disregarded.

3. With $\varphi_{\cdot,\cdot,-i}$ at hand, we have the information about how well country i's (potential) trading partners are integrated into the world wide trade network. To establish how integrated country i itself is, we need to have an indicator which measures the proximity of country i to each of its (potential) trading partners. Notice that it is the direct links from i to all other countries which is critical when it comes to the issue of endogeneity. Therefore, it is essential that an indicator is used which is disconnected as much as possible from country i's contemporaneous growth performance. Here we suggest to use the geographical distance, measured in kilometers, between countries. This choice has several merits: (a) it is strictly exogenous to country i' current and past GDP, (b) it has been shown that the geographical distance between two countries is a good proxy for the intensity of their bilateral trade relations, and (c) the data it is accurate.

4. Let $geo_{i,m} = geo_{m,i}$ denote the geographical distance, in kilometers, between countries i and m. We use the inverse of which as a measure of proximity, i.e. $\omega_{i,m} = \frac{1}{geo_{i,m}}$.

The higher is the distance between i and m the lower will be the implied weight $\omega_{i,m}$. The weights are rescaled in the following way:

$$\tilde{\omega}_{i,m} = \frac{\omega_{i,m}}{\sum_{m \neq i} \omega_{i,m}} \qquad \text{such that} \quad \sum_{m \neq i} \tilde{\omega}_{i,m} = 1 \tag{13}$$

5. Using the weights $\tilde{\omega}_{i,m}$ together with the average path length from country j to each country $m \neq i$, $\varphi_{j,m,-i}$, we compute the expected number of steps from country j to country i as follows:

$$\tilde{\varphi}_{j,i} = \sum_{m \neq i} \tilde{\omega}_{i,m} \varphi_{j,m,-i} \tag{14}$$

6. Lastly, after repeating the previous step for all $j = 1, 2, ..., n$ we can construct the *indirect* measure of integration of country i as

$$\sum_{j} \beta_j \tilde{\varphi}_{j,i} \qquad \text{where} \quad \tilde{\varphi}_{i,i} = 0 \tag{15}$$

To illustrate the difference between the benchmark indicator and the indirect integration measure, Figures 2 - 3 depict how the expected number of steps between j and i, $\varphi_{j,i}$, are computed in the benchmark case and in the modified version.

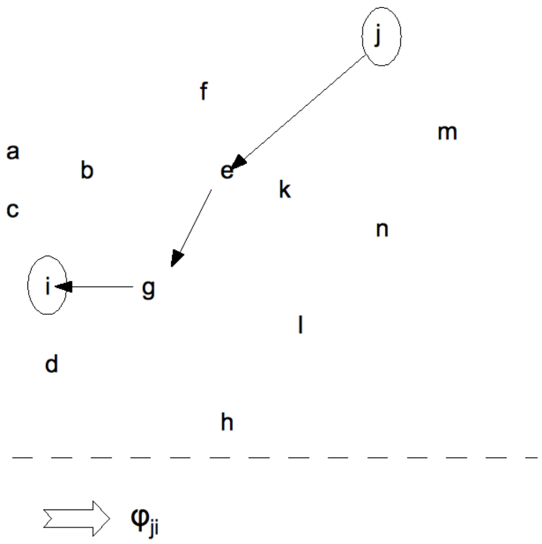

Figure 2: Computation of $\varphi_{j,i}$ in the benchmark case

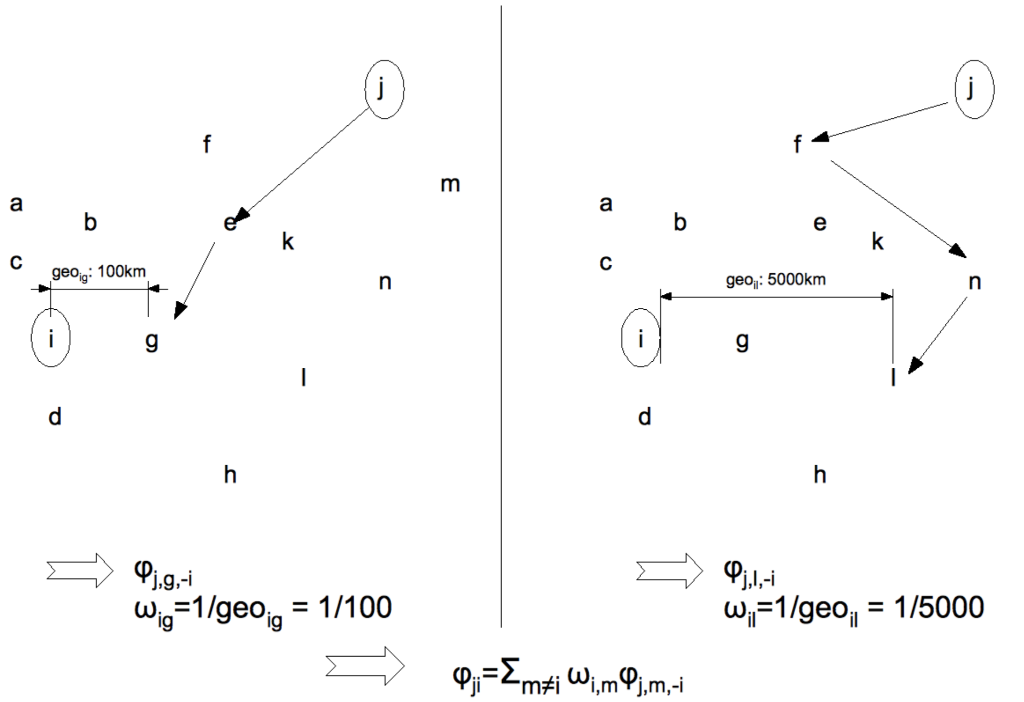

Figure 3: Computation of $\varphi_{j,i}$ using only higher-order connections

D Integrated likelihood

First, let $m(\boldsymbol{\theta}) = \log(p(\mathbf{y}|M_j, \boldsymbol{\theta})f(\boldsymbol{\theta}|M_j))$ denote the posterior mode, and construct a Taylor-series expansion of $m(\cdot)$ around $\tilde{\boldsymbol{\theta}}$, where $\tilde{\boldsymbol{\theta}} = \arg\max_{\boldsymbol{\theta}} m(\boldsymbol{\theta})$:

$$m(\boldsymbol{\theta}) = m(\tilde{\boldsymbol{\theta}}) + (\boldsymbol{\theta} - \tilde{\boldsymbol{\theta}})' m'(\tilde{\boldsymbol{\theta}}) + \frac{1}{2}(\boldsymbol{\theta} - \tilde{\boldsymbol{\theta}})' m''(\tilde{\boldsymbol{\theta}})(\boldsymbol{\theta} - \tilde{\boldsymbol{\theta}}) \tag{16}$$

m' and m'' are the first and second derivative of m, respectively. $m(\boldsymbol{\theta})$ reaches its maximum at $\tilde{\boldsymbol{\theta}}$, therefore $m'(\tilde{\boldsymbol{\theta}}) = 0$, and Equation (16) becomes

$$m(\boldsymbol{\theta}) = m(\tilde{\boldsymbol{\theta}}) + \frac{1}{2}(\boldsymbol{\theta} - \tilde{\boldsymbol{\theta}})' m''(\tilde{\boldsymbol{\theta}})(\boldsymbol{\theta} - \tilde{\boldsymbol{\theta}}) \tag{17}$$

Inserting (17) into the integral gives:

$$p(\mathbf{y}|M_j) = \int e^{m(\tilde{\boldsymbol{\theta}}) + \frac{1}{2}(\boldsymbol{\theta} - \tilde{\boldsymbol{\theta}})' m''(\tilde{\boldsymbol{\theta}})(\boldsymbol{\theta} - \tilde{\boldsymbol{\theta}})} d\boldsymbol{\theta} = e^{m(\tilde{\boldsymbol{\theta}})} \int e^{\frac{1}{2}(\boldsymbol{\theta} - \tilde{\boldsymbol{\theta}})' m''(\tilde{\boldsymbol{\theta}})(\boldsymbol{\theta} - \tilde{\boldsymbol{\theta}})} d\boldsymbol{\theta} \tag{18}$$

The integral is a Gaussian integral and, therefore we get the following expression:

$$p(\mathbf{y}|M_j) = e^{m(\tilde{\boldsymbol{\theta}})} (2\pi)^{\frac{k}{2}} |-m''(\tilde{\boldsymbol{\theta}})|^{-\frac{1}{2}} \tag{19}$$

where k and $|-m''(\tilde{\boldsymbol{\theta}})|$ are, respectively, the rank and the determinant of $-m''(\tilde{\boldsymbol{\theta}})$. In large sample $\tilde{\boldsymbol{\theta}} \approx \hat{\boldsymbol{\theta}}$, where $\hat{\boldsymbol{\theta}}$ is the maximum likelihood estimator of $\boldsymbol{\theta}$. By taking logs, we obtain:

$$\log p(\mathbf{y}|M_j) = \log p(\mathbf{y}|M_j, \hat{\boldsymbol{\theta}}) + \log f(\hat{\boldsymbol{\theta}}|M_j)) + \frac{k}{2}\log(2\pi) - \frac{1}{2}\log|-m''(\tilde{\boldsymbol{\theta}})| \tag{20}$$

According to Raftery (1995), in large samples, $-m''(\hat{\boldsymbol{\theta}}) \approx N\mathbf{I}$, where N is the number of observations and $\mathbf{I}$ is the expected Fisher information matrix. Using that, we get $|-m''(\hat{\boldsymbol{\theta}})| \approx N^k|\mathbf{I}|$ and:

$$\log p(\mathbf{y}|M_j) = \log p(\mathbf{y}|M_j, \hat{\boldsymbol{\theta}}) + \log f(\hat{\boldsymbol{\theta}}|M_j)) + \frac{k}{2}\log(2\pi) - \frac{k}{2}\log N - \frac{1}{d}\log|\mathbf{I}| \tag{21}$$

The first and the fourth term on the right-hand side of this expression are of order N and $\log N$ respectively, whereas all other terms are of order 1 or less. When we remove these terms we arrive at the following expression for the (approximated) integrated likelihood:

$$\log p(\mathbf{y}|M_j) = \log p(\mathbf{y}|M_j, \hat{\boldsymbol{\theta}}) - \frac{k}{2}\log N \tag{22}$$

This is a well-known expression, and it is actually very similar to the Akaike information criterion. With this expression at hand, we are almost ready to compute the posterior model probability given in (5).

One more step is required since the model in (3) does not give us $p(\mathbf{y}|M_j, \hat{\boldsymbol{\theta}})$ but rather $p(\mathbf{y}, \mathbf{X}_j|M_j, \hat{\boldsymbol{\theta}})$, which is the joint conditional likelihood of $(y, \mathbf{X}_j)$, and where M_j contains the relevant $\mathbf{Z}$-regressor variables. In the BMA, we consider different models each consisting of a particular combination of explanatory variables. Using the joint likelihood $p(y, \mathbf{X}_j|\cdot)$ means that we would compare different likelihoods, for instance, $p(\mathbf{y}, \mathbf{X}^1, \mathbf{X}^2, ...\mathbf{X}^k|\cdot)$ and $p(\mathbf{y}, \mathbf{X}^4, \mathbf{X}^5, ...\mathbf{X}^k|\cdot)$ which are not comparable at all.

We address this issue in the following manner. For a given model M_j, we, first, maximize (4) to obtain the maximum likelihood estimate of θ_j. Given that, we then compute the likelihood of the outcome variable y conditional on the estimated model, that is $p(\mathbf{y}|M_j, \hat{\boldsymbol{\theta}}_j)$. Most importantly this statistic is comparable across the different models and, hence, we can use this expression to compute the posterior probability of the underlying model. The conditional likelihood $p(\mathbf{y}|M_j, \hat{\boldsymbol{\theta}}_j)$ can be obtained in a relatively straightforward manner by transforming the model given in (3) as follows:

Given $\hat{\boldsymbol{\theta}}$, we, first, substitute the feedback process into the outcome-equation which yields:

$$y_{n,1} = (\hat{\alpha} + \hat{\gamma}_0)y_{n,0} + \left(\hat{\boldsymbol{\gamma}} + \hat{\boldsymbol{\beta}}\right)\mathbf{x}_{n,1} + \hat{\boldsymbol{\delta}}\mathbf{z}_n + \epsilon_n + v_{n,1} \tag{23}$$

and for $t = 2, ..., T$, we get:

$$y_{n,t} = \hat{\alpha} y_{n,t-1} + \left[\hat{\gamma}_0 + \hat{\boldsymbol{\beta}}\hat{\boldsymbol{\pi}}_{t0}\right] y_{n,0} + \left[\hat{\boldsymbol{\gamma}} + \hat{\boldsymbol{\beta}}\hat{\boldsymbol{\pi}}_{t1}\right] \mathbf{x}_{n,1} + \left[\hat{\boldsymbol{\delta}} + \hat{\boldsymbol{\beta}}\hat{\boldsymbol{\pi}}_{t2}\right] \mathbf{z}_n + \hat{\boldsymbol{\beta}}\boldsymbol{\xi}_{n,t} + \epsilon_n + v_{n,t} \quad (24)$$

For each country observation i, the model in (23)-(24) is a system of T equations which can be compactly written as:

$$\mathcal{A}\mathbf{y}_i = \mathcal{B}\mathbf{Z}_i + \mathcal{C}\mathbf{U}_i \quad (25)$$

where the following definitions are applied:

$$\mathcal{A} = \hat{A}_{11} \qquad \mathcal{B} = \begin{bmatrix} 0 \\ \left(\mathbf{I}_{T-1} \otimes \hat{\boldsymbol{\beta}}\right) \hat{B}_2 \end{bmatrix} + \hat{B}_1 \qquad \mathcal{C} = \left[\mathbf{I}, -\hat{A}_{12}\right].$$

$\mathbf{I}_{T-1}$ is an identity matrix of order $T-1$. The variables $\mathbf{y}_i$, $\mathbf{Z}_i$ and $\mathbf{U}_i$ are defined as above in (3) and so are the matrices $\hat{A}_{11}$, $\hat{\boldsymbol{\beta}}$, $\hat{B}_2$, $\hat{B}_1$, $\hat{A}_{12}$ which are evaluated at the ML-estimate $\hat{\boldsymbol{\theta}}$. Finally, we can write the log-likelihood of observation $\mathbf{y}$, conditional on $\mathbf{Z}$ and $\hat{\boldsymbol{\theta}}$ as follows:

$$\log p(\mathbf{y}|M_j, \hat{\boldsymbol{\theta}}) \propto -\frac{N}{2} \log |\mathcal{C}\hat{\boldsymbol{\Omega}}\mathcal{C}'| - \frac{1}{2} tr(\hat{\boldsymbol{\Omega}}^{-1}\mathbf{U}\mathbf{U}') \quad (26)$$

where M_j is the specific model and contains the relevant $\mathbf{Z}$-regressor variables. Finally, the expression in (26) can be substituted into (22) to obtain the approximated integrated likelihood.

E Diagnostics for the MC^3

We compute various stationarity measures to check the convergence properties of the Markov Chain Monte Carlo algorithm. These measures include the following:

- **Corr(Π, Freq)** tests the convergence of the Markov Chain and it is computed as follows. (1) discard the first S_0 steps of the chain to eliminate possible effects from influential starting values. (2) split the remaining chain into two parts: the first S_1 steps and the subsequent S_2 steps. (3) compute the transition matrix T_1, where an element of T_1, say t_{ij}, records how many times the chain has moved from model m_i to model m_j. The dimension of T_1 is equal to the number of different models in S_1. (4) convert T_1 into the transition probability matrix P_1. An element of P_1, say p_{ij}, is determined as $t_{ij}/\sum_{k=1}^{\dim(T)} t_{ik}$ and it measures the probability of the chain moving from m_i to m_j, conditional on being in m_i. (5) calculate the ergodic probability of being in m_i (from P_1^{∞}), which gives the unconditional probability of observing model m_i. (6) derive for every $m_i \in S_1$, the empirical frequency in S_2 as $c_i/\dim(S_2)$, where c_i counts how often model m_i is visited in S_2. (7) compute the correlation coefficient *Corr(*Π*, Freq)* between the ergodic probabilities of all models in S_1 and their empirical frequencies in S_2. *Corr(*$\Pi, Freq$*)* approaches one when the Markov chain reaches stationarity. This is because any two subsets of a stationary chain give rise to the same stationary distribution, and the stationary distribution is (in a large sample) identical to the empirical frequencies of each state.

- **Corr(Bayes, Freq)** is another stationarity test and it is computed as follows: (1) eliminate a burn-in period and identify the model with the highest posterior probability. Denote it by $\bar{m}$. (2) for each model in the chain, compute the empirical frequency and denote it by f_i. (3) calculate the relative frequency for each model with respect to the best model: $f_i/f_{\bar{m}}$. (4) determine the Bayes factor for each model with respect to the best model: $b_i/b_{\bar{m}}$ [The Bayes factor is the ratio of the posterior probabilities of two models]. (5) compute the correlation coefficient *Corr(Bayes, Freq)* between $f_i/f_{\bar{m}}$ and $b_i/b_{\bar{m}}$. *Corr(Bayes, Freq)* approaches 1 as the chain reaches stationarity. This is because the model selection along the chain is based upon the Bayes factor (the probability that the chain accepts to move to a candidate model is equal to the Bayes factor between the current model and the candidate model), and as a result, the chain visits models more often that have a high posterior probability.

- We calculate the **Raftery-Lewis** dependence factor which is an indicator for the mixing behavior of the Markov chain. Dependence factors above 5 are critical and indicate bad mixing of the chain or influential starting values. See Raftery and Lewis (1992) for details (the parameter values required in the test are as in Raftery and Lewis (1992) and given by $q = 0.025$, $r = 0.005$, $s = 0.95$, $\epsilon = 0.001$).

- To obtain an accurate representation of the posterior distribution, it is important that the chain explores those areas in the model space which have a high probability mass. To address this issue, we follow George and McCulloch (1997) and use a capture-recapture algorithm to estimate what fraction of the total posterior probability mass the Markov Chain has visited.

F Empirical analysis: data sources and variables

Description	Mm.	Variable(s) in original dataset	Computation	Remarks
		Penn World Tables (PWT), Version: PWT 7.0		
Logarithm of real GDP per capita		*rgdpch*	$log(rgdpch)$	
Population in thousands of people	IV	*POP*	s.v.	PWT 7.0 reports two
Annual growth rate of population	AV	*POP*	$POP_{t+1}/POP_t - 1$	versions of data for
Price level of investment	AV	*pi*	s.v.	China: *China Version*
Exports + imports as a share of GDP	AV	*openk*	$openk/100$	*1* (based on official
Consumption share of real GDP	AV	*kc*	$kc/100$	statistics) and *China*
Investment share of real GDP	AV	*ki*	$ki/100$	*Version 2* (corrected
Government share of real GDP	AV	*kg*	$kg/100$	statistics). Here, we
Ratio of workers to population	IV	*rgdpch, rgdpwok*	$rgdpch/rgdpwok$	use *China Version 2*
		World Development Indicators		
Life expectancy at birth	IV	*Life expectancy at birth, total (years)*	s.v.	
Population density	IV	*Population density (people per sq. km of land area)*	s.v.	
Urban population	IV	*Urban population (% of total))*	*Urban population (% of total))*/100	
Population share aged 0-14 years	IV	*Population aged 0-14 (% of total))*	*Population aged 0-14 (% of total)*/100	
Population share aged 65+ years	IV	*Population aged 65 and above (% of total))*	*Population aged 65 and above (% of total))*/100	
		Sachs and Warner: "Trade Openness Indicators", Dataset: sachswarneropen.xls		
1/0 dummy if country is open to trade or not	DV	OPEN	s.v.	
		Polity IV Project: Regime Authority Characteristics and Transitions Datasets: p4v2010.xls		
Democracy index, from 0 (lowest) to 1 (highest)	IV	*polity2*	$\frac{polity2-(-10)}{10-(-10)}$	$-10 \leq polity2 \leq 10$
		Centre d'Etudes Prospectives et d'Informations Internationales (CEPII) geo_cepii.xls		
1/0 if country is a former Spanish colony	DV	*colonizer1*	= 1 (=0) if colonizer1 = (≠) ESP	
		Uppsala Conflict Data Program (UCDP), Dataset: 64464_UCDP_PRIO_ArmedConflictDataset_v42011.xls		
1/0 dummy for armed conflict on own territory with ≥ 1000 battle-related deaths in a given year	DV	*Int*	$= 1$ if $Int = 2$	Conflicts can be extrasystemic, interstate, internal, internationalized internal, but have to be on own territory.

Note: s.v. (same variable) means that the variable in the dataset coincides with the variable in the original dataset. For example: $IPR = pi$

Table 5: Data description, data sources and computation of variables

Description	Mm.	Variable(s) in original dataset	Computation	Remarks
Gallup, Mellinger, Sachs, Harvard University Center for International Development				
(1) Dataset: physfact_rev.csv (Physical geography and population)				
Land area in km^2	TI	*areakm2*	s.v.	Data for Mauritius and Singapore is from: geodata.csv (variable names: *landarea* / *tropicar*/*troppop*/*lnd100cr*
Share of land area in the geographic tropics	TI	*tropicar*	s.v.	
Population share in the geographic tropics	IV	*troppop*	s.v.	
Percent of land area within 100km of the nearest coastline or sea-navigable river	TI	*lcr100km*	s.v.	
(2) Dataset: kgzones.csv (Köppen-Geiger Climate zones)				
Percent of land area in Koeppen-Geiger tropics	TI	*kgatr*	s.v.	
(3) Dataset: geodata.csv (Geography and Economic Development)				
1/0 Dummy for landlocked country	TI	*landlock*	s.v.	
Log of minimum air distance in km from country's capital city to New York, Rotterdam, or Tokyo	TI	*airdist*	s.v.	
Timing of national independence	TI	*newstate*	0 if before 1914, 1 if in 1914-1945, 2 if in 1946-1989, 3 if after 1989)	
1/0 dummy for countries under socialist rule for considerable time during 1950 to 1995	DV	*socialst*	s.v.	
Barro and Lee 2000, Dataset: appendix_data_tables_in_panel_set_format.xls				
Average years of primary schooling	IV	*pyr60, pyr65, pyr70, pyr75, pyr80, pyr85, pyr90, pyr95*	= pyr60 (for 1960-64), = pyr65 (1965-69), ...	
Average years of secondary schooling	IV	*syr60, syr65, syr70, syr75, syr80, syr85, syr90, syr95*	= syr60 (for 1960-64); = syr65 (1965-69), ...	

Table 6: Data description, data sources and computation of variables

#	country	1965	1985	2005	#	country	1965	1985	2005	#	country	1965	1985	2005	#	country	1965	1985	2005
1	Afghanistan	9.3	10.5	9.5	43	*Dominican Rep.*	9.7	8.9	8.2	85	Kuwait	8.6	7.7	8.1	127	Saint Vincent	-	12.8	11.2
2	Albania	11.3	10.7	9.5	44	*Ecuador*	9.3	8.8	8.5	86	Kyrgyzstan	-	-	10.4	128	Santa Lucia	-	12.4	10.8
3	*Algeria*	7.9	7.2	7.6	45	*Egypt*	7.4	6.8	7.4	87	Laos	10.9	12.4	11.0	129	Saudi Arabia	8.3	6.1	6.7
4	Angola	8.9	9.1	8.6	46	El *Salvador*	9.2	9.2	8.6	88	Latvia	-	-	8.6	130	*Senegal*	9.1	9.6	9.4
5	*Argentina*	7.4	8.1	7.6	47	Estonia	-	-	8.5	89	Lebanon	8.2	8.7	8.6	131	Serbia-Montenegro	-	-	8.4
6	Armenia	-	-	10.3	48	Ethiopia	9.5	9.1	9.5	90	Liberia	8.1	8.6	9.3	132	Seychelles	-	11.4	11.2
7	*Australia*	6.4	6.3	6.1	49	Fiji	10.4	10.4	10.5	91	Libya	-	-	8.5	133	*Sierra Leone*	10.0	11.3	11.3
8	*Austria*	6.7	6.4	6.1	50	*Finland*	7.0	6.9	6.7	92	Lithuania	-	-	8.3	134	*Singapore*	7.9	6.3	5.8
9	Azerbaijan	-	-	9.1	51	*France*	5.2	4.7	4.6	93	Madagascar	9.6	10.4	10.5	135	Slovakia	-	-	7.5
10	Bahamas	9.4	8.6	8.6	52	French Polyn.	10.6	9.9	10.3	94	*Malawi*	11.4	11.0	11.1	136	Slovenia	-	-	7.8
11	Bahrain	9.9	9.1	9.0	53	Gabon	10.5	9.5	10.3	95	*Malaysia*	7.3	7.0	6.3	137	Solomon Isds.	-	11.7	12.8
12	Bangladesh	-	8.5	8.4	54	*Gambia*	11.7	11.6	11.1	96	*Mali*	10.6	10.4	10.0	138	Somalia	11.0	10.6	11.3
13	Barbados	10.7	10.2	10.3	55	Georgia	-	-	9.7	97	Malta	9.6	9.7	9.0	139	*South Africa*	6.7	7.3	6.9
14	Belarus	-	-	8.4	56	Germany	4.7	4.4	4.2	98	Mauritania	11.3	10.5	10.4	140	*Spain*	6.4	6.1	5.1
15	*Belgium*	5.6	5.4	5.2	57	Germany East	7.8	6.9	-	99	*Mauritius*	10.3	10.4	9.8	141	*Sri Lanka*	8.5	8.8	8.8
16	*Benin*	10.9	10.3	9.9	58	*Ghana*	8.2	9.8	9.0	100	*Mexico*	7.1	6.3	5.2	142	Sudan	8.9	8.6	9.0
17	Bermuda	9.9	9.9	10.0	59	Gibraltar	13.8	11.0	9.3	101	Moldova	-	-	9.8	143	Suriname	10.1	10.7	10.7
18	*Bolivia*	9.8	10.2	10.2	60	*Greece*	7.3	7.0	6.8	102	Mongolia	-	12.0	10.9	144	Swaziland	-	-	12.5
19	Bosnia Herzegovina	-	-	8.8	61	Grenada	-	12.7	11.4	103	Morocco	8.2	8.0	7.8	145	*Sweden*	6.0	6.1	6.2
20	Botswana	-	-	11.5	62	*Guatemala*	9.1	9.1	8.3	104	*Mozambique*	9.1	10.4	9.9	146	*Switzerland*	6.1	5.9	5.8
21	*Brazil*	7.6	6.8	6.4	63	Guinea	10.5	10.4	10.2	105	Namibia	-	-	11.4	147	*Syria*	9.3	8.0	8.4
22	Bulgaria	8.5	8.0	7.9	64	Guyana	10.0	10.8	10.9	106	*Nepal*	10.4	10.5	10.5	148	Tajikistan	-	-	10.8
23	Burkina Faso	11.1	10.8	10.5	65	*Haiti*	10.9	9.7	9.9	107	*Netherlands*	5.4	5.1	4.9	149	*Thailand*	8.0	7.5	6.4
24	Burma	8.8	10.1	9.9	66	*Honduras*	9.7	9.6	8.4	108	New Caledonia	10.1	10.3	10.2	150	*Togo*	10.7	10.3	9.9
25	Burundi	11.4	11.6	11.9	67	Hong Kong	7.1	6.2	5.4	109	*New Zealand*	7.5	7.8	7.6	151	*Trinidad-Tobago*	8.7	9.1	9.0
26	*Cameroon*	9.5	9.0	9.9	68	Hungary	7.1	7.2	6.8	110	*Nicaragua*	9.4	9.4	9.3	152	*Tunisia*	8.9	8.4	8.2
27	*Canada*	5.6	5.0	4.7	69	Iceland	9.4	9.6	9.2	111	*Niger*	11.1	10.8	10.8	153	*Turkey*	7.9	7.0	6.2
28	*Central Afr.Rep.*	11.3	11.7	12.5	70	*India*	6.4	6.6	6.2	112	Nigeria	7.8	7.6	7.8	154	Turkmenistan	-	-	9.9
29	Chad	11.6	11.5	11.5	71	*Indonesia*	8.1	7.4	6.7	113	*Norway*	6.7	6.8	6.8	155	*Uganda*	10.3	10.6	10.1
30	*Chile*	8.0	8.5	7.4	72	*Iran*	7.7	7.1	7.3	114	Oman	10.2	8.5	8.9	156	Ukraine	-	-	7.3
31	*China*	7.2	5.9	4.7	73	Iraq	8.6	7.1	8.1	115	*Pakistan*	7.5	7.6	7.8	157	UAE	-	7.4	6.3
32	*Colombia*	8.3	8.0	7.7	74	*Ireland*	7.5	7.1	6.3	116	*Panama*	8.5	7.6	7.7	158	*United Kingdom*	4.8	4.8	4.6
33	*Congo, Rep.*	10.3	9.9	10.3	75	*Israel*	7.8	7.2	6.9	117	*Papua N.Guinea*	9.9	9.6	10.1	159	*United States*	4.0	3.2	3.1
34	*Congo, Dem.Rep.*	8.8	9.2	10.2	76	*Italy*	5.5	5.0	4.9	118	*Paraguay*	10.4	10.1	9.6	160	*Uruguay*	9.7	9.9	9.3
35	*Costa Rica*	9.4	9.0	8.3	77	Ivory Coast	8.9	9.0	9.4	119	*Peru*	7.9	8.9	8.3	161	Uzbekistan	-	-	9.8
36	Croatia	-	-	8.0	78	*Jamaica*	8.9	9.3	9.0	120	*Philippines*	7.7	7.7	7.0	162	USSR Fmr.	6.3	5.6	5.6
37	Cuba	8.6	8.5	9.2	79	*Japan*	5.6	4.6	4.7	121	Poland	7.4	7.0	6.3	163	*Venezuela*	7.3	7.3	7.5
38	Cyprus	-	8.8	8.1	80	*Jordan*	9.1	7.9	8.5	122	*Portugal*	7.6	7.4	6.5	164	Yemen	12.7	9.0	9.2
39	Czech Republic	-	-	6.7	81	Kazakhstan	-	-	8.1	123	Qatar	10.2	9.2	8.5	165	Yugoslavia Fmr.	7.1	6.9	7.0
40	Czechoslovakia Fmr.	7.4	6.7	6.4	82	*Kenya*	8.8	9.2	9.1	124	Romania	8.2	7.5	7.1	166	*Zambia*	9.5	10.3	10.3
41	*Denmark*	6.5	6.6	6.6	83	Kiribati	-	13.5	13.4	125	Russian Federation	-	-	6.0	167	*Zimbabwe*	9.2	9.9	10.1
42	Djibouti	11.0	10.7	10.6	84	*Korea*	8.4	6.3	5.5	126	*Rwanda*	12.6	11.2	11.4					

Notes: Countries displayed in italic are included in the empirical analysis.

Table 7: Trade Integration