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The Structure and Growth of World Trade, and the Role of Europe in the Global Economy*

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Abstract

This paper presents a simple stochastic model of proportionate growth to describe international trade and it applies this set-up to the relationship between export dynamics and economic development. Trade flows are assumed to grow as a geometric Brownian motion while new trade links follow a preferential attachment mechanism, and these two processes are assumed to be independent. This simple set-up accurately describes many of the empirical features that characterize the structure and growth of the international trade network. Furthermore, it reconciles diverging views of industrial policy in the economic development literature: although export is very concentrated so that large bilateral flows are rare, countries characterized by a large number of export relations are more likely to capture such "big hits". The stochastic model provides a simple benchmark against which we can assess countries' export performance. We then investigate the determinants of deviation of empirical data from the predictions of the model in terms of the number of "big hits".

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1 Introduction

The use of industrial policy as an instrument of export growth has more than often solicited scepticism or even strong opposition in mainstream economics (Stiglitz et al., 2013). The standard argument is based on the view that any government intervention is likely to breed inefficiency and encourage rent-seeking behaviour. Growth models formalising the supremacy of a liberal over a closed-economy have further led economists and policy makers to have greater recourse to markets to redress the economy. However, the free play of markets has not always produced the desired results; for instance, ardent reform in Latin America did not improve their performance by the 1990s. Contrarily, increased state-involvement in other economies has sometimes led to greater economic success, such as, in Japan. As a result of these discrepancies, development economists have recently revived the debate regarding the actual and potential economic merits of industrial policy. We particularly refer to the debate confronting Hausmann and Rodrik (2003) to Easterly et al. (2009).

Hausmann and Rodrik (2003) and subsequent literature (Rodrik, 2004; Hausmann and Rodrik, 2005) provide a formalism of the case for industrial policy through a process they call "self-discovery", where investors learn what they are good at producing among the wide set of investment possibilities. Once an investor discovers what products would bring the highest returns, this knowledge generates positive spillovers in the economy as it signals other investors where to direct their entrepreneurial efforts. While these informational externality is good for the economy, it discourages initial investment. Consequently, investment is under-supplied or, in other words, there is too little "search" and "discovery". Hence, these authors argue that there is a need for some optimal industrial policy to counteract this distortion. It is made clear in Rodrik (2004) that industrial policy is not about imposing taxes or subsidies but it refers to a greater collaboration between the state and the private sector so as to discover what investment decision would benefit the economy and what kind of intervention is needed or not. In sum, industrial policy is simply the "provision of public goods for the productive sector", such as R&D, infrastructure and training (p.39). In Hausmann and Rodrik (2005), they emphasise that the focus is on process rather than on specific policies, in their words "[i]n view of the inherent uncertainty about what is likely to work, it is more important to design robust institutional arrangements than to adopt an agenda of specific policy actions. The process of self-discovery is as much about policy learning–which types of policies work and which do not under existing realities–as it is about entrepreneurial learning" (p.77).

On the other side of the debate, Easterly et al. (2009) contend that policy aimed at "picking winners"–selective industrial policy–is bound to be unsuccessful.[1] They build their argument on the fact that manufacturing exports are highly concentrated where a few product-destinations account for a disproportionately large share of export values. These few exports that make up most of total export value are termed "big hits"; they capture both the right product and the right market. With such specialisation, the shape of the distribution of exports is highly skewed (close to being a power law) which implies that the probability of identifying a "big hit" is very low, as this probability decreases exponentially with the size of the hit. Hence, these authors claim that it is better to leave markets unhindered by policy. Nevertheless, they

[1] The authors document that manufacturing export success is intricately related to development success.

do mention that in the presence of externalities, "discovery efforts" could be subsidised while letting the market "pick winners" and, hence, getting the best of both worlds.

In this paper, we show that our modelling strategy nicely accommodates the "two worlds"– Hausmann and Rodrik (2003) versus Easterly et al. (2009) as it is able to account for several stylised facts simultaneously. While the distribution of exports is fat-tailed, i.e. "big hits" are rare events, the probability of drawing a large export flow increases with the number of trade relationships. This follows that countries characterised by large "discovery efforts", stimulated or not through industrial policy, are much more likely to draw "big hits".

We describe international trade as a set of transactions of different magnitude occurring between countries using a simple stochastic model of proportionate growth and we apply this set-up to describe the relationship between export dynamics and economic development. Stochastic models have long been used in the literature to assess the economic relevance of a given phenomenon and to establish a benchmark for measuring its extent (Simon, 1955; Simon and Ijiri, 1977). More recently, Ellison and Glaeser (1997), propose a stochastic process whereby firms choose their location by throwing darts on a map; they compare this measure with the observed level of geographic concentration of economic activities. The balls-and-bins model of Armenter and Koren (2010) probably represents the closest approach to our own. These authors describe US exports as balls falling into bins of different sizes each representing a product-destination pair and their simple set-up is able to predict the pattern of zero-trade flows at the extensive margin and to match some stylised facts of US trade flows. They argue that such a model can be more informative to theory when it *misses* an empirical fact rather than when it succeeds to match it. The present paper departs from Armenter and Koren (2010) by focusing on global trade rather than just US trade with the rest of the world. Our model is also able to match many of the stylised facts regarding international trade both at the intensive and extensive margins.

One of the facts that is recurrent in many trade studies and relevant to this paper is the large share of zeros in trade. Such sparsity has been documented by Helpman et al. (2008) who using data for 158 countries for the period 1970-1997 report that about only 50% of country-pairs engage in trade. Similarly, Baldwin and Harrigan (2011), describing US trade at the 10-digit Harmonised System, find that zeros are as present in import as in export data, making up about 82% of the latter. Both papers build on the heterogeneous firms trade model of Melitz (2003) which they improve to account for the share of zeros and other trade patterns. Second, we refer to the literature which report the high concentration of trade both at the intensive (the value of trade) and extensive margin (the number of trade relationships). These facts are well-documented in Easterly et al. (2009). They find that the top 1% export products accounts for 49% of the median export share. At the intensive margin, they report that the top 1% product-destination makes up about 53% of the median export value. Trade concentration seems to have been here for long; investigating the role of distance and the patterns of intra-European trade, Beckerman (1956) stresses the non-normal distribution of trade where trade accumulates at the extremities instead of around the mean. He finds that on average each country exported about 56% of its total export to its 3 major markets in 1938 and about 50% in 1953.

Another pattern closely related to trade concentration is the observation that most countries export only a few products to a few destinations while a small club of countries export most products to many destinations (Riccaboni and Schiavo, 2010). Similarly, the distribution of bilateral trade values is highly skewed assuming a log-normal form (Bhattacharya et al., 2008; Fagiolo et al., 2009) and this shape holds for different level of aggregation of the data. Here too, a small fraction of very large trade relationships exists alongside a large number of small trade flows.

Hence, skewness is evident both at the intensive and at the extensive margin. There is extensive debate and disagreement in recent trade literature as to what role do the intensive and extensive margins play in trade growth. While some papers find that the extensive margin drives trade growth (Hummels and Klenow, 2005), other authors report the dominant role of the intensive margin (Besedeš and Prusa, 2011). In fact, the extensive margin seems to exert a greater influence on trade at the cross-sectional level, for instance, Hummels and Klenow (2005) find that it accounts for 60% of export. On the contrary, the intensive margin explains most of the dynamics of trade over time. Helpman et al. (2008) report that the rapid growth of world trade since the 1970s was mostly trade between existing countries rather than with new partners. Similarly, Besedeš and Prusa (2011) emphasise the temporal nature of extensive trade in export growth so that extensive trade has no effect in the long-term.

While there is a largely held view and empirical evidence that diversification of exports is positively related to economic development, Cadot et al. (2009) and previously Imbs and Wacziarg (2003) find that there is an increase in concentration at higher level of development. They show that most of the action happen at the extensive margin by using the Theil Index of concentration. The latter is an interesting measure as it can be decomposed additively into a between-group and a within-group components. Changes in the between-group component can be matched into changes in the extensive margin of trade while changes in the within-group component can be mapped into changes in the intensive margin of trade. This property is explained and proved by Cadot et al. (2009).

We also draw from studies that explore the dependency of growth rates on size of firms. Stanley et al. (1996) find that the variances of growth rates differ with firms of different sizes and decreases with larger sizes. Indeed, the distribution of growth rates is not Gaussian but rather exponential. The same holds for the size of an economy as reported in Canning et al. (1998) and for many other economic phenomena. Plotting the log of the standard deviation of firms' growth rate against the log of their initial sales value, a power-law relationship emerges. This result challenges beliefs that volatility in growth rates decreases quickly with size.

Among other branches of research, we refer much to development literature that attempt to explain export success, or in our case, the identification of "big hits". We look into the literature on country capabilities which contends that economic development rests on both tradable and non-tradable capabilities present in a country (Hidalgo and Hausmann, 2009; Hausmann and Hidalgo, 2011). Further, we draw from literature that stresses the importance of financial development, institutions and geography in economic performance.

2 The model

We describe international trade as a set of links (bilateral transactions) of different magnitude occurring among pair of nodes (countries). Consistently with the empirical analysis, we define a trade link as a product-destination pair. We assume the binary structure of trade (i.e. the presence/absence of a link between two specific countries and the number of links maintained by each country) is governed by a process of "preferential attachment": countries establish new trade links based on the number of connection they already have. Hence, more active exporters are more likely to export new products and/or reach new markets.[2]

Apart from being remarkably consistent with a large number of empirical networks, this mechanism of network formation and growth is consistent with the notion that exporting represents a key engine of economic growth thanks to the endogenous forces set in motion by learning effects in the manufacturing sector (Kaldor, 1957). More recent framings of this view of cumulative causations are the "self-discovery" story presented by Hausmann and Rodrik (2003) and the "complexity" approach proposed by (Hidalgo and Hausmann, 2009). The former postulates that attempts to set up new businesses and export new products to new destinations generate valuable public information as they signal profitable opportunities or dead ends. The latter builds on the notion that by producing a given set of goods each country cumulates a number of capabilities: the more capabilities are present, the easier it is to recombine them and put them to a novel use. Microfounded accounts of preferential attachment are offered by Chaney (2011) and Krautheim (2012). The first assumes that firms can establish links with suppliers either at random or via existing connections (meeting friends of friends); the second models the fixed costs associated with penetrating a foreign market as a decreasing function of the number of firms already exporting there (from a given source country) due to the presence of spillover effects.

Building on the extension to weighted networks proposed by Riccaboni and Schiavo (2010) we assume that, while the binary structure of international trade follows a purely preferential attachment mechanism, the dollar value of each trade flow grows according to a geometric Brownian motion. Moreover, the two processes governing the formation of links and their growth are assumed to be independent.

More formally, we can describe the stochastic model as follows:

- at time $t = 0$ there are N_0 countries each characterized by a self loop;[3]

- at each time step $t = \{1, \ldots, T\}$, a new link among two countries arises: thus the number of links existing at time t is $m_t = t$;

We identify the number of links of country i at time t with $K_i(t)$, whereas $K_{ij}(t)$ represents the number of products traded between countries i and j. To identify the countries connected to each link we adopt the following procedure:

[2]Preferential attachment is typically associated with the pioneering work by Barabási and Albert (1999) and gives rise to a very skewed connectivity distributions (few well-connected nodes coexist alongside a large number of peripheral actors), which is found to characterize many real-world applications beside trade (the internet, world-wide air trasportation, mobile communication, interbank payments to quote just a few; see Faloutsos et al., 1999; Guimera et al., 2005; Onnela et al., 2007; Soram aki et al., 2007).

[3]This only serves for initialization purpose: self loops are never considered in the analysis.

- with probability a the new link is assigned to a new country, whereas with probability $1-a$ it is allocated to an existing country;
- in the latter case, the probability of choosing country i is given by $p_i(t) = K_i(t-1)/2t$; i.e. the probability depends on the number of links already secured by country i;
- the same process governs both side of the trade link, meaning that the two partner countries are chosen symmetrically with $i \neq j$;

Hence, at each time t this set of rules identifies the pair of (distinct) countries to be linked and the process generates the binary structure of the network, meaning the number of active bilateral links, the number of zero trade flows, the number of links associated with each country.

For what concerns the value of each trade flow, we assume that it grows in time according to a simple random process:

- at time t each (existing) trade flow between countries i and j has weight $w_{ij}(t) > 0$;[4]
- at time $t+1$ the weight of each link is increased or decreased by a random shock $x_{ij}(t)$, so that $w_{ij}(t+1) = w_{ij}(t)x_{ij}(t)$. All we need to assume is that the shocks and initial link values are taken from a distribution with finite mean and standard deviation.[5]

We therefore combine a preferential attachment mechanism, with an independent geometric Brownian motion characterizing the magnitude of bilateral trade flows. As detailed in Riccaboni and Schiavo (2010), this simple setup gives rise to very skewed distributions that are consistent with the empirical evidence. In particular, in the limit of large t, with $a > 0$ and small, the connectivity distribution converges to a power-law with an exponential cutoff (Yamasaki et al., 2006). For what concerns the distribution of bilateral trade flows, the proportional growth process described above implies that the distribution of the weights $P(w)$ converges to a lognormal.

We do not regard this setup as a full-fledged economic model that *explains* bilateral trade flows, but rather as a stochastic benchmark against which to compare actual data.

3 Data and Empirics

3.1 Data

We use data on bilateral trade flows contained in the BACI dataset that reconciles data reported by exporting and importing countries to the United Nations Statistics Division.[6] The bilateral trade flows we use in the present paper cover a maximum of 194 countries and 5039 product categories at the 6-digit Harmonised System(HS) level. We clean the data for very small countries (such as the Cook Islands) for which data are sparse and not reliable, and end up with a dataset covering 186 countries over a 15-year period between 1995 and 2009.

[4]We further assume that K_i, K_j and w_{ij} are independent random variables, i.e. the value of bilateral trade is independent of the connectivity of the two partner countries.

[5]So in principle the initial value of trade could be 1, or can be defined in terms of some exogenous determinant such as size and distance, as in a standard gravity model.

[6]For more information on the construction of BACI, refer to Gaulier and Zignago (2010).

3.2 Regularities in empirical data

As mentioned previously, sparsity of trade is one of the most documented stylised facts regarding bilateral trade flows. We also find in our data that the number of active trade links is far below the potential one. Over the period 1995-2009, in terms of aggregate trade flows to a destination, the average share of zeros is about 47%, and the highest share of 57% is in 1995. Since many products are exported to just one or few destinations, we also look at the share of zeros at the product-destination level and the average is as high as 97%. As shown in figure 1, both shares exhibit a declining trend over the years, except in 2009, but remain high.

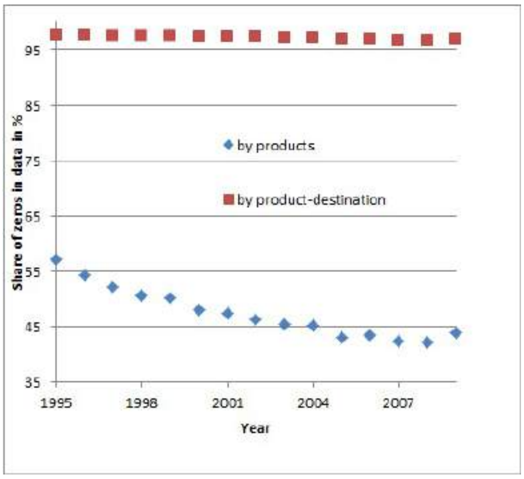


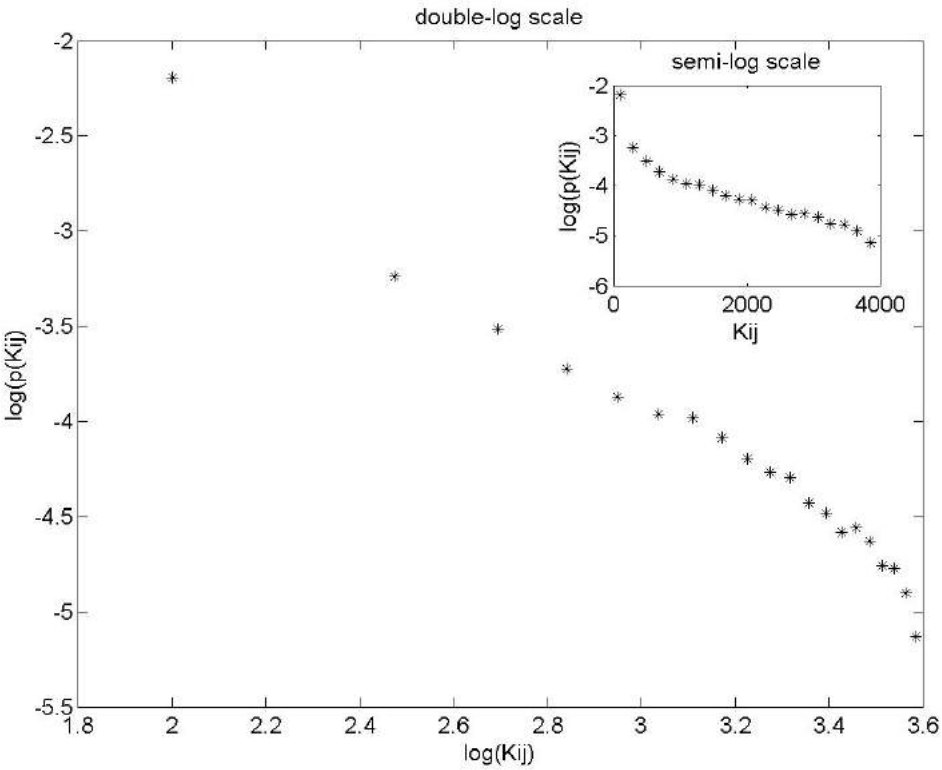
Figure 1 Share of zero trade flows at the products and product-destinations level

Focusing now on active trade links, we look at the distribution of the number of trade relationships (at the product-destination level) maintained by each country. Figure 2 shows such distributions for the years 2000 (panel a) and 2005 (panel b). These distributions are well approximated by a Pareto in the body (the straight line behaviour is apparent in the plot), with an an exponential cut-off in the upper tail, where the number of product-destinations is very large. This departure is magnified in the inset (in semi-log-scale) of the figures where the exponential part now appears as a straight line. This behaviour conforms to the prediction of our model.

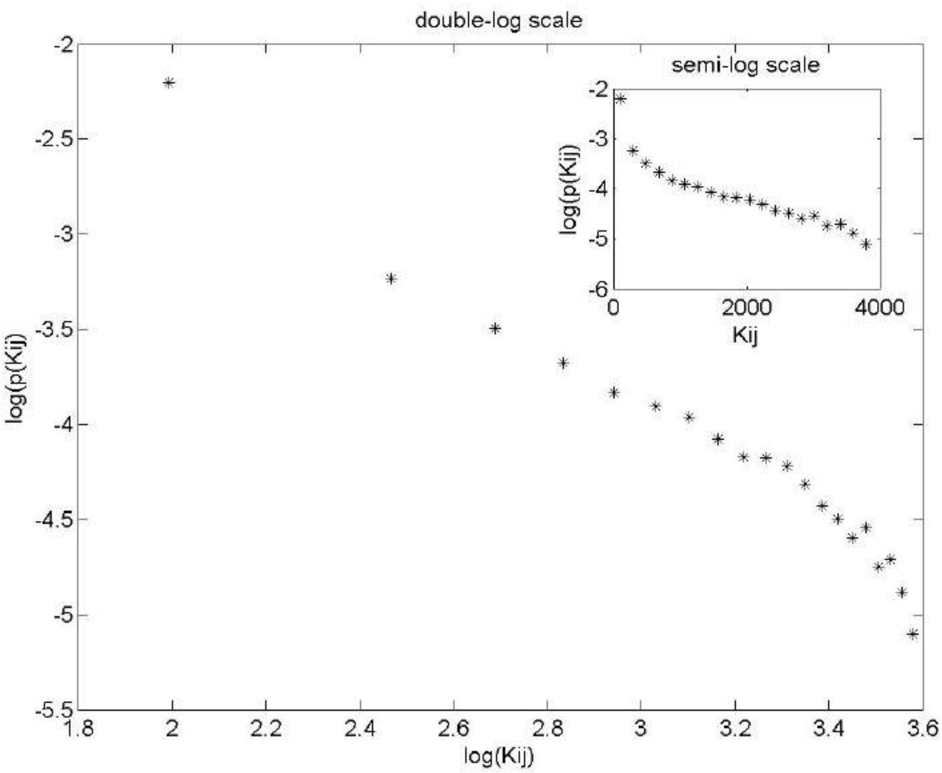
We also expect the distribution of trade values to be log-normally distributed as implied by the Gibrat process of proportionate growth driving the intensive margin. Figure 3 a) shows the complementary cumulative distribution function of manufacturing trade for both bilateral trade values and total trade values, i.e., total trade values of country i, together with the log-normal estimates for the year 2005. The log-normal estimates are calculated using maximum likelihood for truncated data.[7] Figure b) shows the probability-probability plot using least-square estimation method. The distributions of trade values is fat-tailed and in the aggregate the lognormal estimates provide a good fit. Using the method of least-square a log-normal distribution fits well even the disaggregated data as shown in figure 3 b).

The data also show the striking degree of specialisation in exports. For example, in 2005, the median export shares for the top 20%, 10% and 1% products are 97%, 93% and 66% re-

[7] See Bee (2006).

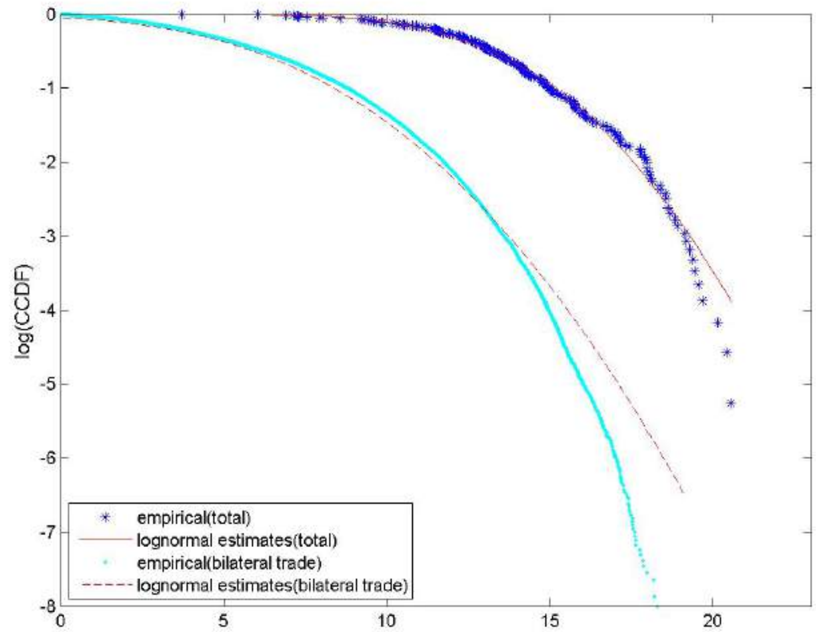


(a) Year 2000

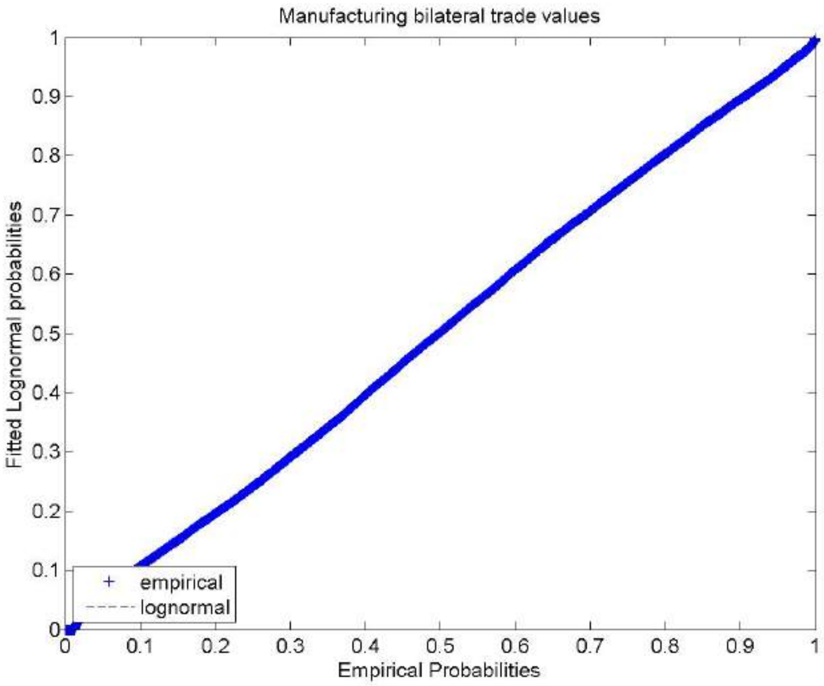


(b) Year 2005

Figure 2 Connectivity distributions at HS6: Main plot in double log and inset in semi-log



(a)



(b)

Figure 3 Distributions of bilateral and total manufacturing trade flows and lognormal fits spectively as shown in table 1. The median share for just the top 3 products is as high as 42%. A comparison of the 2005 figures with those of 1995 show that export concentration has increased slightly over time. Concentration at the product-destination level is very high and increases over time. At low levels, such as, for the top 10 or top 3 products the figures are lower than those at the product level since there are many more product-destinations than products.[8]

Table 1 Export share for the year 1995, 2000, 2005 and 2009 (top 20% stands for top 20 percent and top 10 stands for top 10 products)

Share of exports by products										
Year 1995	*mean*	*p50*	*sd*	*min*	*max*	*Year 2000*	*mean*	*p50*	*sd*	*min*	*max*
top 20%	94.7	96.9	6.7	54.8	99.9	**top 20%**	95.1	96.9	5.7	58.5	100
top 10%	89	92.3	10.7	35.5	99.8	**top 10%**	89.8	92.6	9.9	34.3	100
top 1%	59.9	59.4	20.3	9.2	97.7	**top 1%**	62.2	61.3	19.7	14.1	100
top 10	61.9	65.6	28.1	10.4	100	**top 10**	62.3	63.7	26.1	12.1	100
top 3	45.5	40.1	28.5	4.2	100	**top 3**	45.1	40.2	26.8	5	100
top 1	28.3	20.4	23.6	1.7	97.4	**top 1**	28.7	20.5	23.7	1.8	100
Year 2005	**mean**	**p50**	**sd**	**min**	**max**	**Year 2009**	**mean**	**p50**	**sd**	**min**	**max**
top 20%	95.8	97.2	5.2	60.1	100	**top 20%**	96.8	97.6	3.1	76	100
top 10%	91.2	93.4	8.2	49.6	99.9	**top 10%**	92.9	93.9	5.6	59.6	100
top 1%	65.5	65.5	18.9	16.4	99.5	**top 1%**	66	65.5	14.5	13.6	95.6
top 10	62	62.8	26.2	12.3	100	**top 10**	46.9	43.9	28	3.4	97.9
top 3	45.7	41.9	27.5	6.5	100	**top 3**	30	25	22.4	1.4	94.9
top 1	28.9	20.9	23.8	2.9	98.2	**top 1**	16.8	13.2	15.8	0.5	86.7
Share of exports by product-destinations											
Year 1995	*mean*	*p50*	*sd*	*min*	*max*	*Year 2000*	*mean*	*p50*	*sd*	*min*	*max*
top 20%	95	96.1	6.2	54.8	99.8	**top 20%**	95.6	96.8	5.2	58.4	100
top 10%	89.4	91.2	9.4	35.5	99.4	**top 10%**	90.7	92.3	8.9	34.3	100
top 1%	58.6	58.8	16.3	9.2	97.4	**top 1%**	62	60.4	16.5	14.1	100
top 10	47.5	43.5	29	3	100	**top 10**	47.4	44.5	28	3.3	100
top 3	31.4	22.9	24.8	1.3	100	**top 3**	30.8	23.6	23.8	1.3	100
top 1	17.6	11	17.9	0.5	97.4	**top 1**	17.2	11.9	17.7	0.6	100
Year 2005	*mean*	*p50*	*sd*	*min*	*max*	*Year 2009*	*mean*	*p50*	*sd*	*min*	*max*
top 20%	96.5	97.3	4.4	60.1	100	**top 20%**	96.8	97.6	3.1	76	100
top 10%	92.6	93.7	6.6	49.6	99.9	**top 10%**	92.9	93.9	5.6	59.6	100
top 1%	66.5	65.1	14.8	16.4	96.8	**top 1%**	66	65.5	14.5	13.6	95.6
top 10	46.6	42.9	27.9	2.9	100	**top 10**	46.9	43.9	28	3.4	97.8
top 3	30.6	24.6	23.6	1.2	100	**top 3**	30	25	22.4	1.4	94.9
top 1	17.2	11.1	16.7	0.5	90.3	**top 1**	16.8	13.2	15.8	0.5	86.7
Share of exports by destinations											
Year 1995	*mean*	*p50*	*sd*	*min*	*max*	*Year 2000*	*mean*	*p50*	*sd*	*min*	*max*
top 20%	92.3	93.3	5.3	71.6	100	**top 20%**	92.9	94	5.5	63.5	100
top 10%	80.8	81.9	9.9	52.4	100	**top 10%**	82.9	83.9	9	50.8	100
top 1%	39.9	35.8	20	11.4	100	**top 1%**	41.2	36.1	18.8	13.1	100
top 10	84.3	83.7	11.3	59.6	100	**top 10**	82.4	82.7	11.8	53.6	100
top 3	59.7	57	19.2	27.2	100	**top 3**	57.6	53.5	19.5	24.1	100
top 1	36	30.5	21.2	11.4	100	**top 1**	35.1	28.6	20.9	10.3	100
Year 2005	mean	p50	sd	min	max	**Year 2009**	mean	p50	sd	min	max
top 20%	93.7	94.5	4.2	71.6	99.6	**top 20%**	93.5	94.1	4.3	63.7	100
top 10%	83.5	84.1	7.9	55.1	97.9	**top 10%**	83	83.2	8.6	39.3	100
top 1%	39.4	35.2	17.3	14.3	97.6	**top 1%**	39.1	34.4	18	15.1	100
top 10	80.6	81.4	11.9	51.4	100	**top 10**	80.2	81.2	13.1	49.4	100
top 3	54.8	50.9	18.3	21.8	100	**top 3**	54.6	50.8	19.4	22.5	100
top 1	32.2	25.2	19.1	8	97.6	**top 1**	32.1	24.5	19.9	8.6	100

[8]Our figures are higher than those reported by Easterly et al. (2009). They restrict their analysis to manufacturing exports, thus dropping export of natural resources which is dependent on a country's endowments and therefore inflate concentration. For comparative purposes, we also consider the restricted sample of manufacturing exports for the year 2000 (the same used by Easterly et al., 2009): as we expected, we obtain lower concentration figures than using the whole sample, and figures that are even lower than those reported by Easterly et al. (2009). This may be due to the fact that their dataset contains fewer categories of products (2950) and fewer countries (151) than ours.

Table 2 further investigates the issue of concentration by reporting the standard concentration indices.[9] Except for the Herfindahl index, the Gini, relative entropy and Theil index, all show that export is highly concentrated and confirm the previous findings. The Theil can be decomposed additively into a between- and a within-group component: the former reflects changes in the extensive margin of trade while the latter mirrors the behaviour of the intensive margin (Cadot et al., 2009). Results (not displayed) confirm the findings obtained by Cadot et al. (2009): diversification appears to be mainly driven by the extensive margin. Furthermore, while at the intensive margin there is a positive relation between the Theil index and GDP per capita (concentration increases with income), at the extensive margin this relationship is U-shaped.

Table 2 Concentration indices and descriptive statistics

	mean	**st. dev.**	**min**	**max**	**obs.**
Gini	0.998	0.004	0.977	1.000	194
Entropy	0.639	0.150	0.291	0.893	194
Theil	8.823	2.074	4.022	12.327	194
Herfindahl	0.079	0.098	0.000	0.470	194

Finally, figure 4 shows the relationship between connectivity (the extensive margin) and the value of bilateral trade flows (intensive margin) for manufacturing exports on a log-log scale. A positive relationship emerges with the coefficient of the interpolating line being $\theta \approx 1.32$ for $W = K^{\theta}$ for the year 2005.[10] In economic terms, a $\theta > 1$ implies a positive relationship between the extensive and the intensive margin so that countries entertaining a larger number of trade links feature higher average and total trade. This is consistent with the empirical evidence that the extensive margin plays a prominent role in explaining cross-country differences in total exports (Hummels and Klenow, 2005) and with the findings reported in Easterly et al. (2009).

4 Big hits

In this section, we lay down our contribution to the debate regarding the role of industrial policy in export success. To re-frame, Hausmann and Rodrik (2003) regard development as a self-discovery process wherein policies are designed to discover the productive potential of a country. Without public support, entrepreneurial activity (discovery efforts) will be underprovided because of the non-appropriability of the returns from the investment. In fact, since “search and discovery” provides more than just private returns, so that the knowledge that is produced tends to spillover to the whole economy, other entrepreneurs can exploit the information and the returns to the society are larger than private returns. This entails a market failure and call for public intervention.

This idea is well captured by our preferential attachment assumption which can be interpreted in the following way: countries that make a successful discovery are more likely to

[9]We calculated these indices for both the empirical and theoretical maximum number of product-destinations. The theoretical statistics do not differ much from the empirical ones because the theoretical maximum number of product-destinations is not very different from its empirical counterpart (5039 and 5014 respectively) The table only shows the empirical results.

[10]This coefficient increases over time (results are not reported here).

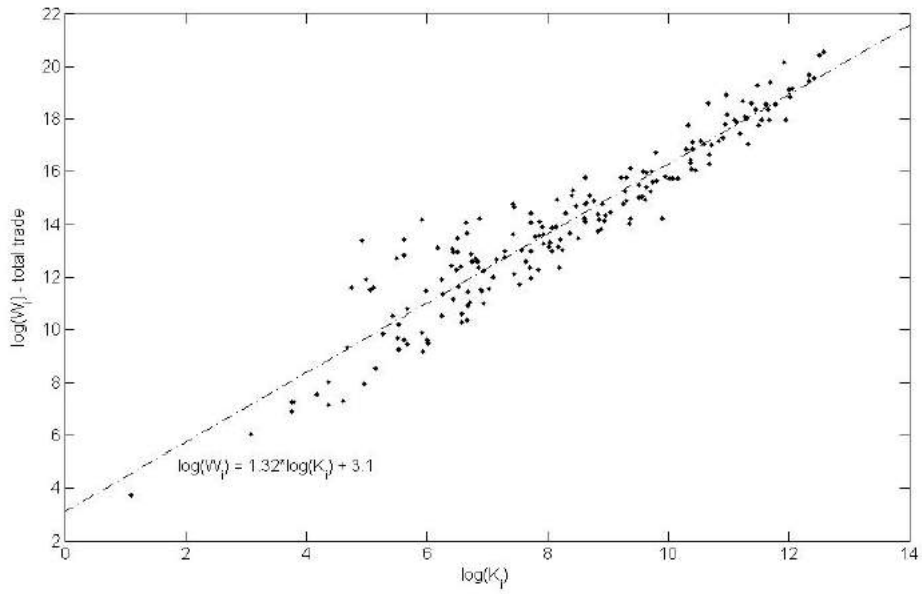


Figure 4 Relationship between the intensive and extensive margin

discover in the future. That is to say, the probability of capturing a new export link is increasing in the number of links already established. This also means that discovery costs will be spread over more products or links, hence, further encouraging initial investment.

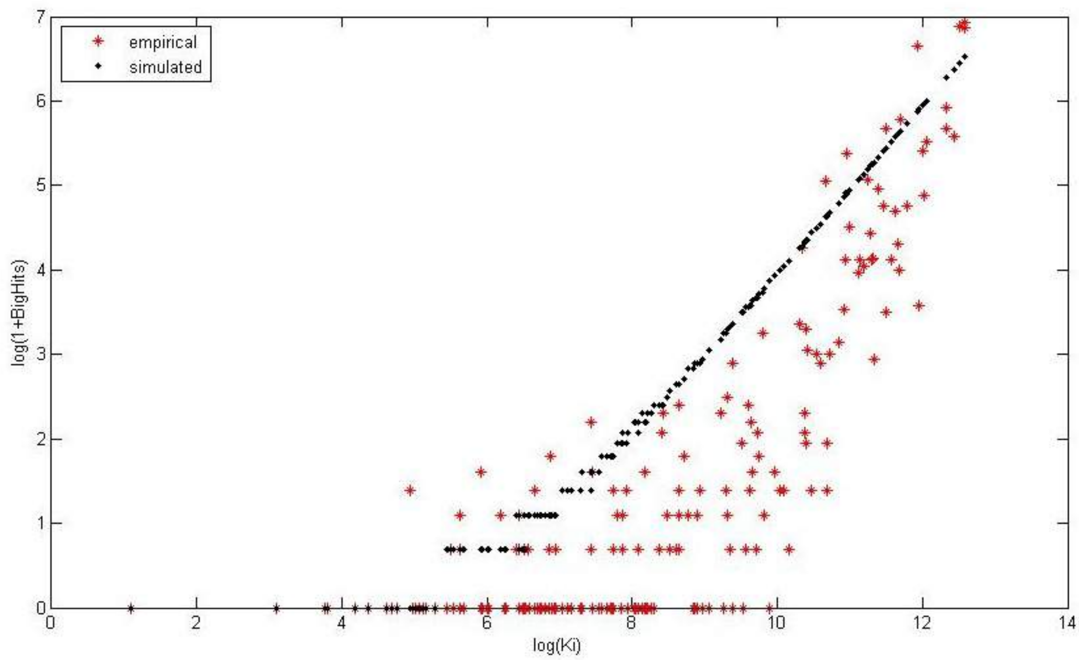


Figure 5 Big Hits versus number of product-destinations flows (K) – empirical and predicted values (year 2005)

Although Easterly et al. (2009) are of the view that a strategy of "picking winners" is unlikely to be successful, we argue that the role of industrial policy is to stimulate as much search as is optimally desirable. As Easterly et al. (2009) contends, we agree that "big hits" are rare

Table 3 Descriptive statistics: predicted and empirical Big Hits

	Predicted	Empirical
No. of Countries	187	187
Mean	92	49
Std. Dev.	177	165
Max.	928	1182
1^{st} Quartile	3	0
Median	12	1
3^{rd} Quartile	96	11
No. of big hits = 0	11	72
No. of big hits = 1	19	23
No. of big hits < 20	107	146
No. of big hits > 200	32	15
No. of big hits > 500	12	7

events. This follows from the skewness of the distribution of export values. However, we focus on the fact there exists a more than proportional relationship between the extensive (the number of export links) and the intensive margin of trade (export values) as shown in figure 4. It follows that the probability of drawing a large flow increases with the number of trade relationships. The more a country searches, the more likely it is to discover a successful export link. As such, policies that stimulate "search" (the establishment of as many links as possible) and "discovery" efforts (the identification of a big hit) would be beneficial for development.

To prove our argument, we plot the number of big hits against the number of product-destinations as shown in figure 5 and we note the positive relationship. An export value, w_{ij} is defined as a big hit if w_{ij} > three standard deviations from the mean export value.[11] The figure also shows the simulated big hits which we obtained by counting the number of big hits from drawing a hundred simulations from a log-normal distribution with the empirical parameters. Thus, we can compare how the observed data deviate from the simulated benchmark. Table 3 reports the descriptive statistics which show that on average the actual data have less big hits than the simulated benchmark and the actual data have 61 more countries with zero big hits.

4.1 Big hits in the world and in Europe

Table 4 lists the 13 countries that are doing better than what the model predicts. Of those countries that have more than a 100 "big hits", Japan exceeds the model prediction by a remarkable 83% and Mexico by 30% respectively. Germany and Ireland are the only European countries with positive deviations. On the other side, there are many more countries (159) that fall short of the benchmark (see list of all countries in appendix A.2, these include countries such as Italy, Spain, Turkey and Singapore. Table 5 shows the position of the EU countries.

In terms of percentage deviation from the benchmark, the Baltic countries perform poorly with both Lithuania and Latvia having a single empirical big hit much less than their simulated benchmark. They are small economies, hence, they have a limited market size. Despite their recent integration to the EU, they are technologically less-advanced than most developed

[11]While Easterly et al. (2009) imply that a big hit is a large export value, they do not provide a definition of big hits.

Table 4 List of countries doing better than the benchmark (year 2005)

Country	**Empirical**	**Predicted**	**Deviations**
China	1182	928	254
USA	1079	860	219
Germany	1072	902	170
Japan	876	478	398
Canada	326*	309	17
Mexico	236	181	55
Ireland	166	135	31
Zambia	8*	5	3
Bahamas	4*	3	1
Mozambique	4*	3	1
Liberia	3	1	2
Cayman Isds	2*	1	1
Marshall Isds	2*	1	1

Note: * indicates that the empirical values fall within the 95% CI of the simulated big hits

countries. Their economic structure is mainly agricultural and light industry, hence further reducing their probability of having big hits in manufacturing. Most eastern European countries also lag behind their benchmark by a great deal. However, the actual big hits of the Czech Republic, Hungary and Poland ranks fairly well, doing even better than the advanced nation Denmark which only has 39 empirical “big hits”. Other advanced European countries, such as, France, Netherlands, Italy or the UK, show good performances. Greece shows a very poor performance given its size and its high simulated benchmark.

Table 5 The European picture (2005)

Country	**Empirical**	**Predicted**	**% Dev.**	**Country**	**Empirical**	**Predicted**	**% Dev.**
Germany	1072	902	*19*	**Finland**	62	213	-71
France	416	720	-42	**Portugal**	40	177	-77
UK	322	714	-55	**Denmark**	39	313	-88
Italy	307	787	-61	**Slovakia**	24	114	-79
Netherlands	267	543	-51	**Romania**	19	124	-85
Belgium-Lux	240	514	-53	**Slovenia**	8	126	-94
Ireland	166	135	*23*	**Malta**	6	19	-68
Spain	150	529	-72	**Croatia**	3	69	-96
Sweden	119	353	-66	**Greece**	3	133	-98
Austria	81	359	-77	**Estonia**	2	60	-97
Hungary	71	170	-58	**Latvia**	1	52	-98
Poland	70	251	-72	**Lithuania**	1	83	-99
Czech Rep.	67	256	-74	**Cyprus**	0	27	-100

None of the country’s empirical values fall within the 95% CI of the predicted values

4.2 Big Hits, concentration and export volatility

From a policy perspective it is not clear whether governments or policymakers should pay attention to the number of big hits, and if so why. After all, one could argue that countries may be better off with a larger number of “average” flows rather than a small number of very large ones. In this section we investigate the matter by looking at the relationship between a country's performance in terms of big hits (defined as the distance between their actual and predicted number), export diversification, and export volatility.

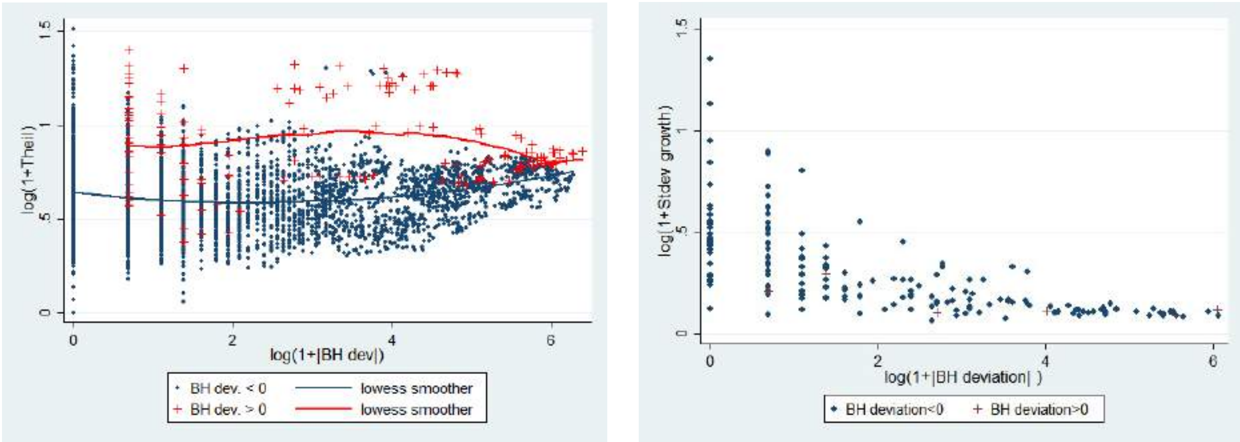


Figure 6 Left panel: Export concentration (Theil index) and Big Hits deviations. Right panel: Standard deviation of export annual growth rate and Big Hits deviations. Both panels are in double log scale.

The left panel of Figure **??** displays the relationship between BH deviations (i.e. the difference between the actual and the predicted number of big hits) and export concentration as measured by the Theil index. The figure pools all years together and adds a nonparametric local smoother (Lowess) to the data. Since we use a double log scale, we take the absolute value of deviations (where a negative number signals that a country has fewer large flows than our model predicts) and distinguish between observations where the deviation is negative (the vast majority of country-year observations) or positive (around 5% of the sample). No clear-cut pattern emerges from the data, with concentration indexes spread widely at each level of BH deviation. If anything, a clearer picture appears at relatively large values of negative deviations: when the data fall severely short of predictions, there is a positive relationship between the number of "missing" big hits and concentration. Intuitively, this suggests that when countries are characterized by a very low number of big hits, their exports tend to be concentrated.

To dig deeper we run a regression of the (log of the) Theil concentration index computed across product-destination pairs on (the log of) big hits deviation in absolute terms: to accommodate for the fact that we have both negative and positive deviations we run a fully interacted model where positive deviations are identified by a dummy (D^{pos}). Results are reported in Table 6, column 1. There is a positive relationship between BH deviations and export concentration for country-years where the data fall short of the model predictions (suggesting that a lower number of big hits is associated with higher concentration). The relationship turns negative when we consider positive deviations, i.e. observations for which the actual number of big hits is larger than the model predicts. In this case, a better performance is associated with lower concentration.

This result is robust to the use of a different measure of concentration, namely the normalized Herfindahl-Hirschman (HH) index (see columns 2–3 of Tables 6). In this case, however, it is necessary to control for the size of the country or, better, for the number of product-destination flows exported (Ki). This is because as the number of items across which the HH index is computed grows, its value goes down mechanically. This is not the case for the Theil index, which is both scale and population independent.

Table 6 Deviations in Big Hits (empirical Vs predicted), export diversification and export volatility

	Concentration			Stand. deviation of export growth	
	Theil Index	Herfindahl			
log(BH dev.)	0.009***	-0.005***	0.014***	-0.082***	0.085***
	[0.002]	[0.000]	[0.001]	[0.007]	[0.017]
$D^{pos}\times$ log(BH dev.)	-0.012*	-0.002	-0.008***		
	[0.007]	[0.001]	[0.003]		
log(K_i)			-0.015***		-0.128***
			[0.001]		[0.012]
$D^{pos}\times$ log(K_i)			0.004**		
			[0.002]		
Observations	3,179	3,178	3,178	180	180
R-squared	0.118	0.083	0.179	0.421	0.645

Coefficients for the constant term and the D^{pos} dummy not reported.
Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1

However, export diversification *per se* is not necessarily a policy objective. This is especially true in our sample where we concentrate on manufacturing export and therefore exclude natural resources and other commodities that may generate dependence and high volatility. The main reason why export diversification is normally considered good is that is can reduce exposure to shock, thus reducing volatility.

We address this question by looking at the relationship between BH deviations in 1995 and the standard deviation of annual export growth between 1995 and 2011. More specifically, we run the following regression

$$log(1 + std.dev(\hat{(}X_{it}) = \beta_0 + \beta_1 log(1 + BHdev) + \beta_2 log(1 + K_i) + \varepsilon_{it}$$

where we have 1 observation for each county and the standard deviation of export growth is computed across 16 time periods. In 1995 only 7 countries outperform the benchmark number of big hits predicted by the model, and since this is too small to run a regression we exclude them from the analysis and concentrate on negative deviations. When we do not control for size (column 4) we find that initial deviations from the benchmark have a negative effect on the variability of future growth rates: the more a country deviates from the model's prediction, the lower the standard deviation of growth. This counterintuitive result is reversed when we include the number of export flows (K_i) into the analysis: since larger countries trade more they will be simultaneously less volatile (because they are larger and more diversified) and display larger deviations (because the predicted number of big hits depends on the number of export flows). This negative relationship between size and volatility is depicted in the right panel of Figure 6.

We therefore need to control for size as is done in column 5: indeed, exporting a larger number of products and/or serving more destinations (higher K_i) lowers volatility, whereas a worse performance in terms of big hits (a larger deviation in absolute terms) increases volatility ($\beta_1 = 0.085 > 0$).

Hence, one possible reason of concern for countries that fall significantly short of our stochastic benchmark is not only that this may signal possible bottlenecks and distortions in their productive structure, but that this further results in higher volatility of future export growth.

4.3 Potential determinants of big hits deviation

To investigate why some countries fare better while others lag behind as compared to the benchmark, we regress the deviations in "big hits" from the simulated benchmark on a number of potential determinants of these deviations. We get our inspiration from the industrial policy debate and the larger development literature that tries to assess the determinants of economic performance.

Industrial policy is a tricky term; what it implies depends much on the context. In his work, Rodrik stresses that there is no one recipe that fits all when it comes to policy formulation. What is understood is that the main role of industrial policy is both to inform the private sector of externalities and to provide the optimal environment for growth through implementation of policies. He made it clear that it cannot also be reduced to the application of taxes or subsidies. Thus, it becomes very difficult to find a measure of industrial policy and even more challenging to assess the impact of industrial policy on economic performance.

Even Rodrik himself warns that nothing can be learnt from regressing economic growth or any other performance indicator on policies (Rodrik, 2012). This is because while policy endogeneity can be dealt with, the problem lies beyond econometrics and is conceptual since the endogeneity is an integral part of the null hypothesis. We operationalise the concept of industrial policy through crude measures, such as, tariffs and other institutional variables, such as, rule of law and ease-of-doing business variables.

The next set of potential determinants of big hits deviation comes from closely related literature, namely the literature on country capabilities as recently developed by Hidalgo et al. (2007) and further explored in Hidalgo and Hausmann (2009). The classical view is that the performance of a country is dependent upon factor accumulation. Increases in total factor productivity results in increases in income per capita. Hence, policy implies human and physical capital accumulation. However, total factor productivity explains only a fraction of economic performance.

According to the capability discourse the productive structure of a country depends on the availability of a specific set of capabilities, including tradables and non tradables, such as, norms, institutions, and social networks. Countries differ in their capabilities; high-income ones tend to produce more varieties and more complex products, which require many capabilities whereas poor countries make few and less complex products that require fewer capabilities. Countries have capabilities and products require capabilities. More sophisticated products require a larger range of capabilities and will tend to be produced by fewer countries, i.e. these products are less ubiquitous. They show a combination of the diversification of a country and product ubiquity are indirect measures of a country's capability.

Since the work of Schumpeter (1934), the role of financial development in economic growth has received considerable scholarly attention. The latter theorises that a well-developed financial system nurtures innovation and economic growth by providing entrepreneurs with the necessary conditions for success including better allocation of resources, lesser information asymmetries and so on. Using cross-country regressions for 77 countries over the period 1960-1989, King and Levine (1993) observe a significant positive impact of financial depth on growth. Their results are consistent with different definitions of financial depth and, more interestingly, with different growth measures, namely, real GDP per capita growth, real per capita capital growth and productivity growth. We, thus, include financial development variables which could potentially influence big hits.

We also include a set of network measures to assess the importance of connectivities on deviations in big hits (Miura, 2011). Degree centrality refers to the importance of a node in a network based on its number of connections. Closeness centrality gives higher centrality scores to nodes that are situated closer to other nodes of their component where closeness refers to the inverse of the average shortest paths. Betweenness centrality gives larger centrality scores to nodes that lie on a higher proportion of shortest paths linking nodes other than itself; in simpler terms, a node that lies on a communication path between two other nodes, is an important node. The extent to which nodes in a network are concentrated is measured using the clustering coefficient[12].

4.4 Quantile and WALS regression

We estimate the following regression model, using quantile regression and model averaging techniques:

$$BHdev._i = \alpha + \beta_1 InitialY_i + \beta_2 Size_i + \beta_\theta \mathbf{X}_i + \epsilon_i$$

where $InitialY_i$ is initial GDP per capita (year 1995), $Size_i$ is GDP in constant US$ to control for size, and X_i is a set of controls. A full description of the variables and their sources is reported in the appendix.

The use of quantile techniques is motivated by the shape of the distribution of the deviation of big hits which is fat-tailed[13]. Quantile regression (Koenker and Bassett Jr, 1978) differs from standard least-square regression techniques as it allows the estimation of different quantiles of the dependent variable, whereas standard least-square provides summary estimates that approximate the mean effect of the dependent variable given a set of values of the independent variables. Hence, quantile regressions provide a more complete picture of the relationship between the response and predicted variables.

The fact that there are only 13 countries out of 188 doing better than the benchmark gives a non-Gaussian distribution of deviations in big hits as shown in figure 7. As such, we cannot assume normally distributed errors. Hence, we suspect there might be different factors working at different portions of the distribution. It is as informative to understand what factors cause some countries to perform badly compared to the benchmark as it is to uncover why others excel as regards the reference point. Quantile techniques allow the estimation of coefficients at different quantiles of the dependent variable. In our case, it allows us to acknowledge the heterogeneity of countries in their export performance.

[12] See the appendix for mathematical definitions

[13] with a positive kurtosis of more than 13

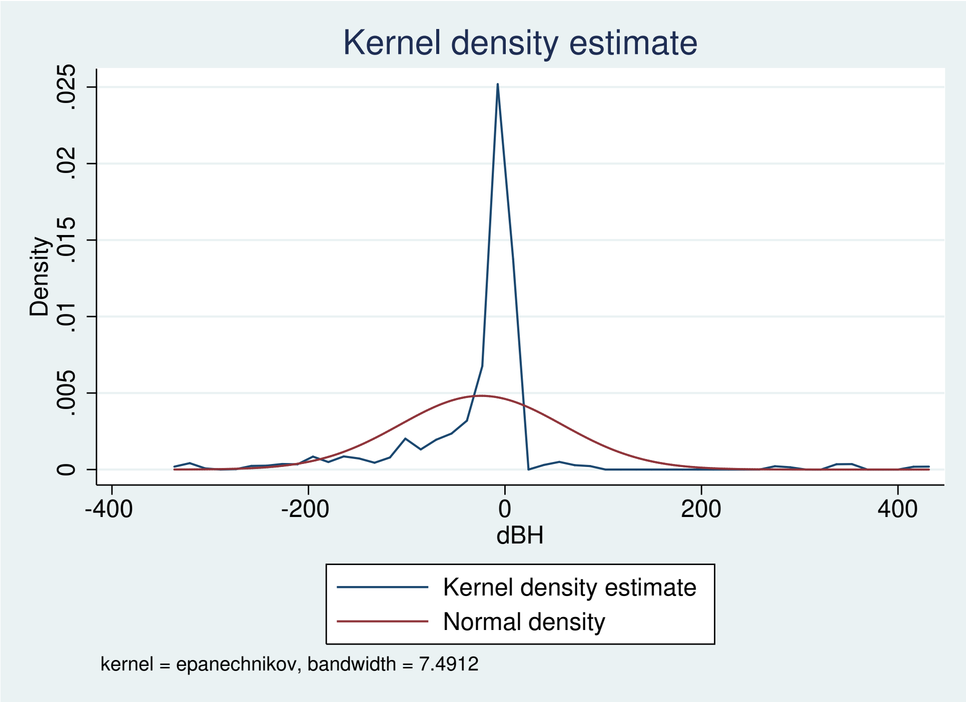


Figure 7 Kernel density of deviations in big hits

Furthermore, our largest deviation 398 is much larger than the mean deviation of -43. In our case, it would be major loss of information to remove such extreme observations because they form the basis of successes or failures in big hits. Since the objective function of a quantile regression is a weighted sum of absolute deviations, it provides a robust measure of location (Buchinsky, 1998). As quantile regressions are more robust to outliers and skewed distributions, it remains one of our preferred estimation technique.

Koenker and Bassett Jr (1978) introduced the quantile regression model which can be written as

$$y_i = x_i^{'}\beta_\tau + u_{\tau i} \text{ with } Q_\tau(y_i|x_i) = x_i^{'}\beta_\tau \tag{1}$$

where $Q_\tau(y_i|x_i)$ is the conditional quantile of y_i given the regressor x_i, β is the vector of parameters to be estimated and u is a vector of residuals. The τ^{th} regression quantile estimator is found by minimising:

$$\min_{\beta} \frac{1}{n}\left[\sum_{i \in y_i \geq x_i^{'}\beta} \tau|y_i - x_i^{'}\beta| + \sum_{i \in y_i < x_i^{'}\beta} (1-\tau)|(y_i - x_i^{'}\beta|\right] \tag{2}$$

Linear programming is used to solve Eq. 4.4 (Buchinsky, 1994; Koenker, 2006).

Figure 8 shows the graphical results of the quantile regression for selected variables of interest over the conditional deviation in “big hits” distribution. The horizontal lines represent the OLS estimates. The graphs clearly shows how the effect of the different variables vary over quantiles, for instance, as shown in figure 8a country capabilities have a negative effect at low quantiles but a positive one for well-performing “big hits” at the upper quantile. The OLS estimate fail to capture this effect. As for betweenness centrality, figure 8b demonstrates that

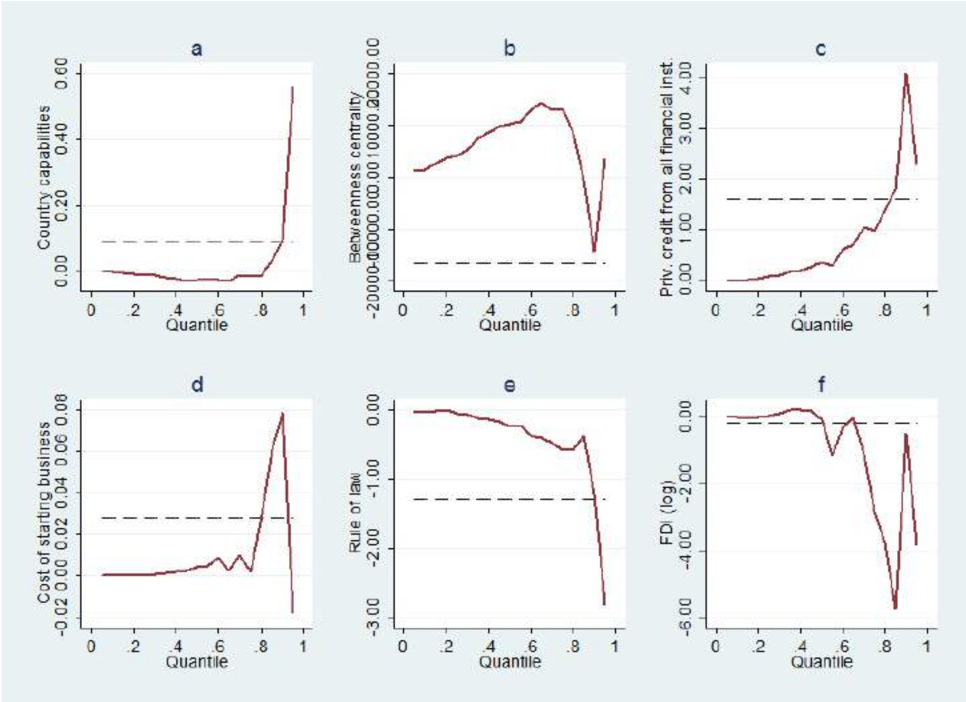


Figure 8 Quantile results for selected variables

the OLS regression provides a misrepresentation of the variation in the variable.

While we are guided by related theory, there is no established theoretical background for finding the best model specification for the deviations in big hits, let alone for economic performance. Model averaging techniques are useful to overcome the uncertainty linked in finding the "true" modelling strategy when there exists a large number of potential regressors. They are best used as robustness check to confirm that inferences of the estimated coefficients do not vary widely between model specifications. They aim at finding the best possible estimates as opposed to the best possible model. As such, we also check the robustness of our results by making use of the recent model averaging technique developed by Magnus et al. (2010), the weighted average least square (WALS).

Model averaging, such as WALS, consists of making inferences on the estimates from all models in a model space and the estimates are weighed according to their statistical strengths, i.e. their posterior model probabilities. In fact, the WALS estimator is a Bayesian combination of frequentist estimators. WALS is considered theoretically and practically superior to standard techniques such as Bayesian model averaging (BMA) as it explicitly takes into account model uncertainty and the amount of computing time is linear in the number of regressors rather than exponential as in standard BMA[14]. In fact, the WALS estimator is a Bayesian combination of frequentist estimators. Explanatory variables can be distinguished between focus and auxiliary. Focus regressors are those included on theoretical or other basis while auxiliary regressors are those over which uncertainty exists and over which model selection takes place.

The numerical results of the different regressions are shown in table 7. Column OLS is a robust ordinary least square regression, columns Q(0.20), Q(0.50), Q(0.70), Q(0.90) are the 20%,

[14]See Magnus et al. (2010) and Magnus et al. (2011) for a description of the theoretical and practical superiority of WALS over BMA.

50%, 70% and 90% quantiles respectively. Column WALS_0 is a WALS regression with no focus regressors, that is, we perform model selection and assume uncertainty over all the regressors. WALS_f includes 10 focus regressors included as such based on their significance level in previous regressions;they are country capabilities, betweenness centrality, start-up costs and the regional dummies. They are marked by (f) in the regression table 7. WALS_33 is a model with a restricted sample of 102 observations but boasting 33 auxiliary regressors.

Table 7 Regression results, dependent variable: deviation in Big Hits

	OLS	**Q(0.20)**	**Q(0.50)**	**Q(0.70)**	**Q(0.90)**	**WALS**	**WALS_f**	**WALS_33**
Initial income	-36.03+	-7.250*	-5.502	-11.68*	-15.01	-27.63+	-27.13+	-32.73
GDP	10.55	-1.251*	-1.950	0.760	18.38	7.765	7.037	-5.750
Capabilities	-0.123+	-0.105*	-0.076	-0.065*	0.078	-0.092*	-0.110* (f)	-0.160*
Prod. ubiquity	-7.223*	-0.0616	-0.545	-0.766	-5.514	-5.837*	-5.403*	-3.448
Between. Centr.	-29552*	-20466*	-11684	-11390*	-27671	-23670*	-24908* (f)	-17444*
Clustering	89.60	25.72*	23.75	23.30	17.01	67.95	66.45	95.45
Private credit	0.486	-0.366*	-0.106	0.0915	0.305	0.449	0.359	0.223
Tariffs	-1.871	-0.211*	-0.058	-0.333	2.323	-1.837	-1.477	-3.395
Start-up costs	-0.050*	-0.046*	-0.014	-0.013+	-0.024	-0.036	-0.040 (f)	-0.118
Export docs	-8.352*	-2.994*	-2.831	-0.459	-1.371	-6.187	-6.396+	-8.903+
Inflation	-1.560	0.177	0.449	-0.642	-0.685	-1.084	-1.181	-2.979
Export/GDP	-0.657	0.0181	-0.158	0.0432	-0.736	-0.497+	-0.615* (f)	-0.486
Rule of law	-1.117*	0.009	-0.188	-0.101	-0.612	-0.940+	-0.756	-1.475+
Telephones	1.589	0.341*	-0.0239	0.160	0.772	0.906	0.951	1.210
FDI	1.188	1.156*	0.698	0.0804	-3.963	1.289	0.738	0.138
D^{Oil}	40.22	7.274*	9.747	2.315	31.25	28.27	29.62	32.38
D^{SSA}	53.61+	6.295*	8.649	13.44+	27.76	44.43	45.29 (f)	134.5*
D^{SA}	34.62	21.56*	17.62	16.14	-3.334	29.65	21.70 (f)	87.49
D^{NA}	212.5*	248.6*	168.7*	363.3*	74.21	177.7*	234.9* (f)	62.66
D^{MENA}	74.95*	46.26*	27.56	19.11*	-18.36	63.44*	66.67* (f)	106.3*
D^{LAC}	45.47*	9.702*	17.65	13.46+	48.96	33.07	42.52 (f)	78.49+
D^{EAP}	116.2*	3.971*	17.11	9.098	102.1	87.41*	106.5* (f)	110.0*
Capital stock								0.017*
Investment								1.776
Savings								0.414
Pop.								0.005
Ki								9.978
Herfindahl								-124.5
Afgricultural empl.								0.934
Industrial empl.								3.846+
Primary school								5.924
Secondary school								15.90+
Export volatility								13.48
Observations	140	140	140	140	140	140	140	102

Significance level: + p<0.1 * p<0.05

The impact of the variables on deviations in "big hits" differ between quantiles and also differ considerably from the OLS results. While the OLS result implies that initial income has a negative impact on deviations, looking only at the OLS result would be misleading since initial income has a significant impact only at the 20% and 70% quantile regressions with different magnitudes. Model averaging results confirm the negative impact of initial income level. Size of an economy or GDP appears to have a positive impact on deviations but quantile results show that size has a negative impact and significant impact at the lowest quantile where deviations are small and negative. Size, however, is not identified as robust as shown by WALS results.

Although country capabilities have positive and significant impact on deviations in "big hits" at the 90% quantile, they have a negative significant effects at lower quantiles. Model averaging also found this negative effect and it is significant as a focus regressor. Since this measure of country capabilities is synonymous with product diversification, it follows that countries that have very large positive deviations in "big hits" benefit from an increase in diversification. Contrarily, where deviations are negative, diversification does not encourage "big hits"; this result is plausible since "big hits" are by definition large export flows, hence, diversifying too much would not facilitate the formation of large exports. Product ubiquity impacts deviations negatively but is significant for the OLS regression and is robust to model averaging estimations with and without focus regressors. In simple words, the more a certain product is popular, the worse will it perform in terms of deviations in "big hits".

Centrality in the network (betweenness) has a consistent negative and significant impact on deviations. However, the extent of the impact differs between low and high quantiles. The negative impact is strongly robust to the OLS and model averaging estimation techniques. The betweenness centrality measure takes the number of connections, which reflects diversification, as a core element in its computation, as such, the negative impact is thus consistent with the diversification argument explained above.[15]

Financial development (private credit) has a positive impact on deviations at the highest quantiles where there are positive deviations while a negative and significant impact at the 20% quantile. This implies that more developed manufacturers or "big hits" are more likely to benefit from well-developed financial structure than the less developed ones or "smaller hits". Beck et al. (2008), using a firm level survey covering about 3000 firms in 48 countries, find that small firms are less able to take advantage of external finance than larger firms, hence if we assume that small firms are less likely to be "big hits", Beck's et al. reasoning can explain our result. Moreover, they also find that less-developed institutions negatively impact the use of external finance so that small firms resort to informal finance. In our data, we find a positive correlation between rule of law and financial development for lower quantiles to support such an argument. Results are not robust to model averaging estimations.

Tariffs on manufactured goods have a negative impact on deviations but only significant at lower quantiles. The result is not robust and points towards the ineffectiveness of direct and obsolete policy measures as warned by Rodrik (2004). We expect cost of starting a business to negatively affect deviations. We observe a significant effect at the lowest and the 70% quantiles and at the OLS. Being a "policy" measure reflecting ease of doing business, we include it as a focus regressor in WALS_f; while it has the expected sign, it has low probability of inclusion. Interestingly, the number of export documents required has the same negative effect and appears to be a robust estimator as shown by the WALS results.

Openness to trade, as measured by share of exports to GDP, has mixed effects but model averaging confirms their negative impact on deviations. Contrary to common and academic belief (Rigobon and Rodrik, 2005; Barro, 2001), rule of law which reflects a sound institutional and legal system negatively influences deviations and is a robust estimator.

The effect of FDI on deviations is also mixed: while it exerts a significant positive impact

[15] See appendix for a formal definition of this measure.

at low quantiles, it has a negative effect at the highest quantile but is not robust to model averaging. In other words, FDI positively affects countries that are lagging behind in "big hits" but is detrimental to countries that are already well-performing. The former result is well-explained by the FDI-led growth in developing countries literature (Blomstrom et al., 1994). Recent empirical studies may explain the latter result, for instance, using robust mixed fixed random estimator Nair-Reichert and Weinhold (2001) find that the effect of FDI on growth suffers from considerable heterogeneity.

The estimated coefficients of the regional dummies show that they are doing better than the reference region EU-Central Asia[16]. North America is the best performing region followed by East Asia Pacific region and Middle East and North Africa region; they are robust to model averaging estimation.

Clustering coefficient, inflation, basic telecommunication development (telephones) and the Oil dummy (D^{Oil}) appear not to matter. The model averaging estimation with the restricted sample identifies capital stock, the percentage of employment in industry and years of secondary schooling as positive determinants of deviations.

4.5 Panel regressions

Table 8 Panel regressions: dependent variable: deviation in Big Hits

	Fixed effects		**Random effects**		**Random effects - regions**	
Initial income	-0.001*	(-3.05)	-0.001*	(-4.09)	-0.001*	(-4.43)
GDP	-7.041*	(-2.16)	-3.780	(-1.61)	-4.501*	(-1.98)
Capabilities	-0.085*	(-9.35)	-0.095*	(-11.1)	-0.094*	(-11.0)
Prod. ubiquity	-0.467	(-1.58)	-0.552+	(-1.89)	-0.541+	(-1.86)
Between. Centr	279.5	(0.81)	297.9	(0.88)	239.4	(0.70)
Export/GDP	-0.042	(-0.63)	-0.077	(-1.21)	-0.0619	(-0.97)
Rule of law	0.085	(0.97)	0.036	(0.44)	0.017	(0.20)
D^{SSA}					29.03+	(1.72)
D^{SA}					1.960	(0.07)
D^{NA}					374.1*	(7.17)
D^{MENA}					51.15*	(2.60)
D^{LAC}					43.02*	(2.46)
D^{EAP}					51.16*	(2.86)
Observations	2131		2131		2131	
Hausman test(p-value)	9.64	(0.09)	9.64	(0.09)	9.35	(0.10)
Breusch-Pagan LM test			11006*	(0.00)	11006*	(0.00)

p-values in parentheses, significance level: + p<0.1 * p<0.05

While the use of cross-sectional quantile regressions alongside model averaging estimations provide a complete picture of the forces at work as regards the performance of countries in terms of deviations in "big hits" from the established benchmark, the results are constrained by the limited amount of observations and the possible effects of unobservable components. Hence, we further explore our results by estimating panel regressions using the robust variables we identified from the cross-sectional results. The underlying specification is a model of the form:

$$BHDev._{it} = \alpha_i + \beta_\theta \mathbf{X}_{it} + u_{it}$$

[16]except for Middle East and North Africa(MENA) and South Asia(SA) at the 90% quantile.

where $\mathbf{X}_{it}$ represents the set of variables, initial income, GDP, capabilities, product ubiquity, betweenness centrality, export/GDP, rule of law and regional dummies (where specified), $i = 1$ to 169 and $t = 1995$ to 2011.

Figure 9 illustrates the trends in deviations for a sample of countries. While USA shows a declining trend from the year 2000 onwards, China's deviations in big hits have kept increasing over the 1995-2011 period. Italy's deviations are peristently negative and worsen towards the end of the period.

Table 8 shows the results of the panel regressions. Hausman test favours the random over the fixed effects model at 5% significance level. Breusch-Pagan Lagrange multiplier test favour the random effects model over the OLS; we nevertheless show the fixed effects result to facilitate sensitivity analysis. Indeed, the coefficients of the fixed and random effects differ as is expected when the hausman test reject the null-hypothesis of no correlation of the error term with the regressors (Hausman, 1978). Results concord with cross-sectional results except for GDP which shows a clear negative impact on deviations, in other words, larger economies have negative deviations. This is probably due to the fact that larger economies tend to diversify more than expected and this reduces the occurrences of "big hits". Contrarily to the cross-sectional results, betweenness centrality shows a positive sign but is not significant. Share of export to GDP and rule of law are not significant in the panel approach. Regions matter as evidenced by their positive and significant coefficients of the regional dummies in the random effects model-with regions (save South Asia).

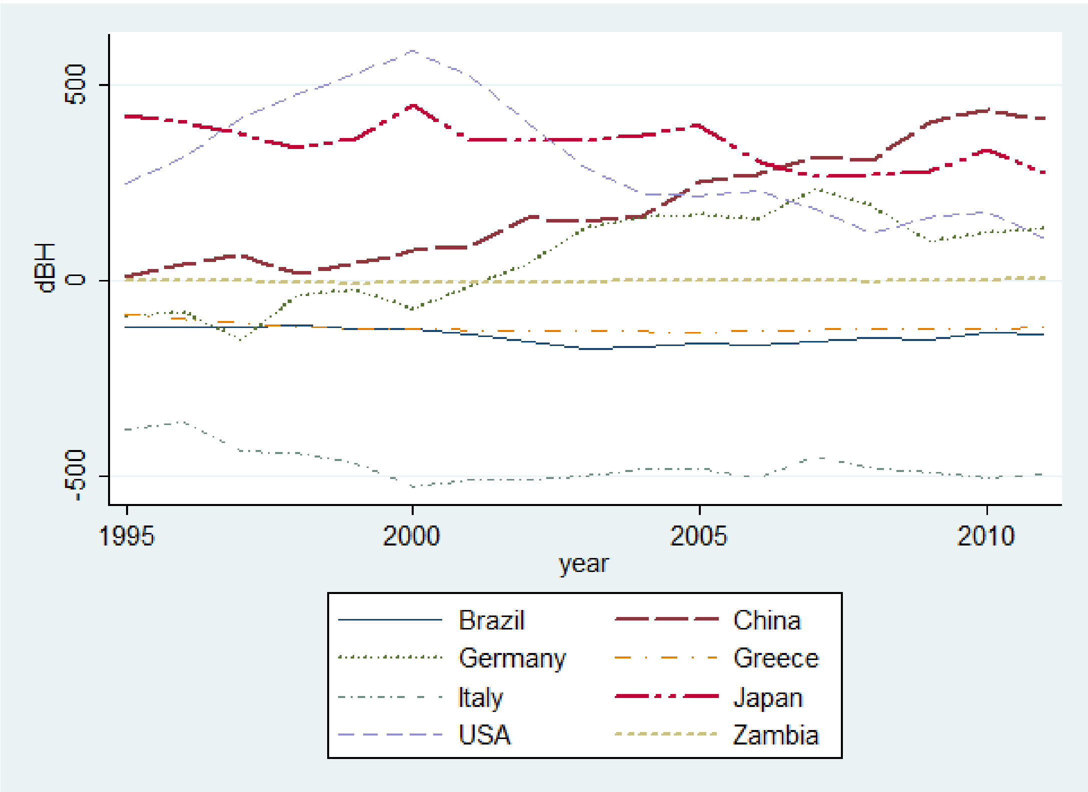


Figure 9 Patterns of deviations in Big Hits for selected countries 1995-2011

5 Conclusion

In this paper, we show that a simple stochastic model of proportionate growth is not only able to match a number of stylised facts documented in the literature but it also reconciles diverging views in the economic development literature as regards the potential merits of industrial policy. On the one hand, Hausmann and Rodrik (2003) argue for industrial policy that would lead to successful export-led growth. Growth is achieved by subsidising discovery efforts that would be under-supplied in an unregulated market. On the other hand, Easterly et al. (2009) argues against policies aimed at picking winners as they are likely to be unsuccessful given that the distribution of exports is fat-tailed, that is, "big hits" are rare. Our model suggests that the probability of drawing a big hit is larger for countries that engage in more discovery efforts, that is, trying to establish more trade links. It, thus, brings together the above mentioned diverging views regarding industrial policy.

We exploit the model as a benchmark against which we evaluate the export performance of different countries in terms of big hits. Given the number of export relationship of each country and the skewed distribution of export values, we can derive (by simulations) an expected number of big hits for each country. These represent the "normal" performance of countries according to our model. By comparing actual and expected "big hits" we can define whether countries perform better or worse than the benchmark. Interestingly, we find that most European countries (save Germany and Ireland) underperform, while the best performers are no surprise and include countries such as China, Germany, USA and Japan which have a solid manufacturing sector. At the bottom of the list appears many of the countries that have been hit by the recent financial crisis, or are plagued by structural problems such as Italy and Spain.

What are the reasons behind the good and bad performance of countries in terms of big hits? The use of quantile regressions provide some insights into the determinants of these deviations. It further shows that countries are heterogeneous so that the impact of many variables are different for countries that are at the bottom of the list from those that are at the top. We check the robustness of our results with the recently developed model averaging estimation WALS. Initial income, country capabilities, product ubiquity, betweenness centrality, financial development, openness of an economy and rule of law negatively affect deviations in "big hits". The regional dummies, North America, Middle East and North Africa, and East Asia Pacific positively affect deviations and perform better than EU-Central Asia. We further confirm these results by adopting a panel method over 15 years and the results strongly emphasise the positive impact of regions on deviations. Further research is needed to identify the policy actions that can revamp competitiveness and help European countries to improve their performance.

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A Appendix

A.1 List of variables and their description

- **Initial Income** is GDP per capita at PPP (constant 2005 international $) in logarithm for the year 1995 which is the beginning of the period under consideration (source from World Development Indicators (WDI)).

- **GDP** represents the size of the economy. It is total GDP amount in logarithm for each country at constant US$.

- **Country capabilities** is calculated as in Hidalgo and Hausmann (2009) ,

  $$k_{c,0} = \sum_p M_{cp}$$

  i.e. the diversification of country c as the sum of M_{cp} over all products p where

  $M_{cp} = 1$ if country c exports product p with a Revealed Comparative Advantage above 1, $M_{cp} = 0$ otherwise. We use our own data and average the figure for each country.

- **Product ubiquity** is also taken from Hidalgo and Hausmann (2009) and represents the pervasiveness of the products of a country,

  $$k_{p,0} = \sum_c M_{cp}$$

- **Between. centr.**, following Jackson (2008), is defined as

  $$\sum_{ij:i \neq j, k \notin ij} \frac{P_{ij}(k)}{P_{ij}}$$

  where P_{ij} denotes the number of shortest paths from node i to j and $P_{ij}(k)$ denotes the number of shortest paths from node i to j that node k lies on. It is a measure of the importance of a country based on its connections.

- **Clustering**, where the clustering coefficient of a node is the probability that two randomly selected neighbours are connected to each other. The clustering coefficient C_c of node i:

  $$C_c(\mathbf{A}) = \frac{\sum_{j \neq i; k \neq j; k \neq i} A_{ji} A_{ik} A_{jk}}{\sum_{j \neq i; k \neq j; k \neq i} A_{ji} A_{ik}}$$

- **Private credit** is credit from all financial institutions and sourced from the Financial Development and Structure Dataset, World Bank developed by Beck et al. (2000). The April 2013 version has been used. The variable is Private Credit by Deposit Money Banks and Other Financial Institutions to GDP (%) which is defined as claims on the private sector by deposit money banks and other financial institutions divided by GDP. As described in

Beck and Demirguc-Kunt (2009), this asset side variable captures one of the most important function of financial intermediaries, that is, allocation of credit.

- **Tariffs** is average tariff rate on manufactured products (%) (source WDI).
- **Start-up costs** represents costs of business start-up procedures as a percentage of gross national income per capita (source WDI).
- **Export docs** is simply the number of documents required per shipment to export goods such as documents required for clearance by government ministries, customs authorities, port and container terminal authorities, health and technical control agencies and banks are taken into account. It is an ease of doing business indicator.
- **Inflation** is used to capture changes in the price level. It reflects annual percentage changes in consumer prices (source WDI).
- **Export/GDP** is a standard indicator of openness to trade (source WDI).
- **Rule of law**, percentile rank, is a World Governance Indicator, World Bank.
- **Telephones** captures technological development (source WDI).
- **FDI** is net inflows of Foreign Direct Investment in current US$ in logarithm (source WDI).
- D^{Oil} is a dummy variable capturing whether a country is a significant oil-producer, that is, its oil rents is more than 40% of its GDP (source WDI).
- D^{SSA}, D^{SA}, D^{NA}, D^{MENA}, D^{LAC} **and** D^{EAP} are regional dummy variables representing regions as per the WDI 7 regions classification, namely, Sub-Saharan Africa, South Asia, North America, M. East & N. Africa, Latin Ame & Caribbeans, East Asia Pacific .
- **Capital Stock, Investment and Savings** are capital stocks in billions constant 2005 $US, investment rate as a percentage of GDP, Savings rate as a percentage of GDP respectively (source CEPII Econmap baseline database 2.1).
- **Pop.** is population density (people per sq. km of land area) (source WDI).
- Ki is the number of product-destinations in logarithm.
- **Agricultural and Industrial empl.** represent employment in the agricultural sector and employment in industry (% of total employment) respectively (source WDI).
- **Primary school and Secondary school** are years of primary schooling and secondary schooling for population aged 15 and over respectively (source (Barro and Lee, 2012)).
- **Export volatility** is the standard deviation in export growth from 1995 to 2005 (calculated using data from BACI database).

  All the variables are for the year 2005 except where specified above. To maximise the number of observations, where data was missing for the year 2005, averages of previous and successive years were used.

A.2 List of all countries with simulated and empirical big hits, and the actual deviations between simulated and empirical big hits

Country	Empi.		Simul.	Dev.	Country	Empi.		Simul.	Dev.
Afghanistan	0	*	3	-3	Kenya	1		37	-36
Albania	0		9	-9	Kiribati	0	*	0	0
Algeria	1		7	-6	Kuwait	1		13	-12
Andorra	0		6	-6	Kyrgyzstan	0		7	-7
Angola	0	*	3	-3	Lao P. D. Rep.	0		5	-5
Antigua & Barbu.	1		3	-2	Latvia	1		52	-51
Argentina	9		104	-95	Lebanon	0		62	-62
Armenia	1	*	6	-5	Liberia	3		1	2
Australia	62		228	-166	Libya	0	*	2	-2
Austria	81		359	-278	Lithuania	1		83	-82
Azerbaijan	1		8	-7	Madagascar	0		11	-11
Bahamas	4	*	3	1	Malawi	0	*	3	-3
Bahrain	1		19	-18	Malaysia	164		243	-79
Bangladesh	18		38	-20	Maldives	0	*	2	-2
Barbados	0		8	-8	Mali	0	*	5	-5
Belarus	10		46	-36	Malta	6		19	-13
Belgium-Lux.	240		514	-274	Marshall Isds	2	*	1	1
Belize	0	*	3	-3	Mauritania	0	*	1	-1
Benin	1	*	3	-2	Mauritius	3		25	-22
Bermuda	1	*	1	0	Mexico	236		181	55
Bhutan	0	*	1	-1	Mongolia	0		5	-5
Bolivia	0		10	-10	Morocco	8		55	-47
Bosnia Herz.	1		25	-24	Mozambique	4	*	3	1
Brazil	95		253	-158	Myanmar	2		8	-6
Brunei Darus.	0	*	3	-3	Nauru	0	*	0	0
Bulgaria	3		104	-101	Nepal	0		11	-11
Burkina Faso	2	*	4	-2	Netherlands	267		543	-276
Burundi	0	*	1	-1	New Zealand	6		103	-97
Cambodia	7		15	-8	Nicaragua	3	*	8	-5
Cameroon	1		11	-10	Niger	1	*	4	-3
Canada	326	*	309	17	Nigeria	0		10	-10
Cape Verde	0	*	3	-3	Norway	28		165	-137
Cayman Isds	2	*	1	1	Oman	1		18	-17
Central Afr. Rep.	0	*	1	-1	Pakistan	9		101	-92
Chad	0	*	1	-1	Palau	0	*	0	0
Chile	26		59	-33	Panama	3		52	-49
China	1182		928	254	Papua No. Guinea	1	*	2	-1
China, HK	77		336	-259	Paraguay	0		7	-7
China, Macao	2		24	-22	Peru	8		44	-36
Colombia	4		69	-65	Philippines	76		96	-20
Comoros	0	*	1	-1	Pitcairn	0	*	0	0
Congo	0	*	3	-3	Poland	70		251	-181
Costa Rica	11		36	-25	Portugal	40		177	-137
Côte d'Ivoire	2		16	-14	Qatar	2		17	-15
Croatia	3		69	-66	Rep. Moldova	1		14	-13
Cuba	3	*	8	-5	Rep. of Korea	349	*	381	-32
Cyprus	0		27	-27	Romania	19		124	-105
Czech Rep.	67		256	-189	Russian Fed.	105		186	-81
D. P. Rep. Korea	0		22	-22	Rwanda	0	*	2	-2
D. Rep. Congo	0		2	-2	Samoa	0	*	1	-1
Denmark	39		313	-274	Sao Tome & Prin.	0	*	1	-1
Djibouti	0		2	-2	Saudi Arabia	34		94	-60
Dominica	0	*	2	-2	Senegal	1		17	-16
Dominican Rep.	10		19	-9	Seychelles	0	*	2	-2
Ecuador	0		24	-24	Sierra Leone	0	*	3	-3

Country	Empi.		Simul.	Dev.	Country	Empi.		Simul.	Dev.
Egypt	4		72	-68	Singapore	158		279	-121
El Salvador	4		23	-19	Slovakia	24		114	-90
Equator. Guinea	1	*	1	0	Slovenia	8		126	-118
Eritrea	0	*	1	-1	Solomon Isds	0	*	0	0
Estonia	2		60	-58	Somalia	0	*	1	-1
Ethiopia	0		4	-4	Spain	150		529	-379
Fiji	0		11	-11	Sri Lanka	4		48	-44
Finland	62		213	-151	Sudan	0	*	3	-3
Fr. S. Antarctic T.	0	*	0	0	Suriname	2	*	3	-1
France	416		720	-304	Sweden	119		353	-234
FS Micronesia	0	*	0	0	Switzerland	133		413	-280
Gabon	1		5	-4	Syria	0		40	-40
Gambia	0		2	-2	Tajikistan	2	*	2	0
Georgia	1		10	-9	TFYR of Macedonia	0		20	-20
Germany	1072		902	170	Thailand	135		302	-167
Ghana	1		12	-11	Timor-Leste	0		2	-2
Gibraltar	0	*	1	-1	Togo	0		8	-8
Greece	3		133	-130	Tokelau	0	*	1	-1
Greenland	0	*	1	-1	Tonga	0	*	0	0
Grenada	0	*	1	-1	Trinidad & Toba.	2		21	-19
Guatemala	5		36	-31	Tunisia	9		50	-41
Guinea	1	*	3	-2	Turkey	66		366	-300
Guinea-Bissau	0	*	0	0	Turkmenistan	0		2	-2
Guyana	0		4	-4	Tuvalu	0	*	0	0
Haiti	2	*	2	0	UAE	19		263	-244
Honduras	8	*	15	-7	Uganda	0		8	-8
Hungary	71		170	-99	Ukraine	28		106	-78
Iceland	3		18	-15	United Kingdom	322		714	-392
India	42		495	-453	Uruguay	0		23	-23
Indonesia	72		222	-150	USA	1079		860	219
Iran	5		54	-49	Utd Rep. Tanzania	0		11	-11
Iraq	0		2	-2	Uzbekistan	4	*	6	-2
Ireland	166		135	31	Vanuatu	0	*	0	0
Israel	21		144	-123	Venezuela	13		32	-19
Italy	307		787	-480	Viet Nam	24		107	-83
Jamaica	3		10	-7	Yemen	0		5	-5
Japan	876		478	398	Zambia	8	*	5	3
Jordan	4		34	-30	Zimbabwe	0		8	-8
Kazakhstan	14	*	18	-4					

Values marked with an * indicates that the empirical big hits fall within the 95% CI of the simulated big hits