The Power of Exports*

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Abstract

We systematically document remarkably high degrees of concentration in manufacturing exports for a sample of 151 countries over a range of 3,000 products. For every country manufacturing exports are dominated by a few "big hits", which account for most of export value and where the "hit" includes both finding the right product and finding the right market. Higher export volumes are associated with higher degrees of concentration, after controlling for the number of destinations a country penetrates. This further highlights the importance of big hits. The distribution of exports closely follows a power law, especially in the upper tail. These findings do not support a "picking winners" policy for export development; the power law characterization implies that the chance of picking a winner diminishes exponentially with the degree of success. Moreover, given the size of the economy, developing countries are more exposed to demand shocks than rich ones, which further lowers the benefits from trying to pick winners.

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1 Introduction

How do countries succeed at economic development? Many descriptions of success stories have stressed the important role of manufacturing exports as a vehicle for success. Indeed, manufacturing exports per capita have a striking correlation with GDP per capita across countries, see **Figure 1**. Causality could go either way in this association, or both variables may reflect other factors. The figure does support a descriptive statement that success at manufacturing exports and success at development are close to being the same thing. This naturally warrants a close examination of the characteristics of success in export.

In this paper we show that manufacturing export success shows a remarkable degree of specialization for virtually all countries. Manufacturing exports in each country are dominated by a few "big hits", which account for most of export value and where the "hit" includes both finding the right product and finding the right market. Moreover, we show that higher export volumes are associated with higher degrees of concentration, after controlling for the number of destinations a country penetrates (i.e. absolute advantage and size). This highlights the importance of big hits. In addition, we estimate that most of the variation, and hence concentration, in export is driven by technological dispersion of the exporting country, rather than demand shocks from the importing destinations. However, given the size of the economy, developing countries are more exposed to demand shocks than rich ones.

Hausmann and Rodrik (2006), in a seminal paper which helped inspire this one, had previously pointed out the phenomenon of hyper-specialization, although only for a few countries and products, and not including the destination component, in contrast to the comprehensive scope of our work. We also make a very significant addition to the Hausmann and Rodrik findings, in that we characterize the probability of "big hits" as a function of the size of the hit – by a power law.

We specify a "hit" as a product-by-destination export flow. We chose this categorization because some export products are shipped to several destinations, while the typical export product is shipped to few destinations (with a mode of one). A few examples of big hits and their relationship to concentration are in order. Out of 2985 possible manufacturing products in our dataset and 217 possible destinations, Egypt gets 23 percent of its total manufacturing exports from exporting one product – "Ceramic bathroom kitchen sanitary items not porcelain" – to one destination, Italy, capturing 94 percent of the Italian import market for that product. Fiji get 14 percent of its manufacturing exports from exporting "Womens, girls suits, of cotton, not knit" to the U.S., where it captures 42 percent of U.S. imports of that product. The Philippines get 10 percent of their manufacturing exports from sending "Electronic integrated circuits/microassemblies, nes" to the U.S. (80 percent of U.S. imports of that product). Nigeria earns 10 percent of its manufacturing exports from shipping "Floating docks, special function vessels nes" to Norway, making up 84 percent of Norwegian imports of that product.

Examining big hits that are exported almost exclusively to one destination for what one would think would be fairly similar countries reveals a surprising diversity of products and destinations. Why does Colombia export paint pigment to the U.S., but Costa Rica exports data processing equipment, and Peru exports T-shirts? Why does Guatemala export candles to the U.S., but El Salvador exports toilet and kitchen linens? Why does Honduras export soap to El Salvador, while Nicaragua exports bathroom porcelain to Costa Rica? Why does Cote d'Ivoire export perfume to Ghana, while Ghana exports plastic tables and kitchen ware to Togo? Why does Uganda export electro-diagnostic apparatus to India, while Malawi exports small motorcycle engines to Japan?

The remarkable specialization across products and destinations shows up in high concentration ratios. The top 1 percent of product-destination pairs account for an average of 52 percent of manufacturing export value for 151 countries on which we have data.[1]

The difference between successful and unsuccessful exporters is found not just in the degree of specialization, but also in the scale of the "big hits." For example, a significant part of South Korea's greater success than Tanzania as a manufacturing exporter is exemplified by South Korea earning $13 billion from its top 3 manufacturing exports, while Tanzania earned only $4 million from its top 3.

The probability of finding a big hit ex ante decreases exponentially with the magnitude of the hit. We show that the upper part of the distribution of export value across products

[1] At this point we do not analyze specialization (concentration) along the time dimension. One attempt to do so is Imbs and Wacziarg (2003). However, they address specialization in total production, not exports, and, hence, do not analyze the destination dimension, which we believe captures additional product differentiation.

(defined both by destination and by six-digit industry classifications) is close to following a power law.[2] On average across our sample, the value of the 10th ranked product-destination export category is only one tenth of the top ranked product-destination export category.[3] The value of top ranked product-destination export category is on average 770 times (median 34 times) larger than the 100th ranked product-destination export category. In this paper we will estimate just how much the entire distribution of export values within each country is explained by a power law, and will place it in context of a trade model with demand and productivity shocks.[4]

Realizing that export success is driven by a few big hits changes our understanding of "success" and poses challenges for economic policy. Power laws may arise because many conditions have to be satisfied for a "big hit," and hence the probability of success is given by multiplying the probability of each condition being satisfied times each other (if probabilities are independent). Source country s's success at exporting product p to destination country d depends on industry-specific and country-specific productivity factors in country s, the transport and relational connections between s and d in sector p, and the strength of destination country d's demand for product p from country s. All of these components are subject to shocks in country-industry technology, firms, country policy, input sectors, shipping costs and technologies, trading relationships, brand reputation, tastes, competitors, importing countries, etc.

The policy discussion about making such success more likely tends to be sharply polarized. Hausmann and Rodrik argue that a firm in country s that first succeeds at exporting product p (they do not examine the destination dimension) is making a discovery that such a product export is profitable, which then has an externality to other firms who can imitate success. They argue therefore that such a discovery process should receive a public subsidy,

[2] Pareto distributions follow a so-called "power law", in which the probability of observing a particular value decreases exponentially with the size of that value. The distributions of word frequencies (Zipf's law), sizes of cities, citations of scientific papers, web hits, copies of books sold, earthquakes, forest fires, solar flares, moon craters and personal wealth all appear to follow power laws; see Newman (2005). See also Table 1 in Andriani and McKelvey (2005) for more examples. Describing concentrated distributions in economics has a long tradition, starting with Pareto (1896). Sutton (1997) provides a survey of the literature on the size distribution of firms starting with the observation of proportional growth by Gibrat (1931) (Gibrat's law).

[3] The corresponding median is lower – one fourth – because of the skewness of this number in our sample.

[4] Luttmer (2007) constructs a general equilibrium model with firm entry and exit that yields a power law in firm size. He combines a preference and a technology shock multiplicatively to obtain a variable he refers to as the firm's total factor productivity.

which may imply a conscious government industrial policy.

Our analysis raises a new issue. In addition to the possible knowledge externality to a successful export, there is also a knowledge problem about the discovery itself. Who is more likely to discover the successful product-destination category – the public or private sector? We show that success (in both the product and destination dimensions) closely follows a power law. Hence, ex ante picking a winning export category (or discoverer) would be very hard indeed. A traditional argument for private entrepreneurship against the government "picking winners" is that private entrepreneurship is a decentralized search process characterized by many independent trials by agents who have many different kinds of specific knowledge about sectors, markets, and technologies. This a priori seems more likely to find a "big hit" than a process relying on centralized knowledge of the state. However plausible these arguments may be, in the end it is an empirical question which approaches work. We hope to stimulate this debate in this paper, but do not believe that we can resolve it definitively.

A complementary point to ours is made by Besedes and Prusa (2008). They find that most new trade relationships fail within 2 years and that the hazard rate of such failure is higher for developing countries.[5] Nevertheless, developing countries have the highest increase in trade relationships: there seems to be a lot of attempts in discovery as it is. However, entry (the extensive margin) does not account for much growth in trade. Together with our stress on the importance and difficulty of discovering big hits (at a higher level of disaggregation), this implies that Hausmann and Rodrik's point might be misplaced.

Although addressing the Hausmann-Rodrik argument is our main goal, our work is related to a few other recent papers. The observation that trade is concentrated has not been lost on economists. Bernard, Jensen, Redding, and Schott (2007) document concentration across U.S. exporting firms, while Eaton, Eslava, Kugler, and Tybout (2007) find that Colombian exports are dominated by a small number of very large (and stable) exporters. Arkolakis and Muendler (2009) make a similar point for Brazilian and Chilean exporting firms and find that the distribution is approximately Pareto.

In contrast to these and other contributions, we document concentration and Pareto-like distributions for many more countries (151); we do so at the product-destination level; and

[5] Their sample is 1975-2003 and relates to bilateral 4-digit SITC relationships.

we try to assess how much of this concentration is driven by technological dispersion versus demand. Eaton, Kortum, and Kramarz (2008) also relate trade patterns to productivity and demand shocks. But while they dissect trading patterns only for French firms, regardless of which products each firm exports (there could be more than one product per firm), we analyze trade at the product level for many countries.[6]

In the next section we document concentration and distributions of exports for 151 countries in the product-destination dimension and perform preliminary analysis. In section 3 we estimate the contribution of technology versus demand to the distribution and concentration of exports. Section 4 concludes.

2 Empirical Facts

Our main data source is the UN Comtrade database. The U.N. classifies exported commodities and manufactured products by source and destination at the six-digit level (roughly 5000 categories). We use the 1992 Harmonized System classification (HS1992) for the year 2000, to maximize the available bilateral trade pairs. Using a less disaggregated classification might have lead to better coverage of countries (say, 4-digit SITC), but would miss the extreme concentration within finely defined products.[7]

We restrict our sample to manufactured categories, i.e. we drop from the sample all agriculture and commodities exports. Our focus on manufactured products stems from our interest on exports that are not dependent on country-specific natural endowments, and could potentially be produced everywhere in the world. We basically exclude products that rely directly on natural resources. Natural resources create strong comparative advantage for extracables and agricultural products. Therefore, *a priori*, focusing on manufacturing also reduces the degree of concentration, especially for developing countries.

Some importers in the original dataset did not correspond to well-defined destinations, so we dropped those destinations from the analysis.[8] Eventually, our sample contains 151 exporters, 2984 export categories, which may be shipped to at most 217 destinations (importers).

[6] The distribution of exports across products is similar to what they find for French firms.

[7] An analysis of the distribution of product-destination export flows at the 4-digit SITC level reveals similar patterns, but lower levels of concentration, as one might expect.

[8] For example, "Antarctica", "Areas, nes", "Special Categories", etc.

2.1 Concentration of exports

Our first observation is that exports are highly concentrated. That is, for each country a few successful products and destination markets account for a disproportionately large share of export value. We initially examine manufactured products, while ignoring the destination market dimension (we will incorporate the destinations shortly). **Table 1** shows that the median export share of the top 1%, 10% and 20% within nonzero export products for a country is 49%, 86% and 94%, respectively.[9] In fact, for the median country, the top 3 products account for 28% of exports, and the top 10 products account for a staggering 52%. The median share for the bottom 50% of exported products is a mere 0.57%. This implies a high degree of concentration indeed.[10]

One issue that complicates the interpretation of the concentration ratios is that countries also differ a lot in how many export products they export at all (i.e. product exports with nonzero entries for each country) – from a minimum of 10 to a maximum of 2950, with a median of 1035. We will examine the role of number of products in the next section.

Another striking fact is just how few destination markets each product penetrates. **Figure 2** shows the average across all 151 exporters of the share of export value accounted for by products that have the number of destinations shown on the X-axis. The largest shares go to products that are exported to only one destination, the next largest share goes to products that are exported to only two destinations, and then it falls off to a long tail. This observation led to our decision to treat the product-destination pair as the unit of analysis for the bulk of our analysis.

We now incorporate the destination dimension. In all the analysis that follows, we stick to one unit of account: the product-destination export flow. The same observation about concentration at the product level holds for product-destination trade flows, i.e. when each observation is an export of a particular product to a particular destination. **Table 2** shows that for the median exporter the top 1% of product-destination pairs account for 52.5% of total export value! The top 10% account for 89% and the bottom 50% for only 0.8%.[11]

Once again, the number of nonzero entries in the product-destination matrix varies enor-

[9] Our basis for comparisons are always nonzero export flows for each country separately. In calculating percentages we never compare to potential export products that are exported by all countries (2984 in total).

[10] **Table A1** in the appendix reports these shares for all 151 countries in our sample.

[11] **Table A2** in the appendix shows these numbers for all countries.

mously across countries, and is always far below the potential number implied by exporting all products to all destinations. The median number of nonzero product-destination entries per exporter is 3,055, going from a minimum of 10 to a maximum of 195,417. The median number of nonzero entries is less than half of one percent of the potential number. Baldwin and Harrigan (2007) have previously made the observation that many potential product-destination flows are absent and relate the incidence of zeros to distance and importer size. Here we show that this is another important dimension of variation in the degree of success of exports. In the next section we systematically relate this to concentration and the prevalence of big hits.

2.2 Correlates of concentration

Our main focus is on the distribution of value across product-destination export flows. However, we want to first place the statistics above in context. To do so, we provide a brief descriptive analysis of export patterns and concentration ratios. We start by illustrating the very strong (log-linear) association between the number of nonzero product-destination export flows and the value of total manufacturing exports, as can be seen in **Figure 3**. One way to succeed at exporting is to export more products to more places. This is a result of absolute advantage, which allows penetrating more markets with more products.

Larger economies export more products to more destinations by virtue of sheer size and diversity, and richer countries might have a better chance to penetrate more markets due to better technology. This relationship between the number of product-destination export flows, size and income is well captured by the following regression, which we fit to data on 135 countries

$$\log(\text{number of nonzero export flows}) = \underset{(0.084)}{-12.73} + \underset{(0.043)}{0.64} \cdot \log(\text{GDP}) + \underset{(0.084)}{0.65} \cdot \log(\text{GDP per capita}) ,$$

where robust standard errors are reported in parentheses and $R^2 = 0.8$.[12] Poorer and smaller economies indeed penetrate less markets with less products.

However, in terms of explaining export success, this is not the entire story, as **Figure 4** shows. Even after controlling for size (GDP) and income (GDP per capita) the association between export success and the number of nonzero product-destination export flows remains

[12] We could obtain GDP data for only 135 countries in our sample.

strong. In addition, **Table 3** shows that the number of nonzero export flows is the most important factor: the beta coefficient is three times larger and six times larger than those of GDP and GDP per capita, respectively. We take this feature into account in our model. We show how favorable productivity or demand shocks are necessary to overcome a threshold to realize a non-zero entry (for either product or destination). Therefore, countries that exhibit higher productivity levels also get to draw from a more favorable productivity distribution and penetrate more destinations with more products.

We now return to describe concentration of exports across products and destinations. **Table 4** shows the bivariate correlations between all the concentration statistics given above. We see that the "top x" and "top x percent" concentration ratios are not measuring the same thing; they are sometimes actually negatively related to each other. The problem is that neither statistic is invariant to the number of nonzero product-destination flows, which varies a lot across countries, as we have seen. For mechanical reasons, a larger number of nonzero product-destinations drives down the share of the "Top 3" or "Top 10", but drives up the share of the "Top 1 percent" or "Top 10 percent" (exactly the same effect on the concentration ratios is true for total manufacturing export value).

It is not clear whether we can construct an ideal concentration ratio when the number of nonzero product-destinations varies so much. Our main results below don't rely on concentration ratios; instead, we characterize the entire shape of the distribution of nonzero entries. The statistics on ratios of the top product-destination to the 10th ranked or 100th ranked are closely related to the shares of the top 3 or top 10, and are related to the other variables in the same way.

Finally, **Table 5** examines the partial correlations between the concentration ratios and the number of nonzero product-destinations export flows and total manufacturing export value (both in logs). The interesting result is that controlling for the number of nonzero product-destination export flows, total value is always positively associated with concentration (with both the top x and top x percent measures). It seems that the most successful exporters by total value also have the highest concentration ratios for top x products or top x percent of product-destination exports, conditional on the number of nonzero product-destination export flows they have. Given the level of total export value, a larger number of product-destinations is associated with lower concentration. This makes sense, because the same amount of export value must be distributed across more product-destinations. We take this into account in our estimation below, in which we allow destination-specific demand shocks.

The different effects on concentration of the number of nonzero product-destination export flows versus total export value can be related to absolute and comparative advantage. Countries that export a large number of products to many destinations exhibit absolute advantage, or higher productivity, on average. For a given exporter facing all possible destinations with entry fixed costs, a higher average productivity will allow it to penetrate more destinations and export more products. But given the number of destinations an exporting country penetrates, higher values come from productivity draws that are high relative to the rest, which increases concentration. In our estimation procedure below we will take this into account.

2.3 The distribution of exports: mixed lognormal-power law

A country's most successful products account for the bulk of its total export value and therefore the distribution of export values appears to be highly right-skewed. A candidate distribution to describe this distribution would be the Pareto distribution which, as detailed above, is used to explain a variety of highly skewed phenomena.

The Pareto distribution would imply a straight line on a log-log scale of export rank and export value. We plot these rank graphs for all countries but observe that we have a straight line only in the tails of the distributions as illustrated in **Figure 5** for a selection of countries.[13] Eaton, Kortum, and Kramarz (2008) document similar rank graphs for French firms. Here we show that the shape holds for practically every country in our dataset. These graphs indicate that the whole distribution does not fit the Pareto. But this is not unusual in economic applications of the Pareto distribution; the same holds for income, firm size and city size.[14] In all cases, a log normal distribution explains well the bottom of the distribution, whereas the Pareto distribution fits well the upper tail.

[13] U.S. (an established industrialized OECD economy), Ghana (a poor African country), Argentina (a middle-income South American country), South Korea (a newly industrialized country, new to the OECD), China (the fast-growing giant) and Estonia (a small open transition economy). The data is by product category by destination and is demeaned by destination to control for the effects of gravity and trade barriers.

[14] For example, see Eeckhout (2004).

We simulated a mixed Pareto-log normal random variable and a log-normal random variable, and plotted their respective rank graphs in **Figure 6**. The simulated mixed Pareto-log-normal random variable remarkably resembles our empirical distributions in **Figure 5**. A visual comparison of the two simulated random variables in **Figure 6** indicates that the empirical graphs are "too straight" to fit the log normal. In other words, the distribution of "success" across exports is so skewed that not even the highly skewed log normal can be used to characterize it; it seems to require some combination of the log normal – which is necessary at the least for the lower ranked product-destinations – and the power law (Pareto) – which is required for the top ranked product-destinations. The simulated mixed Pareto-log normal distribution seems to provide a better fit.

To formally reject lognormality of the data we performed two different normality tests on log export values: the Kolmogorov-Smirnoff test and a Normality test based on D'Agostino, Belanger, and D'Agostino (1990). Normality is rejected in 85% with the former and in 93% of the cases using the latter test. We conclude that the data cannot be described by a log-normal alone.

In what follows we construct a simple demand-supply framework that yields a distribution of export values which is determined by log normal demand shocks and Pareto productivity dispersion. Our innovation is to derive the lognormal-Pareto mixture distribution for export values and determine the relative role the power law part plays.[15]

3 Technology versus demand

In this section we raise the following question: how much of the variation in export values is driven by technological dispersion in the source country versus demand shocks from destination countries. Our interpretation of demand is broad, and includes true taste shocks, finding a good match and successful marketing. Answering this question can advise policy on the types of tools that might – and those that might not – be relevant for promoting trade.

Suppose that demand shocks are more important. This would imply that the stress on finding one's comparative advantage is misplaced, because other forces determine trade

[15] Arkolakis (2008) develops a model with market penetration that takes into account marketing costs and matches the distribution of exports better than a simple Pareto or log normal can.

flows. An implication is that penetrating markets is more about marketing and finding a good match than high productivity. On the other hand, if technological dispersion is more important, and if it follows a power law, then it would be very hard to predict big hits, because the probability of predicting diminishes exponentially with the size of the hit (this is the definition of a power law).

To this end we lay out a demand-supply framework which is similar to the backbone of many modern trade models. This framework will allow us to estimate a parameter that governs the distribution of technological dispersion and a parameter that governs demand shocks. We examine empirically which accounts for a larger share of the variation in the data, country by country. Our results indicate that productivity explains a larger percent of variation in exports than demand shocks, and that this share is larger for less developed countries.

In order not to burden the reader with familiar structure we present only the necessary minimum of our framework and relegate the rest to the appendix.

3.1 Revenue and selection equations

Each destination country n is represented by one consumer, whose preferences over products are represented by a CES aggregator. Products are indexed both by the product's "name" j and by source i.[16] Optimal price taking behavior gives rise to the familiar CES demand schedule

$$x_n(i,j) = \alpha_n(i,j)\left(\frac{p_n(i,j)}{p_n}\right)^{-\sigma}\frac{Y_n}{p_n},$$

where $\alpha_n(i,j)$ is a preference shock, $p_n(i,j)$ is the price to serve product j from source i in destination n, p_n and Y_n are the price level and income in country n, respectively.[17] As usual, $\sigma > 1$ is assumed, which is the same in all countries. It is also assumed that $\alpha_n(i,j)$ is independent of $x_n(i,j)$.

In *source* country i, producer j may export to any destination country n, including domestic sales ($n = i$). Technology is linear in labor inputs. For a particular destination n,

[16] This follows the organization of the data in Comtrade and it implies product differentiation at the good-source level. So widgets from Kenya are differentiated from widgets from Costa Rica, even if they are both called "widgets" in the data. This is essentially an Armington assumption.

[17] See the appendix for a more complete description.

it chooses $p_n(i,j)$ to maximize profits

$$\pi_i(n,j) = p_n(i,j)\, x_n(i,j) - c_n(i,j)\, x_n(i,j) - K_n(i)$$

subject to the demand schedule. $c_n(i,j)$ is the producer's (constant) marginal cost, which is given by

$$c_n(i,j) = \frac{w(i)}{z_n(i,j)} \ ,$$

where $w(i)$ are wages in country i and $z_n(i,j)$ is labor productivity. $K_n(i) > 0$ is a fixed setup cost for business in i to penetrate the n market[18]. The implicit assumption here is that there is just one such producer of product j in source country i that exports to destination n, and there are no multiple-destination exporters. Thus, it is possible to produce slightly different products per market.[19] There are no other trade frictions.

Optimal pricing is a fixed markup over marginal cost. Thus, revenue for producer j in source country i selling in destination n is given by

$$r_i(n,j) = \alpha_n(i,j) \left(\frac{\sigma}{\sigma-1} \frac{w(i)}{z_n(i,j)} \right)^{1-\sigma} p_n^{\sigma-1} Y_n \ .$$

Taking logs we get the following expression

$$\ln r_i(n,j) = \beta_0^r - \beta_i^w + \beta_n^{py} + \ln \alpha_n(i,j) + (\sigma-1) \ln z_n(i,j) \ , \tag{1}$$

where $\beta_0^r = (1-\sigma) \ln \frac{\sigma}{\sigma-1}$, $\beta_i^w = (\sigma-1) \ln w(i)$, $\beta_n^{py} = (\sigma-1) \ln p_n + \ln Y_n$.

Equation (1) describes observed revenue, but does not take into account the fact that overall profits need to be non-negative, if we observe revenue at all. The selection equation is

$$\pi_i(n,j) = r_i(n,j) - c_n(i,j)\, x_n(i,j) - K_n(i) \geq 0.$$

Using the previous results, optimal pricing yields

$$\alpha_n(i,j) \cdot z_n(i,j)^{\sigma-1} \geq \sigma^{\sigma} (\sigma-1)^{1-\sigma} \frac{K_n(i)}{Y_n} \left(\frac{w(i)}{p_n} \right)^{\sigma-1} .$$

This expression means that the demand shock and productivity must overcome a threshold.

[18] These capture making connections with potential buyers, adjusting the good to comply with local regulations, shipping costs, bribes at the border, etc'.

[19] The data is aggregated over all producers anyway, so one can think that this represents a different mix of producers.

The threshold is increasing in the size of the fixed cost for entry relative to the size of the destination market $(K_n(i)/Y_n)$ and increasing in the real wage in the source country in terms of the destination country $(w(i)/p_n)$. Taking logs and rearranging yields

$$\ln \alpha_n(i,j) + (\sigma - 1)\ln z_n(i,j) \geq \beta_0^s + \beta_i^w - \beta_n^{py} + \beta_{in}^k, \tag{2}$$

where $\beta_0^s = \ln\left(\sigma^\sigma(\sigma-1)^{1-\sigma}\right)$, $\beta_{in}^k = \ln K_n(i)$ and β_i^w and β_n^{py} were defined above.

3.2 Empirical specification

We would like to estimate the relative contribution of $z_n(i,j)$ versus $\alpha_n(i,j)$ to the variation of export revenues. To this end we will make some distributional assumptions that will enable us to write down a likelihood function for export revenue. We will then maximize it in order to retrieve the distribution parameters of the underlying productivity and demand shocks. Using this information, we will be able to decompose the variance.

We assume that $\alpha_n(i,j)$ is distributed log-normal such that $\ln \alpha_n(i,j)$ is distributed normal with zero mean and variance v^2.[20] We do not index v^2 by destination n, which reflects our assumption that in percent terms demand shocks should not be different across countries. We assume that $z_n(i,j)$ in source country i is distributed Pareto,

$$Z \sim F_i(z) = 1 - \left(\frac{m_i}{z}\right)^{a_i},$$

where $z > m_i > 0$ and $a_i > 0$. Note that m_i varies by source country.[21] It is assumed that α and z are independent.

Equations (1) and (2) can then be written as

$$r_{inj} = \beta_0^r - \beta_i^w + \beta_n^{py} + \delta_{inj} + \varepsilon_{inj} \tag{3}$$

and

$$\delta_{inj} + \varepsilon_{inj} \geq \beta_0^s + \beta_i^w - \beta_n^{py} + \beta_{in}^k. \tag{4}$$

where $\delta_{inj} = \ln \alpha_n(i,j)$ is distributed normal for each destination with zero mean and

[20] Eaton, Kortum, and Kramarz (2008) also include lognormal demand shocks in their analysis of French firms exporting behavior.

[21] Helpman, Melitz, and Yeaple (2004) also assume a Pareto distribution for productivity, but do not let it change by source country.

variance v^2; and $\varepsilon_{inj} = (\sigma - 1)\ln z_n(i, j)$ is distributed conditional exponential

$$F_i(\varepsilon) = 1 - m_i^{a_i} e^{-\frac{a_i}{\sigma-1}\varepsilon},$$

where we condition on $\varepsilon \geq (\sigma - 1)\ln(m_i)$.[22] Define

$$\lambda_i = \frac{a_i}{\sigma - 1}$$

as the exponential parameter for ε. So ε_{inj} is distributed exponential with conditional mean $(\sigma - 1)\ln(m_i) + 1/\lambda_i$.

Note that naively estimating (3) by least squares is not feasible. This is so because the mean of ε_{inj} is not zero in general, so the intercept β_i^w is not separately identified. However, using maximum likelihood will allow us to overcome this issue.

By applying the Convolution Theorem (see appendix), we can characterize the distribution of $\theta_{inj} = \delta_{inj} + \varepsilon_{inj}$. Dropping the subscripts to ease notation, it turns out that the p.d.f. of θ is given by

$$f(\theta) = \lambda \exp\left\{\frac{\lambda^2 v^2}{2} - \lambda\theta\right\} \Phi\left(\frac{\theta - \lambda v^2}{v}\right) , \tag{5}$$

where Φ is the normal CDF. In (5) we assumed that $m_i = 1$ for all i. This assumption is innocuous because it does not affect the estimates of v and λ—we get the right ones regardless. In the appendix we present the distribution of θ for a general m, discuss identification issues in detail and prove this last claim.[23] Loosely speaking, this follows from the characteristics of the underlying distributions: m is just a location parameter, while v and λ determine the shape of the distribution. We know that for the Pareto distribution, the shape parameter a remains the same for any truncation from below. Similarly, for the exponential distribution the shape parameter λ is the same for any truncation from below. As long as in all source countries some firms draw productivities lower than the selection cutoff and do not enter, assuming $m_i = 1$ does not matter. This amounts to saying that $m_i = 1$ is low enough to ensure this.

Thus one can rewrite the revenue equation (3) and the selection equation (4) in terms

[22] Notice that $(\sigma - 1)\ln(m_i)$ can be positive or negative, but since $m_i > 0$ and $\sigma > 1$, $(\sigma - 1)\ln(m_i)$ is bounded away from $-\infty$. This is not a standard exponential random variable, in the sense that ε can be less than zero, but all the properties of the exponential distribution are preserved.

[23] We thank Yijia Wang for useful discussions of this matter.

of θ.

3.3 Maximum likelihood estimation

We can rewrite the revenue equation to get an expression for θ_{inj}

$$\theta_{inj} = r_{inj} - \beta_0^r + \beta_i^w - \beta_n^{py} \tag{6}$$

and then use it in the selection equation to get

$$r_{inj} \geq \beta_0^r + \beta_0^s + \beta_{in}^k \equiv t_{in}^r,$$

where t_{in}^r is the cutoff for observed revenue. Rearranging the expression for t_{in}^r and plugging it into the selection equation yields

$$\theta_{inj} \geq t_{in}^r - \beta_0^r + \beta_i^w - \beta_n^{py}. \tag{7}$$

Of course, this follows directly from (6), if we replace r_{inj} with its minimum value. Eventually, we have a modified pair of equations for revenue (6) and selection (7) in terms of θ_{inj}.

We estimate the model separately for each source country. Therefore, to ease notation we drop the index i of the source country. For a given source country equations (6) and (7) can be collapsed into the following representation

$$\theta_{nj} = r_{nj} - \beta_n$$

and

$$\theta_{nj} \geq t_n^r - \beta_n,$$

where $\beta_n = \beta_0^r - \beta^w + \beta_n^{py}$. In principle, we could plug all β_n coefficients straight into the likelihood function, but estimating all β_n dummy variables is not feasible, because they are not identified. This follows from the fact that θ_{nj} has a non-zero mean. Luckily, we are not interested in these estimates. Therefore, we take the following route.

For each destination let

$$b_n^{'} = \frac{\sum_j r_{kj} I\left(k=n\right)_j}{\sum_j I\left(k=n\right)_j^2} = \frac{1}{\sum_j I\left(k=n\right)_j} \sum_j r_{nj}, \tag{8}$$

which is just the average export value per destination, and is the OLS estimator from a regression of export values on a set of destination-specific constants and a *zero-mean* error term. The estimator $b_n^{'}$ is a biased estimator of β_n, but we know that the bias is equal to $1/\lambda$, i.e. $E(b_n^{'}) = \beta_n + 1/\lambda$. We take advantage of this in a two-step estimation procedure in the following way.

- **Step 1**: Calculate $b_n^{'}$ as shown above in (8).

- **Step 2**: Define

$$\begin{aligned} \widetilde{\theta}_{nj} &\equiv r_{nj} - b_n^{'} + \frac{1}{\widehat{\lambda}} \\ \widetilde{t}_n^r &\equiv t_n^r - b_n^{'} + \frac{1}{\widehat{\lambda}} \end{aligned}$$

  as our corrected θ and truncation values, and maximize the following likelihood

$$\mathcal{L}(\widehat{v}, \widehat{\lambda}) = \Pi_{nj} \frac{f(\widetilde{\theta}_{nj})}{1 - F(\widetilde{t}_n^r)},$$

  with respect to $\widehat{\lambda}$ and $\widehat{v}$. Note that $\widetilde{t}_n^r = t_n^r - b_n^{'} + 1/\widehat{\lambda}$, so that $\{t_n^r\}$ are also parameters to be estimated. In principle, we could also maximize the likelihood with respect to $\{t_n^r\}$. However, a consistent estimator of t_n^r is

$$\widehat{t}_n^r = \min_j \{r_{nj}\} \ .$$

  We use $\widehat{t}_n^r$ to replace t_n^r in the estimation procedure, which simplifies the estimation and is very robust.

In order to make sure that our procedure works, we performed Monte Carlo simulations and backed out the original parameters successfully. The initial values for the maximum likelihood numerical optimizer were chosen as empirical moments from the data. For each source country the initial value for λ was chosen as the average trade flow, demeaned by destination. The initial value for v was chosen as the standard deviation from that same data. Changing the initial values for the search within a reasonable range did not affect the results.

3.4 Estimation results and variance decomposition

Figure 7 plots the estimated λ parameters by country against log GDP per capita. Almost all estimates of λ fall within 0.5 and 1.[24] Recall our interpretation for $\lambda = a/(\sigma - 1)$. This means that the technology distribution has remarkably similar Pareto coefficients across income levels, assuming elasticities of demand are also similar. Typical estimates of σ in similar settings are well above 2, in the range of 5-12 . This would place the estimate of the Pareto coefficient, a, above 2, which is reassuring, because it restricts the primitive distribution of productivity in the model to have finite first and second moments.

However, this would not imply that the *level* of the distributions of technology are the same in all countries. As discussed in the end of section 3.2, we do not estimate the m_i parameters, which govern the actual level of productivity. Higher m_i makes it more likely to penetrate any given destination market. Countries that penetrate more destinations must have higher m_i. Nevertheless, the shape of the productivity distribution across countries is similar.

We want to decompose the variance of θ into variance due to the normal demand shocks δ, and the exponential technology component, ε. We need to perform the variance decomposition under the condition that the selection equation holds. For a given cutoff of a specific destination n, we have

$$V(\theta|\theta \geq t(n)) = V(\delta + \varepsilon|\theta \geq t(n)) = V(\delta|\theta \geq t(n)) + V(\varepsilon|\theta \geq t(n)) \ ,$$

where $t(n)$ varies over destinations and captures the fact that the cutoff changes by destination. The covariance term is zero due to the assumed independence of δ and ε. Closed form solutions for the last two variance expressions are very complicated to derive, so we simulate these expressions instead.[25] The simulation procedure is described in the appendix. A complication arises from the fact that the cutoff, t, varies by destination n. In order to address this issue, we decompose each conditional variance according to the variance version of The Law of Iterated Expectations as follows

$$V(X|\theta \geq t(n)) = V_n[E(X|\theta \geq t(n))] + E_n[V(X|\theta \geq t(n))] \ , \tag{9}$$

[24] **Table A3** in the appendix presents all the estimates for λ. The countries with extremely high estimates of λ are Burundi (2.9) and Benin (2), both of which have few observations.

[25] We thanks Jorg Stoye for suggesting this.

where X represents either δ or ε. We report the percent contribution to the variance of θ of δ and ε:

$$p_{\delta} = 100 \times \frac{V(\delta|\theta \geq t(n))}{V(\theta|\theta \geq t(n))} \text{ and } p_{\varepsilon} = 100 \times \frac{V(\varepsilon|\theta \geq t(n))}{V(\theta|\theta \geq t(n))} .$$

In doing so, we report two sets of results; once where we do not use weights in (9), and then using the number of observations per destination as weights.

Table 6 presents our main result: on average 66% of the variance is due to the Pareto part of the distribution.[26] In **Table 7** we report some correlates of p_{δ} in order to investigate potential determinants of the percent of variance due to technology.

Figure 8 and column (1) of **Table 7** indicate a negative relationship between the percent of variance due to technology and the log of GDP. As we know from above, large countries export to more destination and that should expose them to more demand shocks. Indeed, there is also a negative relationship between the number of product-destination export flows and the percent of the variance due to technology, as can be seen in **Figure 9** and in columns (2) and (3) of **Table 7**.

In column (4) of **Table 7** we control for both the number of export flows and for income (GDP per capita). We find that the contribution of technology to the dispersion of export is in fact higher in richer countries, controlling for the number of destinations they export to.[27] This is a point of interest. We know that richer countries do export more products to more markets due to absolute advantage, which should expose them to more demand shocks. However, it seems that developing countries are more exposed to demand shocks, over and above their ability to penetrate more markets with more products.

4 Conclusion

In this paper we document the high degree of specialization in exports in a sample of 151 economies. Specialization is remarkably high in exporting manufactures, as in many other areas in economics. The distribution is remarkably skewed. We find that very few "big hits" account for a disproportionate share of export volumes and can also explain high

[26] **Table A4** in the appendix shows the percent of the variance due to the Pareto component for all countries.

[27] Given the result in **Figure 7**, it is not surprising that we did not find a univariate correlation between income and p_{δ}.

degrees of specialization. We also find that higher concentration (i.e., big hits) is positively correlated with higher trade volumes, after controlling for the number of products that are exported and destinations that are reached. Larger countries export more products to more destinations and so do richer countries, where the latter is driven by absolute advantage. Controlling for the number of product-destination export flows, overall export volumes are positively correlated with higher concentration, which are explained by big hits. This is driven by comparative advantage.

We analyze the determinants of these big hits. We find that technology explains most of the variation in export trade flows, relative to demand shocks. This means that export success is mainly driven by technological dispersion, which also explains high levels of specialization. Developing countries export less products to fewer destinations, which helps explaining this. Exporting to more destinations exposes a country to more demand shocks that are uncorrelated with technological dispersion. Therefore, as a country penetrates more markets with more products, demand shocks from those markets and for those products account for a larger percent of variation – and hence concentration – in exports. When we control for the number of markets and products we find that the relative contribution of technology to the variation in exports is lower in developing countries. This implies that developing countries are more exposed to demand shocks within the set of product-destinations that they export.

Our analysis leads us to some important conclusions that are relevant for policies that aim to promote trade. We find that a power law plays an important role in the distribution of export value across possible product-destination pairs. This makes the fierce debate about the relative weights on the government and the market in "picking winners" even more relevant than previously realized in the literature. A power law means that successfully picking a winner becomes less likely exponentially with the degree of success that is predicted. Over and above this mechanism, the higher relative exposure of developing countries to demand shocks, given their successful export flows, implies an even smaller role for picking winners.

The "picking winners" debate is about two things: probability of discovering a "winner" and externalities from identifying the winner to other firms. The traditional argument for relying on free markets to decide what to produce is that they make possible a decentralized search by myriads of entrepreneurs, and provide means for scaling up successful hits through reinvestment of profits and financing by capital markets. The probability of any one agent – such as a government policymaker – finding which product-destination combination will be the big hit is very small. In fact, the track record of governments in picking winners is not great, as Lee (1996) demonstrates for Korea.[28] Hence, an alternative implication – nearly the opposite of Hausmann-Rodrik conclusion – of the hyper-specialization phenomenon is that entrepreneurs and financiers should be as unhindered as possible from any government intervention.

However, if there are externalities from the discovery of a "big hit" to other firms who can also export the same good-destination pair, then there is a market failure leading to too little discovery effort by any one entrepreneur. This lead to the traditional argument for government intervention to subsidize "discovery", as Hausmann and Rodrik emphasized. Perhaps one could try to get the both of best worlds by designing a blanket government subsidy to all "discovery" efforts, while leaving the process of identifying the winners to private entrepreneurs. How to design such a policy in practice, and whether the traditional arguments fully apply to the stylized facts we have uncovered is far from definitive. Our main contribution is to show that finding winning hyper-specializations is even harder —and yet the rewards to finding these hyper-specializations are also even larger – than previously thought.

[28] We are not saying that industrial policy in Korea did not contribute to its subsequent success. We only point out that the "picking winners" part of that policy has not proven to be successful.

Appendix

A Demand structure

There are N countries. Let preferences in destination country n be given by

$$U_n = \left(\int \alpha_n (i,j)^{1/\sigma} x_n (i,j)^{\frac{\sigma-1}{\sigma}} d(i,j) \right)^{\frac{\sigma}{\sigma-1}} ,$$

where $x_n(i,j)$ denotes product j from source country i and $\alpha_n(i,j)$ are preference weights (shocks) associated with those products. As usual, $\sigma > 1$ is assumed. We assume that elasticities of substitution in demand, σ, are the same in all countries. We assume that $\alpha_n(i,j)$ are independent of $x_n(i,j)$.

Maximizing this utility function under the following budget constraint

$$\int p_n (i,j)\, x_n (i,j)\, d(i,j) \leq Y_n$$

gives rise to demand

$$x_n (i,j) = \alpha_n (i,j) \left(\frac{p_n (i,j)}{p_n} \right)^{-\sigma} \frac{Y_n}{p_n} ,$$

where Y_n denotes nominal national income and p_n is the perfect price index for destination n,

$$p_n = \left(\int \alpha_n (i,j)\, p_n (i,j)^{1-\sigma} d(i,j) \right)^{\frac{1}{1-\sigma}} .$$

B The distribution of $\theta = \delta + \varepsilon$ for general m

Theorem 1 *(Convolution Theorem[29]): if X and Y are independent continuous random variables with p.d.f.s $f_X(x)$ and $f_Y(y)$, then the p.d.f. of $Z = X + Y$ is*

$$f_Z(z) = \int_{-\infty}^{\infty} f_X(t) f_Y(z-t) dt .$$

Define the convoluted random variable $\theta = \delta + \varepsilon$, where δ is distributed normal with zero mean and variance v^2 and ε is distributed conditional exponential with exponent λ and $\varepsilon \geq (\sigma - 1)\ln(m)$. Using the Convolution Theorem (see Casella and Berger (2002))

$$f_\theta(\theta) = \int_{-\infty}^{\infty} f_\varepsilon(t) \frac{1}{v} \phi\left(\frac{\theta - t}{v}\right) dt = \int_{(\sigma-1)\ln m}^{\infty} f_\varepsilon(t) \frac{1}{v} \phi\left(\frac{\theta - t}{v}\right) dt ,$$

where ϕ is the Normal p.d.f. and we omit indexing by source and destination to ease notation. The second equality follows from the fact that $\varepsilon \geq (\sigma - 1)\ln(m)$, and $f_\varepsilon(t) = 0$

[29] Casella and Berger (2002).

when that condition is not met. Explicitly,

$$\begin{aligned} f_\theta(\theta) &= \int_{(\sigma-1)\ln m}^{\infty} m^a \lambda \exp\{-\lambda t\} \frac{1}{\sqrt{2\pi v^2}} \exp\left\{-\frac{1}{2v^2}(\theta-t)^2\right\} dt \\ &= \lambda m^a \int_0^\infty \frac{1}{\sqrt{2\pi v^2}} \exp\left\{-\lambda t - \frac{1}{2v^2}(\theta^2 - 2\theta t + t^2)\right\} dt \ . \end{aligned}$$

Focus on the exponent in the integrand:

$$-\lambda t - \frac{1}{2v^2}(\theta^2 - 2\theta t + t)^2 = -\frac{1}{2v^2}\left[2\lambda v^2 t + \theta^2 - 2\theta t + t^2\right] = -\frac{1}{2v^2}\left[\theta^2 - 2\left(\theta - \lambda v^2\right)t + t^2\right]$$

and complete the square

$$= -\frac{1}{2v^2}\left[\left(\theta - \lambda v^2 - t\right)^2 + 2\lambda v^2\theta - \left(\lambda v^2\right)^2\right] = -\frac{1}{2v^2}\left[t - \left(\theta - \lambda v^2\right)\right]^2 + \frac{\lambda^2 v^2}{2} - \lambda\theta$$

so that

$$\begin{aligned} f_\theta(\theta) &= \lambda m^a \int_{(\sigma-1)\ln m}^{\infty} \frac{1}{\sqrt{2\pi v^2}} \exp\left\{-\frac{1}{2v^2}\left[t - \left(\theta - \lambda v^2\right)\right]^2 + \frac{\lambda^2 v^2}{2} - \lambda\theta\right\} dt \\ &= \lambda m^a \exp\left\{\frac{\lambda^2 v^2}{2} - \lambda\theta\right\} \int_{(\sigma-1)\ln m}^{\infty} \frac{1}{\sqrt{2\pi v^2}} \exp\left\{-\frac{1}{2v^2}\left[t - \left(\theta - \lambda v^2\right)\right]^2\right\} dt \ . \end{aligned}$$

Notice that the integrand is nothing but a p.d.f. of a normal random variable with mean $\left(\theta - \lambda v^2\right)$ and variance v^2. So the integral itself is equal to

$$1 - \Phi\left(\frac{(\sigma-1)\ln m - \left(\theta - \lambda v^2\right)}{v}\right) = 1 - \Phi\left(-\frac{\theta - \lambda v^2 - (\sigma-1)\ln m}{v}\right) = \Phi\left(\frac{\theta - \lambda v^2 - (\sigma-1)\ln m}{v}\right)$$

and

$$f_\theta(\theta) = \lambda m^a \exp\left\{\frac{\lambda^2 v^2}{2} - \lambda\theta\right\} \Phi\left(\frac{\theta - \lambda v^2 - (\sigma-1)\ln m}{v}\right) \ .$$

By setting $m = 1$ we get the result in the text.

One can double-check this result by plugging the dummy variable in ϕ rather than in f_ε and deriving the same result from

$$f_\theta(\theta) = \int_{-\infty}^{\infty} \frac{1}{v}\phi\left(\frac{t}{v}\right) f_\varepsilon(\theta - t)dt = \int_{-\infty}^{\theta-(\sigma-1)\ln(m)} \frac{1}{v}\phi\left(\frac{t}{v}\right) f_\varepsilon(\theta - t)dt \ .$$

where the second equality follows from the fact that $\theta - t \geq (\sigma - 1)\ln(m) = 0$ in this case, i.e., $t \leq \theta - (\sigma - 1)\ln(m)$, and $f_\varepsilon(\theta - t) = 0$ when that condition is not met.

C Identification issues: m and σ are not identified

As we know, θ for a source country i has mean equal to $(\sigma - 1)\ln(m_i) + 1/\lambda_i$. However, since we do not observe θ, but only revenues, we cannot identify m, even if we hold σ at some value. The reason is that in order to get to θ we need to deduct country fixed effects, which are not identified separately from the mean of θ. Moreover, holding m at any value does not affect the estimates of v and λ.

To see this point formally, suppose that we actually used

$$\widetilde{\theta}_{nj} = r_{nj} - b_n^{'} + (\widetilde{\sigma} - 1)\ln \widetilde{m} + \frac{1}{\widetilde{\lambda}}$$

in the likelihood. This is the general expression for $\widetilde{\theta}$ in the two-step procedure. Now plug this into $\ln f(\theta)$ to get

$$\begin{aligned}
\ln f(\widetilde{\theta}) &= \ln\lambda + a\ln m + \frac{\lambda^2 v^2}{2} - \lambda\widetilde{\theta} + \ln\left[\Phi\left(\frac{\widetilde{\theta} - \lambda v^2 - (\sigma-1)\ln m}{v}\right)\right] \\
&= \ln\lambda + a\ln m + \frac{\lambda^2 v^2}{2} - \lambda\left(r_{nj} - b_n^{'} + (\sigma-1)\ln m + \frac{1}{\lambda}\right) \\
&\quad + \ln\left[\Phi\left(\frac{\left(r_{nj} - b_n^{'} + (\sigma-1)\ln m + \frac{1}{\lambda}\right) - \lambda v^2 - (\sigma-1)\ln m}{v}\right)\right] \\
&= \ln\lambda + a\ln m + \frac{\lambda^2 v^2}{2} - \lambda\left(r_{nj} - b_n^{'}\right) - \frac{a}{\sigma-1}(\sigma-1)\ln m - 1 \\
&\quad + \ln\left[\Phi\left(\frac{r_{nj} - b_n^{'} + 1/\lambda - \lambda v^2}{v}\right)\right] \\
&= \ln\lambda + \frac{\lambda^2 v^2}{2} - \lambda\left(r_{nj} - b_n^{'}\right) - 1 + \ln\left[\Phi\left(\frac{r_{nj} - b_n^{'} + 1/\lambda}{v} - \lambda v\right)\right] .
\end{aligned}$$

As one can see, m and σ drop out. Doing the same in $\ln F(\widetilde{\theta})$ yields the same result. So m and σ are completely absent from the likelihood function. This proves that in the estimation procedure we get the same estimates of v and λ—regardless of the values of m and σ.

The two-step estimation procedure described above takes this into account by assuming a particular location ($m = 1$) and identifying v and λ solely from the shape of the distribution. Thus, the variance decomposition is correct regardless of the values of m and σ.

D Simulating conditional variances

Here we describe the algorithm for simulating the conditional variances for each source country i. We start with a set of estimates of λ and v for each source country, and cutoff values $t(n)$ for each destination country, per each source country.

1. Draw a large number D (we use $D = 100,000$) of uniform (u) and standard normal (z) random variables and store them. Both vectors are ($D \times 1$) and will be used for all countries and destinations.

2. Given estimates of λ and v for source i, compute exponential productivity values, e, and normal demand shocks, d, as follows

$$\begin{aligned}
e &= -\ln(1-u)/\widehat{\lambda} \\
d &= \widehat{v} * z
\end{aligned}$$

and

$$\begin{aligned} e2 &= e^2 \\ d2 &= d^2 \ , \end{aligned}$$

where it is understood that we apply the the square operator to each element separately. Thus, the vectors e, $e2$, d and $d2$ are all $(D \times 1)$.

3. Sum d and e to get the simulated theta

$$\widetilde{\theta} = d + e \ .$$

4. For each destination n, generate a $(D \times 1)$ indicator vector

$$I\left(\widetilde{\theta} \geq t(n)\right) \ .$$

5. Compute

$$E\left[X|\theta \geq t\right] = \frac{E\left[X \cdot I\left(\widetilde{\theta} \geq t(n)\right)\right]}{E\left[I\left(\widetilde{\theta} \geq t(n)\right)\right]} = \frac{\frac{1}{D}X'I\left(\widetilde{\theta} \geq t(n)\right)}{\frac{1}{D}\iota'I\left(\widetilde{\theta} \geq t(n)\right)} \ ,$$

where ι is just a $(D \times 1)$ vector of ones, and X can be either e , $e2$, d or $d2$. Thus, we get simulated values for $E\left[\delta|\theta \geq t\right]$, $E\left[\delta^2|\theta \geq t\right]$, $E\left[\varepsilon|\theta \geq t\right]$, $E\left[\varepsilon^2|\theta \geq t\right]$. We use these values to compute variances according to

$$V\left(X|\theta \geq t(n)\right) = E\left(X^2|\theta \geq t(n)\right) + \left[E\left(X|\theta \geq t(n)\right)\right]^2 \ .$$

6. Repeat $4-5$ for each destination n, and store the results.

7. Use

$$V\left(X|\theta \geq t\right) = V_n\left[E\left(X|\theta \geq t(n)\right)\right] + E_n\left[V\left(X|\theta \geq t(n)\right)\right]$$

to compute the conditional variance of δ and ε, where the values inside brackets are calculated in $4-6$ and the operators over n ($V_n[\cdot]$ and $E_n[\cdot]$) use sample analogues. Calculate $V_n[\cdot]$ and $E_n[\cdot]$ in two ways: once without weights and then using the number of observations per destination for each exporter as weights.

Repeat $2-7$ for each source country.

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Table 1: Concentration Ratios for Export Products by Country, Summary Statistics

	Median	Mean	Minimum	Maximum
Percent of the following in total manufacturing export revenues:				
Top 3 products	28	34	5	96
Top 10 products	49	52	13	100
Top 1%	47	48	18	92
Top 10%	86	85	43	99
Top 20%	94	93	66	99
Bottom 50%	0.8	1.3	0.1	17.3
Other statistics:				
Ratio of Top product value to 10th ranked product value	7.2	20.3	1.8	626.6
Ratio of Top product value to 100th ranked product value	104.8	1004.1	10.8	84478.2
Share of Top product in world import market for that product	0.018	0.066	0	0.698
Number of products exported (# of nonzero entries)	1035	1302	10	2950

Notes: 151 observations (countries). The numbers are for export vlaues by product, regardless of the unmber of export destinations. Source: U.N. Comtrade and authors calculations.

Table 2: Concentration Ratios for Product-Destination Bilateral Trade Flows, Summary Statistics

	Median	Mean	Minimum	Maximum
Percent in manufacturing export value of:				
Top 3 product-destinations	17.9	24.1	1.2	93.5
Top 10 product-destinations	33.7	38.4	3.4	100.0
Top 1%	52.5	52.2	20.4	84.9
Top 10 %	88.9	86.7	53.3	98.7
Top 20 %	95.0	93.6	72.4	99.5
Bottom 50 %	0.8	1.4	0.1	14.5
Other statistics:				
ratio product-dest 1 value to product-dest 10	5.3	13.5	1.6	317
ratio product-dest 1 value to product-dest 100	48.2	1064	5	121154
Share of top product-dest in destination's imports of that product	0.18	0.32	0	1
Nonzero products-destinations	3055	19985	10	195417
Nonzero products-destinations/647,745	0.00472	0.03085	0.00002	0.30169
Total manufacturing export value (dollars)	516,000,000	26,544,261,836	87,105	598,300,000,000

Notes: 151 observations (countries). The numbers are for product-destination export flows. Total product categories = 2985. Total possible destinations = 217. Total possible product-destination pairs per exporter = 647,745. Source: U.N. Comtrade and authors calculations.

Table 3: Export Success and Destinations

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: log of total export value				
Log(Number of Nonzero Export Flows)	1.458***	1.425***	1.164***	1.011***	0.67
	(34.54)	(29.77)	(16.57)	(12.24)	
Log GDP			0.309***	0.358***	0.24
			(4.865)	(6.307)	
Log GDP per capita				0.274***	0.11
				(2.719)	
Observations	151	135	135	135	
R-squared	0.905	0.896	0.909	0.915	

Notes: Number of Nonzero Export Flows is the number of product-destination categories that a country exports. GDP is corrected for PPP. The sample in column (2) is restricted to the sample in columns (3) and (4). Column (5) reports beta coefficients for the specification in column (4). Source: U.N. Comtrade, World Bank World Development Indicators. Robust t statistics in parentheses. *** significant at 1%. A constant was included but is not reported.

Table 4: Correlations Between Export Success and Concentration

	lvalue	N	Top3	Top10	Top1%	Top10%	Top20%	log(g1/g10)	log(g1/g100)
Log Total Export Value	1								
No. of Export Flows	0.71	1							
Top 3 goods	-0.68	-0.45	1						
Top 10 goods	-0.75	-0.54	0.96	1					
Top 1%	0.53	0.27	0.12	0.02	1				
Top 10%	0.65	0.27	-0.11	-0.15	0.8	1			
Top 20%	0.67	0.29	-0.17	-0.21	0.72	0.98	1		
log(good1/good10)	-0.51	-0.4	0.9	0.8	0.26	-0.02	-0.08	1	
log(good1/good100)	-0.56	-0.48	0.93	0.94	0.17	0.09	0.03	0.82	1

Notes: 151 observations (countries). Lvalue is the log of total export value. No. of Export Flows is the number of nonzero product-destination categories a country exports. Top 3 goods (Top3) is the export value of the largest 3 bilateral product-destination export flows from a country; similarly for Top 10 goods. Top 1% (Top1%) is the export value of the largest 1% of bilateral product-destination export flows from a country; similarly for 10% and 20%. log(good1/good10) is the log of the ratio of the largets bilateral product-destination export flow to the 10th largest; similarly for 100. Source: U.N. Comtrade and authors calculations.

Table 5: Export Success and Concentration

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Share of manufacturing export value accounted for by:						
Dependent Variable:	Top3	Top10	Top1%	Top10%	Top20%	log(g1/g10)	log(g1/g100)
logn	-0.145***	-0.182***	-0.056***	-0.037***	-0.022***	-0.531***	-1.373***
	(8.67)	(13.57)	(3.00)	(4.81)	(5.72)	(5.24)	(7.20)
Log Total Export Value	0.049***	0.058***	0.057***	0.038***	0.023***	0.183***	0.556***
	(4.73)	(6.52)	(4.84)	(7.10)	(8.07)	(2.97)	(4.81)
Observations	151	151	151	151	151	151	144
R-squared	0.69	0.81	0.35	0.52	0.55	0.4	0.66

Notes: The dependent variable changes in each column. Top3 is the export value of the largest 3 bilateral export flows from a country; similarly for Top10. Top1% is the export value of the largest 1% of bilateral export flows from a country; similarly for 10% and 20%. log(g1/g10) is the log of the ratio of the largets bilateral export flow to the 10th largest; similarly for 100. logn is the log of number of destinations a country exports to. Source: U.N. Comtrade and authors calculations. Robust *t* statistics in parentheses. *** significant at 1%. A constant was included but is not reported.

Table 6: Variance Decomposition

	Unweighted		Weighted	
Percent variance due to:	Technology	Demand	Technology	Demand
Minimum	9	91	10	90
Median	71	29	68	32
Mean	69	31	66	34
Maximum	97	3	97	3

Notes: 151 observations (countries). Variance decomposition into the part of the variance due to technology (Pareto, λ) and due to demand (log normal). Minimum, median, average and maximum refer to the percent of vatiation due to technology across countries. Unweighted denotes calculation without weights. Weighted denotes calculation that uses the number of observations per destination as weights.

Table 7: Correlates of Variance Contribution of Technology

	(1)	(2)	(3)	(4)
	Dependent Variable: Percent Variance due to Technology			
Log GDP	-2.534***			
	(-4.055)			
Log Export Flows		-2.365***	-2.338**	-3.756***
		(-2.885)	(-2.411)	(-4.019)
Log GDP per capita				3.342***
				(2.723)
Observations	135	151	135	135
R-squared	0.123	0.101	0.094	0.132

Notes: Export Flows is the number of product-destination categories that a country exports. GDP is corrected for PPP. The sample in column (3) is restricted to the sample in columns (1) and (4). Source: World Bank World Development Indicators and author calculations. Robust t statistics in parentheses. *** and ** significant at 1% and 5%, respectively. A constant was included but is not reported.

Table A1: Concentration Ratios for Export Goods by Country (Part 1 of 2)

Exporter	Top 3	Top 10	Top 1%	Top 10%	Top 20%	Bottom 50%	N
Albania	50	67	62	90	95	0.68	667
Algeria	28	56	53	95	99	0.12	821
Andorra	19	46	43	88	95	0.7	824
Anguilla	36	72	36	86	95	0.73	219
Antigua and Barbuda	36	52	52	87	94	0.85	965
Argentina	18	35	49	87	95	0.49	2578
Armenia	42	60	57	86	94	0.91	714
Australia	16	34	48	81	91	1.4	2840
Austria	8	18	31	76	89	1.33	2765
Azerbaijan	40	62	60	93	97	0.36	828
Bahamas	31	50	52	90	97	0.21	1086
Bahrain	53	80	77	98	99	0.1	851
Bangladesh	27	56	41	89	97	0.28	490
Barbados	29	53	58	93	98	0.23	1218
Belarus	21	36	50	86	94	0.66	2240
Belgium	15	22	34	76	88	1.73	2902
Belize	74	86	78	94	98	0.27	322
Benin	26	54	20	73	86	2.75	174
Bolivia	57	71	71	93	97	0.28	969
Botswana	26	45	58	93	97	0.34	1930
Brazil	20	34	47	84	93	0.65	2690
Bulgaria	7	19	34	83	94	0.61	2495
Burkina Faso	24	48	35	83	94	0.75	486
Burundi	90	99	68	90	95	1.03	25
Cambodia	41	65	55	94	98	0.11	507
Canada	27	42	56	86	94	0.66	2856
Cape Verde	50	72	64	93	97	0.36	575
Central African Rep.	29	60	20	66	83	3.19	128
Chile	36	49	60	91	97	0.32	2127
China	7	16	30	75	87	1.96	2928
Colombia	16	30	43	85	95	0.43	2235
Comoros	85	94	69	91	95	1.16	52
Cook Isds	80	99	43	72	80	6.41	14
Costa Rica	57	70	77	97	99	0.1	1706
Cote d'Ivoire	20	38	46	91	97	0.33	1321
Croatia	22	35	48	88	95	0.46	2302
Cuba	43	64	60	91	97	0.24	774
Cyprus	30	45	50	89	95	0.62	1471
Czech Rep.	11	22	35	76	89	1.4	2894
Denmark	9	19	33	77	90	1.09	2733
Dominica	68	92	68	97	99	0.16	264
Ecuador	24	42	39	89	96	0.5	893
Egypt	38	57	59	94	98	0.24	1075
El Salvador	14	30	39	88	96	0.47	1530
Estonia	40	49	58	88	95	0.61	2337
Ethiopia	81	93	73	88	94	0.86	52
Fiji	44	63	63	94	98	0.27	976
Finland	30	45	56	89	96	0.31	2757
France	11	24	40	75	87	2.26	2867
French Polynesia	45	75	65	92	96	0.57	544
Gabon	24	43	36	80	91	1.47	602
Gambia	70	87	64	89	94	1.12	127
Georgia	37	59	57	91	96	0.43	878
Germany	13	24	34	70	84	2.83	2890
Ghana	41	60	57	90	96	0.49	707
Greece	14	29	44	85	93	0.75	2445
Greenland	53	81	53	90	95	1.09	236
Grenada	86	93	86	97	99	0.1	285
Guatemala	19	35	48	90	96	0.37	1960
Guinea	95	98	92	99	99	0.08	145
Guyana	38	66	61	94	98	0.2	707
Honduras	51	69	69	95	98	0.12	962
Hong Kong	11	22	38	83	93	0.81	2813
Hungary	22	40	51	85	93	0.78	2236
Iceland	31	61	61	95	98	0.22	959
India	9	22	38	79	90	1.55	2855
Indonesia	11	24	38	83	94	0.58	2645
Iran	44	54	60	89	96	0.33	1535
Ireland	28	60	75	96	99	0.12	2467
Israel	26	42	54	91	97	0.26	1860
Italy	5	13	27	68	82	2.94	2915
Jamaica	52	76	74	95	98	0.2	839
Japan	16	28	43	83	93	0.74	2900
Jordan	17	32	40	81	90	1.71	1803
Kazakhstan	21	42	51	88	95	0.57	1513
Kenya	18	35	46	90	96	0.47	1652
Kuwait	66	83	83	97	99	0.17	906
Kyrgyzstan	25	46	48	87	95	0.76	1032
Latvia	16	30	42	84	94	0.65	2097

Table A1: Concentration Ratios for Export Products by Country (Part 2 of 2)

Exporter	Top 3	Top 10	Top 1%	Top 10%	Top 20%	Bottom 50%	N
Lebanon	14	28	37	80	90	1.39	1681
Lesotho	54	85	46	87	96	0.16	103
Lithuania	13	28	44	87	94	0.63	2416
Luxembourg	17	36	53	94	98	0.19	2194
Macao	20	44	53	96	99	0.08	1306
Madagascar	44	71	69	96	99	0.08	875
Malaysia	32	50	69	93	97	0.33	2703
Maldives	72	94	32	77	91	1.66	39
Mali	17	42	22	77	90	1.12	353
Malta	74	82	84	98	99	0.06	1249
Mauritius	54	76	81	98	99	0.1	1546
Mexico	16	31	50	88	95	0.38	2877
Mongolia	45	73	60	92	97	0.13	406
Montserrat	47	73	40	80	91	1.77	131
Morocco	22	44	55	93	98	0.1	1632
Mozambique	20	41	33	82	93	0.68	635
Namibia	59	70	76	93	97	0.35	1993
Nepal	50	75	50	88	95	0.35	228
Netherlands	14	30	44	78	89	1.5	2827
New Caledonia	22	40	38	83	92	1.44	845
New Zealand	17	29	44	83	93	0.91	2503
Nicaragua	29	52	43	88	95	0.67	699
Niger	57	73	73	94	98	0.13	909
Nigeria	53	79	46	89	95	0.59	160
Norway	9	22	39	85	94	0.6	2568
Oman	32	56	54	90	96	0.45	820
Panama	28	60	33	87	95	0.72	355
Papua New Guinea	48	75	62	95	98	0.22	437
Paraguay	30	54	35	79	91	1.3	323
Peru	38	54	64	93	98	0.23	1907
Philippines	55	73	79	96	99	0.1	1800
Poland	12	27	37	75	88	2.16	2249
Portugal	15	32	48	87	95	0.46	2592
Qatar	65	82	77	96	98	0.27	646
Rep. of Korea	26	44	57	88	95	0.61	2809
Rep. of Moldova	41	54	56	91	97	0.29	1158
Romania	11	24	38	86	95	0.53	2175
Russian Federation	12	25	41	83	93	0.7	2785
Saint Kitts and Nevis	73	90	77	97	99	0.2	337
Saint Lucia	58	84	70	96	98	0.27	468
Saint Vincent and the Grenadines	50	69	58	90	96	0.67	449
Sao Tome and Principe	64	91	38	71	83	2.22	32
Saudi Arabia	32	55	69	95	98	0.27	2100
Senegal	26	44	40	86	94	0.57	772
Serbia and Montenegro	10	21	31	79	91	1.22	1890
Singapore	31	53	66	91	96	0.57	2897
Slovakia	27	37	48	86	95	0.42	2641
Slovenia	16	26	41	82	93	0.5	2574
South Africa	23	33	46	82	91	1.3	2881
Spain	19	33	45	78	88	1.73	2920
Sudan	78	86	78	94	98	0.03	278
Suriname	26	48	33	82	93	0.75	426
Swaziland	54	73	84	97	99	0.11	1871
Sweden	19	33	43	80	91	0.82	2853
Switzerland	12	22	34	78	91	0.8	2945
TFYR of Macedonia	17	33	43	90	97	0.28	1601
Tanzania	27	59	39	90	96	0.43	458
Thailand	22	36	49	87	95	0.39	2702
Togo	49	75	49	88	95	0.79	261
Trinidad and Tobago	61	73	78	96	99	0.16	1724
Tunisia	20	40	51	89	96	0.25	1682
Turkey	14	28	44	85	94	0.62	2742
Turkmenistan	53	81	53	95	98	0.1	260
Turks and Caicos Isds	31	53	31	78	90	1.05	275
USA	14	25	40	75	86	2.63	2950
Uganda	29	49	33	78	90	1.5	372
Ukraine	12	24	36	82	93	0.65	2309
United Kingdom	10	26	42	76	87	2.37	2900
Uruguay	18	35	38	86	95	0.44	1118
Venezuela	16	36	51	91	97	0.36	1876
Zambia	53	72	70	95	98	0.12	864
Zimbabwe	20	37	46	86	95	0.61	1851
Minimum	5	13	20	66	80	0.03	-
Mean	34	52	52	87	94	1	-
Median	28	49	49	88	95	0.57	-
Maximum	95	99	92	99	99	6.41	-

Notes: Top 3 is the share of the largest 3 export categories. Top 10 is the share of the largest 10 export categories. Top #% is the share of the # percent largest export categories. Bottom 50% is the share of the 50% smallest export categories. N is the total number of export categories.

Table A2: Concentration Ratios for Export Product-Destinations by Country and Destination (Part 1 of 2)

Exporter	Top 3	Top 10	Top 1%	Top 10%	Top 20%	Bottom 50%
Albania	46	61	60	89	95	0.01
Algeria	15	39	37	90	97	0.01
Andorra	12	32	30	80	90	0.02
Anguilla	31	64	23	74	88	0.03
Antigua and Barbuda	32	45	49	81	89	0.03
Argentina	14	24	59	91	96	0.01
Armenia	34	51	51	83	91	0.02
Australia	7	15	59	89	95	0.01
Austria	4	8	56	90	96	0.00
Azerbaijan	30	48	51	87	94	0.01
Bahamas	23	41	49	89	96	0.00
Bahrain	24	44	48	87	95	0.01
Bangladesh	12	25	45	89	95	0.01
Barbados	13	28	47	85	92	0.02
Belarus	10	22	56	91	97	0.00
Belgium	4	9	57	92	97	0.00
Belize	72	85	72	92	96	0.01
Benin	22	41	22	62	78	0.05
Bolivia	56	66	70	91	96	0.01
Botswana	25	38	50	88	94	0.01
Brazil	11	20	63	91	96	0.00
Bulgaria	5	11	45	86	94	0.01
Burkina Faso	19	33	30	73	86	0.03
Burundi	91	100	68	68	81	0.06
Cambodia	32	52	61	95	98	0.00
Canada	27	40	82	98	99	0.00
Cape Verde	46	70	53	88	95	0.01
Central African Rep.	27	49	20	58	76	0.06
Chile	12	24	60	90	96	0.01
China	3	7	62	92	97	0.00
Colombia	5	11	65	94	98	0.00
Comoros	12	27	54	92	97	0.00
Cook Isds	14	20	49	87	94	0.01
Costa Rica	93	100	47	82	93	0.04
Cote d'Ivoire	81	99	43	72	81	0.10
Croatia	41	56	77	95	98	0.00
Cuba	8	16	35	81	91	0.01
Cyprus	12	21	55	89	96	0.01
Czech Rep.	20	36	38	81	91	0.02
Denmark	21	29	49	85	92	0.02
Dominica	4	9	57	91	96	0.00
Ecuador	3	7	46	86	94	0.01
Egypt	33	61	38	87	94	0.01
El Salvador	18	31	47	86	94	0.01
Estonia	30	41	61	90	95	0.01
Ethiopia	6	16	34	81	92	0.01
Fiji	30	41	61	90	96	0.01
Finland	77	90	38	87	94	0.02
France	34	58	69	94	97	0.01
French Polynesia	7	15	60	91	96	0.00
Gabon	3	7	61	91	96	0.00
Gambia	23	60	51	90	95	0.01
Georgia	18	34	34	74	86	0.04
Germany	68	82	63	85	90	0.03
Ghana	24	39	45	87	94	0.01
Greece	4	9	54	90	96	0.00
Greenland	34	51	54	85	92	0.02
Grenada	6	14	50	86	94	0.01
Guatemala	53	81	40	86	93	0.02
Guinea	60	90	60	96	98	0.00
Guyana	10	19	40	85	93	0.01
Honduras	86	97	76	98	99	0.00
Hong Kong	35	58	51	88	94	0.01
Hungary	36	58	60	90	95	0.01
Iceland	16	26	68	94	98	0.00
India	21	36	49	85	94	0.01
Indonesia	3	8	50	86	93	0.01
Iran	5	12	56	90	96	0.01
Ireland	22	35	59	90	95	0.01
Israel	11	22	74	96	99	0.00
Italy	10	21	59	91	96	0.01
Jamaica	1	3	51	87	95	0.01
Japan	51	68	77	93	96	0.01
Jordan	9	14	64	93	98	0.00
Kazakhstan	16	32	50	87	94	0.01
Kenya	13	23	41	83	92	0.02
Kuwait	21	41	71	95	98	0.00
Kyrgyzstan	13	28	34	81	92	0.02
Latvia	6	15	41	84	93	0.01

Table A2: Concentration Ratios for Export Product-Destinations by Country and Destination (Part 1 of 2)

Exporter	Top 3	Top 10	Top 1%	Top 10%	Top 20%	Bottom 50%
Lebanon	6	14	42	79	88	2.59
Lesotho	50	83	42	85	95	0.42
Lithuania	10	18	50	87	94	0.98
Luxembourg	5	13	52	92	97	0.45
Macao	24	46	56	92	97	0.50
Madagascar	18	41	50	88	95	0.60
Malaysia	14	25	74	95	98	0.28
Maldives	69	91	32	83	94	0.84
Mali	13	34	21	68	83	3.43
Malta	51	68	81	97	99	0.24
Mauritius	27	51	71	95	98	0.34
Mexico	14	28	85	99	100	0.06
Mongolia	37	63	50	87	95	0.63
Montserrat	41	66	25	66	81	5.26
Morocco	15	26	57	93	98	0.28
Mozambique	14	31	25	75	87	2.72
Namibia	51	64	73	92	96	0.92
Nepal	36	58	63	94	98	0.40
Netherlands	4	9	60	92	97	0.39
New Caledonia	22	38	38	77	87	3.76
New Zealand	9	16	58	91	96	0.73
Nicaragua	14	33	31	81	90	2.19
Niger	54	70	70	89	94	1.28
Nigeria	41	72	32	87	94	1.05
Norway	3	9	51	88	95	0.66
Oman	17	34	52	87	94	1.00
Panama	23	39	35	78	89	2.09
Papua New Guinea	37	63	42	90	95	1.08
Paraguay	20	38	34	76	88	2.23
Peru	32	42	62	89	95	0.84
Philippines	18	38	81	97	99	0.17
Poland	6	14	42	77	87	3.64
Portugal	7	15	61	92	97	0.41
Qatar	18	40	56	93	97	0.46
Rep. of Korea	10	20	68	94	97	0.30
Rep. of Moldova	33	45	53	88	94	0.94
Romania	6	13	53	90	96	0.50
Russian Federation	6	14	58	92	97	0.43
Saint Kitts and Nevis	73	86	73	93	97	0.91
Saint Lucia	41	68	51	91	95	1.31
Saint Vincent and the Grenadines	46	62	53	82	90	2.34
Sao Tome and Principe	66	93	39	53	72	14.48
Saudi Arabia	62	82	71	96	98	0.30
Senegal	15	28	35	77	88	2.25
Serbia and Montenegro	6	13	35	78	90	1.73
Singapore	10	21	76	95	98	0.21
Slovakia	12	21	57	90	96	0.47
Slovenia	8	14	49	87	94	0.74
South Africa	10	19	62	90	96	0.45
Spain	6	13	62	91	96	0.56
Sudan	62	80	62	91	95	0.78
Suriname	21	40	25	68	83	4.19
Swaziland	22	48	61	95	98	0.37
Sweden	3	7	53	89	96	0.44
Switzerland	3	6	54	90	96	0.39
TFYR of Macedonia	13	23	41	86	94	0.94
Tanzania	8	15	66	94	98	0.32
Thailand	32	51	39	80	90	2.56
Togo	38	57	72	92	96	0.81
Trinidad and Tobago	10	21	50	91	97	0.43
Tunisia	5	11	62	91	96	0.60
Turkey	47	73	47	88	94	0.82
Turkmenistan	31	53	26	68	82	4.27
Turks and Caicos Isds	3	7	66	93	97	0.33
USA	22	36	29	69	82	4.57
Uganda	7	16	50	88	95	0.63
Ukraine	3	8	62	91	96	0.45
United Kingdom	18	44	27	78	90	1.89
Uruguay	15	31	45	84	93	1.06
Venezuela	15	27	52	89	95	0.83
Zambia	31	63	65	93	97	0.62
Zimbabwe	11	24	46	84	92	1.65
Minimum	1	3	20	53	72	0.06
Mean	24	38	52	87	94	1.37
Median	18	34	52	89	95	0.83
Maximum	93	100	85	99	100	14.48

Notes: Top 3 is the share of the largest 3 export flows by product-destination. Top 10 is the share of the largest 10 export flows by product-destination. Top #% is the share of the # percent largest export flows by product-destination. Bottom 50% is the share of the 50% smallest export flows by product-destination.

Table A3: Estimates of Pareto Coefficient

Exporter	Lambda	Exporter	Lambda	Exporter	Lambda
Albania	0.635	France	0.828	Nicaragua	0.576
Algeria	0.459	French Polynesia	0.601	Niger	0.701
Andorra	0.623	Gabon	0.762	Nigeria	0.525
Anguilla	0.598	Gambia	0.947	Norway	0.626
Antigua and Barbuda	0.604	Georgia	0.569	Oman	0.685
Argentina	0.592	Germany	1.197	Panama	0.79
Armenia	0.759	Ghana	0.658	Papua New Guinea	0.594
Australia	0.731	Greece	0.67	Paraguay	0.811
Austria	0.803	Greenland	0.559	Peru	0.582
Azerbaijan	0.595	Grenada	0.566	Philippines	0.557
Bahamas	0.478	Guatemala	0.569	Poland	0.686
Bahrain	0.557	Guinea	0.679	Portugal	0.68
Bangladesh	0.668	Guyana	0.535	Qatar	0.509
Barbados	0.554	Honduras	0.615	Rep. of Korea	0.579
Belarus	0.573	Hungary	0.62	Rep. of Moldova	0.607
Belgium	0.814	Iceland	0.468	Romania	0.615
Belize	0.601	India	0.806	Russian Federation	0.556
Benin	2.028	Indonesia	0.651	Saint Kitts and Nevis	0.631
Bolivia	0.616	Iran	0.605	Saint Lucia	0.529
Botswana	0.531	Ireland	0.473	Saint Vincent and the Grenadines	0.589
Brazil	0.716	Israel	0.645	Sao Tome and Principe	1.071
Bulgaria	0.658	Italy	1.131	Saudi Arabia	0.526
Burkina Faso	0.608	Jamaica	0.652	Senegal	0.745
Burundi	2.928	Japan	0.696	Serbia and Montenegro	0.909
Cote d'Ivoire	0.634	Kazakhstan	0.588	Singapore	0.583
Cambodia	0.609	Kenya	0.569	Slovakia	0.611
Canada	0.681	Kuwait	0.527	Slovenia	0.801
Cape Verde	0.488	Kyrgyzstan	0.63	South Africa	0.709
Central African Rep.	1.365	Latvia	0.637	Spain	0.793
Chile	0.584	Lebanon	0.813	Sudan	0.757
China	0.846	Lesotho	0.561	Suriname	0.63
China, Hong Kong SAR	0.668	Lithuania	0.64	Swaziland	0.514
China, Macao SAR	0.756	Luxembourg	0.469	Sweden	0.796
Colombia	0.674	Madagascar	0.494	Switzerland	0.85
Comoros	0.663	Malawi	0.552	TFYR of Macedonia	0.682
Cook Isds	1.207	Malaysia	0.539	Thailand	0.602
Costa Rica	0.502	Maldives	0.774	Togo	0.67
Croatia	0.588	Mali	1.365	Trinidad and Tobago	0.552
Cuba	0.734	Malta	0.517	Tunisia	0.635
Cyprus	0.662	Mauritius	0.548	Turkey	0.642
Czech Rep.	0.705	Mexico	0.602	Turkmenistan	0.831
Denmark	0.945	Mongolia	0.704	Turks and Caicos Isds	0.848
Dominica	0.538	Montserrat	0.644	Uganda	0.997
Ecuador	0.585	Morocco	0.558	Ukraine	0.636
Egypt	0.703	Mozambique	0.665	United Kingdom	0.836
El Salvador	0.572	Namibia	0.583	United Rep. of Tanzania	0.572
Estonia	0.587	Nepal	0.725	Uruguay	0.736
Ethiopia	1.008	Netherlands	0.799	USA	0.753
Fiji	0.7	New Caledonia	0.657	Venezuela	0.643
Finland	0.67	New Zealand	0.655	Zambia	0.561
				Zimbabwe	0.604

Estimates of $\lambda = a/(\sigma-1)$, where 'a' is the Pareto coefficient and 'σ' is the elasticity of substitution.

Table A4: Variance Decomposition (Part 1 of 2)

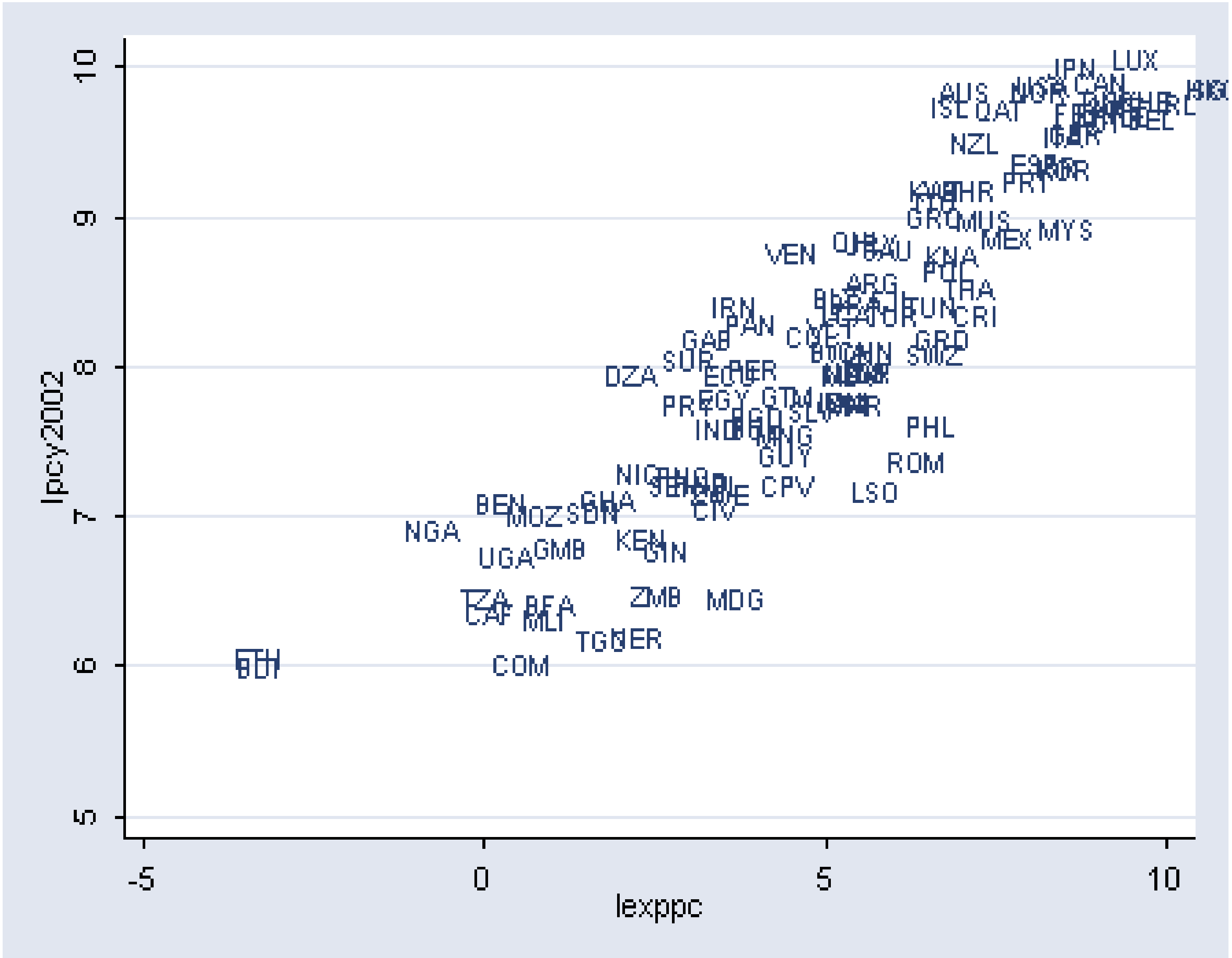
	Unweighted		Weighted	
Percent variance due to:	Technology	Demand	Technology	Demand
Exporter				
Albania	75	25	72	28
Algeria	86	14	85	15
Andorra	76	24	73	27
Anguilla	87	13	86	14
Antigua and Barbuda	94	6	93	7
Argentina	71	29	68	32
Armenia	62	38	57	43
Australia	60	40	55	45
Austria	50	50	45	55
Azerbaijan	77	23	75	25
Bahamas	83	17	81	19
Bahrain	82	18	81	19
Bangladesh	68	32	63	37
Barbados	82	18	80	20
Belarus	73	27	71	29
Belgium	50	50	46	54
Belize	81	19	79	21
Benin	20	80	16	84
Bolivia	73	27	70	30
Botswana	82	18	81	19
Brazil	58	42	54	46
Bulgaria	62	38	58	42
Burkina Faso	79	21	77	23
Burundi	9	91	10	90
Cambodia	65	35	61	39
Canada	76	24	73	27
Cape Verde	70	30	67	33
Central African Rep.	95	5	95	5
Chile	36	64	31	69
China	72	28	70	30
Colombia	50	50	46	54
Comoros	64	36	60	40
Cook Isds	56	44	51	49
Costa Rica	62	38	58	42
Cote d'Ivoire	74	26	71	29
Croatia	77	23	75	25
Cuba	84	16	83	17
Cyprus	69	31	66	34
Czech Rep.	59	41	55	45
Denmark	69	31	66	34
Dominica	58	42	54	46
Ecuador	39	61	35	65
Egypt	79	21	77	23
El Salvador	73	27	70	30
Estonia	63	37	60	40
Ethiopia	72	28	68	32
Fiji	72	28	69	31
Finland	65	35	63	37
France	72	28	69	31
French Polynesia	58	42	55	45
Gabon	50	50	46	54
Gambia	85	15	83	17
Georgia	69	31	66	34
Germany	72	28	69	31
Ghana	80	20	78	22
Greece	29	71	25	75
Greenland	72	28	69	31
Grenada	63	37	60	40
Guatemala	97	3	97	3
Guinea	82	18	81	19
Guyana	72	28	69	31
Honduras	85	15	84	16
Hong Kong	89	11	88	12
Hungary	76	24	73	27
Iceland	67	33	63	37
India	90	10	89	11
Indonesia	53	47	50	50
Iran	66	34	63	37
Ireland	72	28	69	31
Israel	87	13	86	14
Italy	65	35	61	39
Jamaica	33	67	28	72
Japan	72	28	70	30
Jordan	58	42	54	46
Kazakhstan	73	27	71	29
Kenya	80	20	78	22
Kuwait	86	14	85	15
Kyrgyzstan	72	28	69	31
Latvia	66	34	62	38

Table A4: Variance Decomposition (Part 2 of 2)

	Unweighted		Weighted	
Percent variance due to:	Technology	Demand	Technology	Demand
Exporter				
Lebanon	58	42	54	46
Lesotho	74	26	70	30
Lithuania	65	35	61	39
Luxembourg	84	16	83	17
Macao	84	16	83	17
Madagascar	75	25	72	28
Malaysia	80	20	78	22
Maldives	67	33	59	41
Mali	28	72	22	78
Malta	88	12	88	12
Mauritius	80	20	78	22
Mexico	75	25	72	28
Mongolia	63	37	58	42
Montserrat	87	13	87	13
Morocco	72	28	68	32
Mozambique	76	24	72	28
Namibia	83	17	81	19
Nepal	70	30	66	34
Netherlands	52	48	48	52
New Caledonia	83	17	82	18
New Zealand	68	32	65	35
Nicaragua	83	17	81	19
Niger	72	28	68	32
Nigeria	88	12	87	13
Norway	64	36	60	40
Oman	68	32	64	36
Panama	55	45	51	49
Papua New Guinea	77	23	75	25
Paraguay	55	45	50	50
Peru	75	25	73	27
Philippines	81	19	79	21
Poland	81	19	80	20
Portugal	63	37	58	42
Qatar	81	19	80	20
Rep. of Korea	73	27	71	29
Rep. of Moldova	72	28	69	31
Romania	64	36	60	40
Russian Federation	73	27	71	29
Saint Kitts and Nevis	86	14	84	16
Saint Lucia	93	7	93	7
Saint Vincent and the Grenadines	88	12	87	13
Sao Tome and Principe	62	38	62	38
Saudi Arabia	87	13	86	14
Senegal	59	41	55	45
Serbia and Montenegro	44	56	38	62
Singapore	75	25	73	27
Slovakia	65	35	62	38
Slovenia	47	53	43	57
South Africa	59	41	56	44
Spain	54	46	50	50
Sudan	71	29	67	33
Suriname	79	21	77	23
Swaziland	81	19	80	20
Sweden	49	51	44	56
Switzerland	43	57	38	62
TFYR of Macedonia	60	40	56	44
Tanzania	70	30	67	33
Thailand	77	23	74	26
Togo	82	18	81	19
Trinidad and Tobago	65	35	60	40
Tunisia	66	34	63	37
Turkey	60	40	57	43
Turkmenistan	59	41	51	49
Turks and Caicos Isds	54	46	47	53
USA	64	36	61	39
Uganda	51	49	47	53
Ukraine	80	20	79	21
United Kingdom	58	42	52	48
Uruguay	59	41	54	46
Venezuela	67	33	63	37
Zambia	80	20	78	22
Zimbabwe	75	25	73	27
Minimum	9	91	10	90
Mean	71	29	68	32
Median	69	31	66	34
Maximum	97	3	97	3

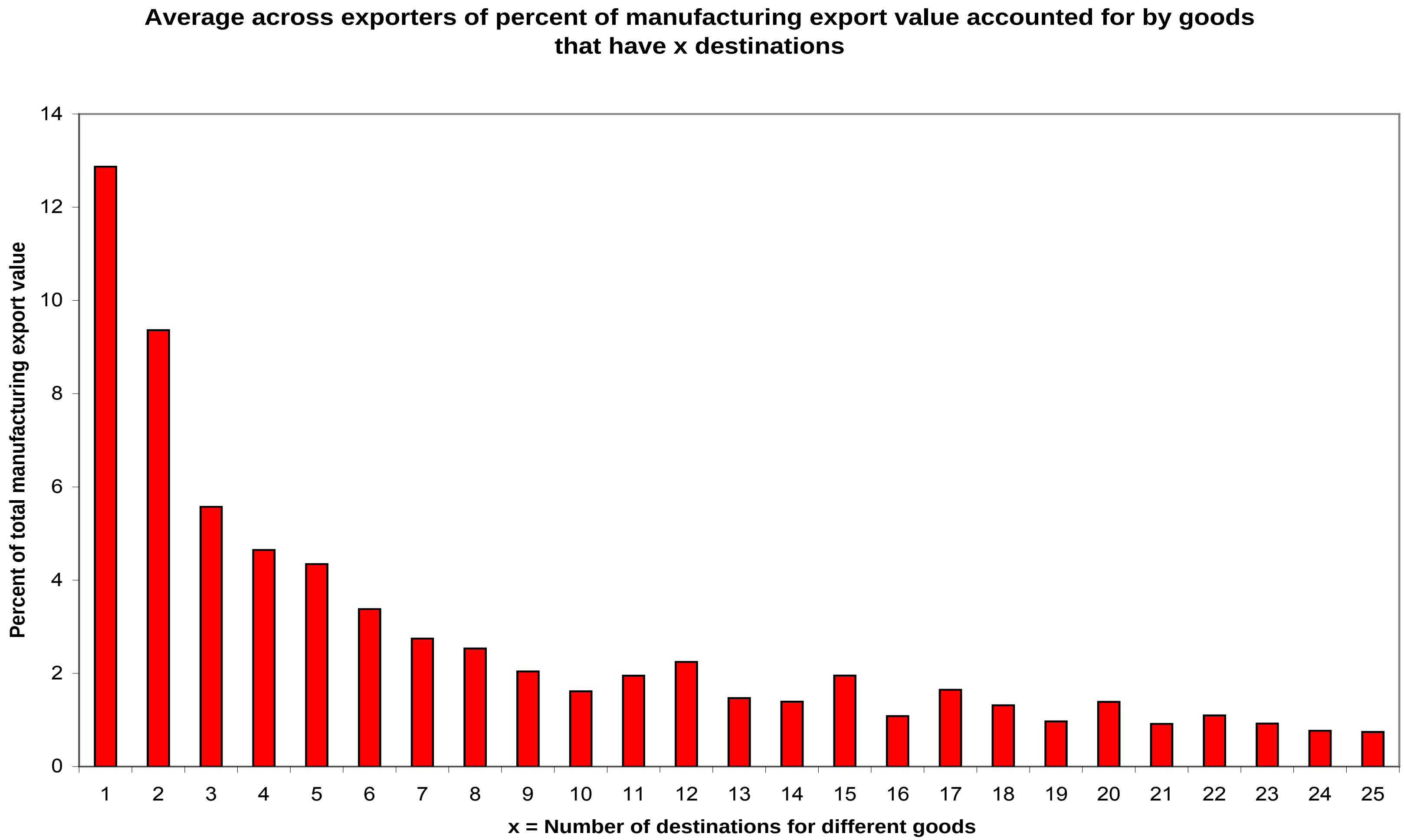
Notes: Variance decomposition into the part of the variance due to technology (Pareto, λ) and due to demand (log normal). Minimum, median, average and maximum refer to the percent of vatiation due to technology across countries. Unweighted denotes calculation without weights. Weighted denotes calculation that uses the number of observations per destination as weights.

Figure 1: Manufacturing Exports and Development



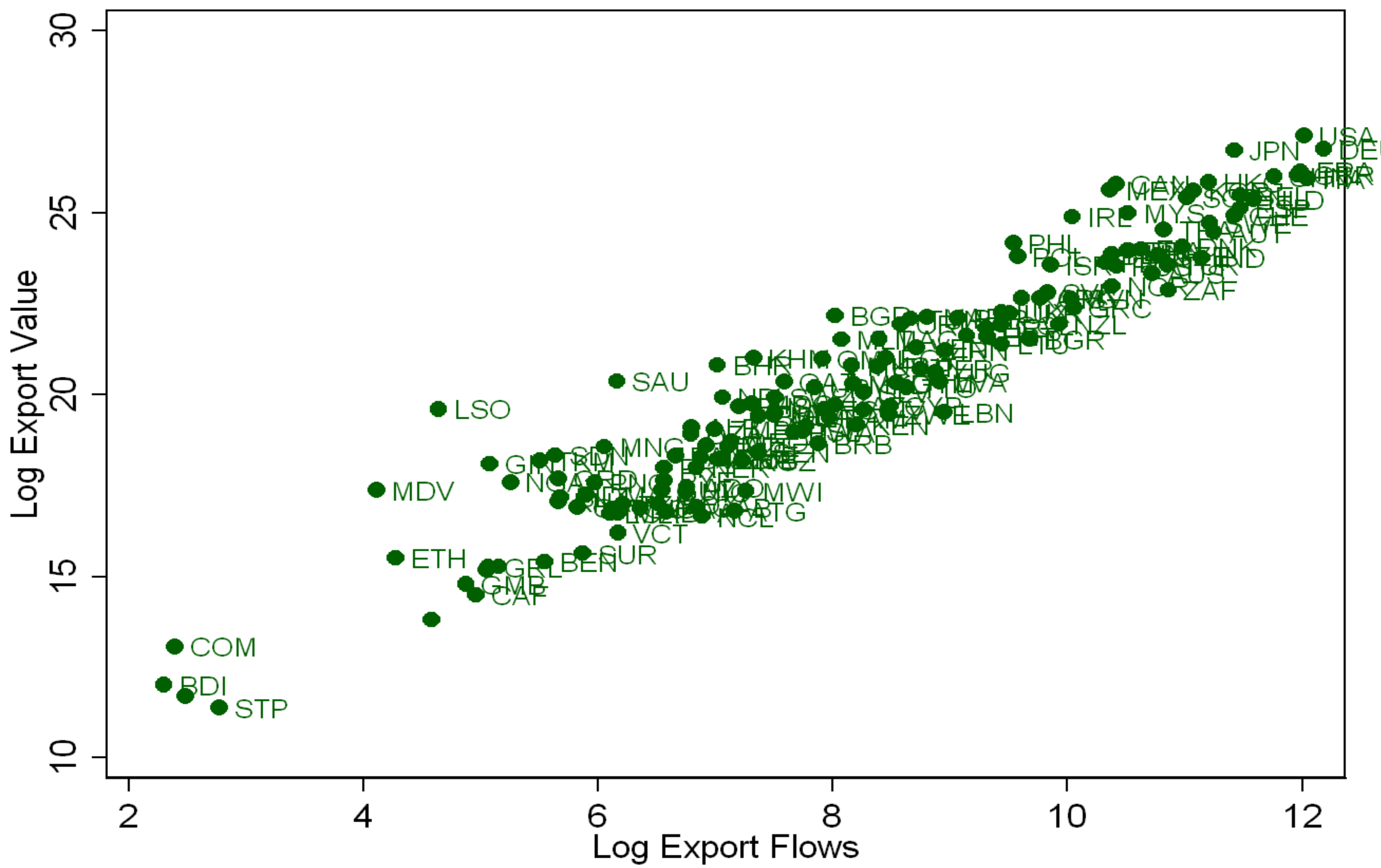
Notes: lexppc is the log of manufacturing exports per capita and lpcy2002 is the log of per capita GDP, corrected for PPP. Source: The World Bank, World Development Indicators.

Figure 2: Export Values and Destinations



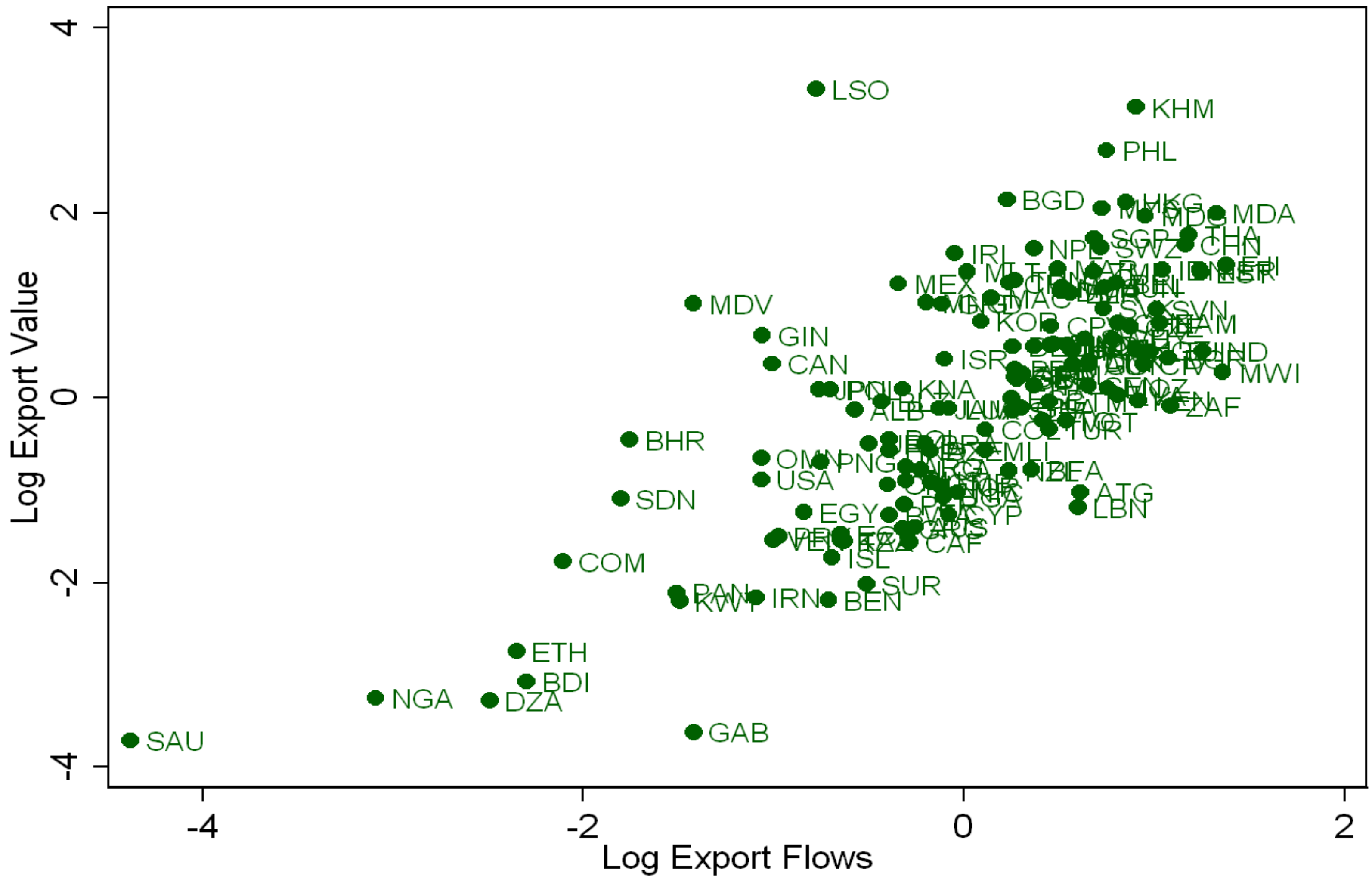
Notes: For each exporter, export values by product were assigned to bins acording to the number of destinations that product was exported to. Each bin was assigned the percent of total export value that it accounted for. The figure displays the percent of exports accounted for by products shipped to x destinations, averaged over all 151 exporters in the sample.

Figure 3: Export Success and Product-Destination Flows



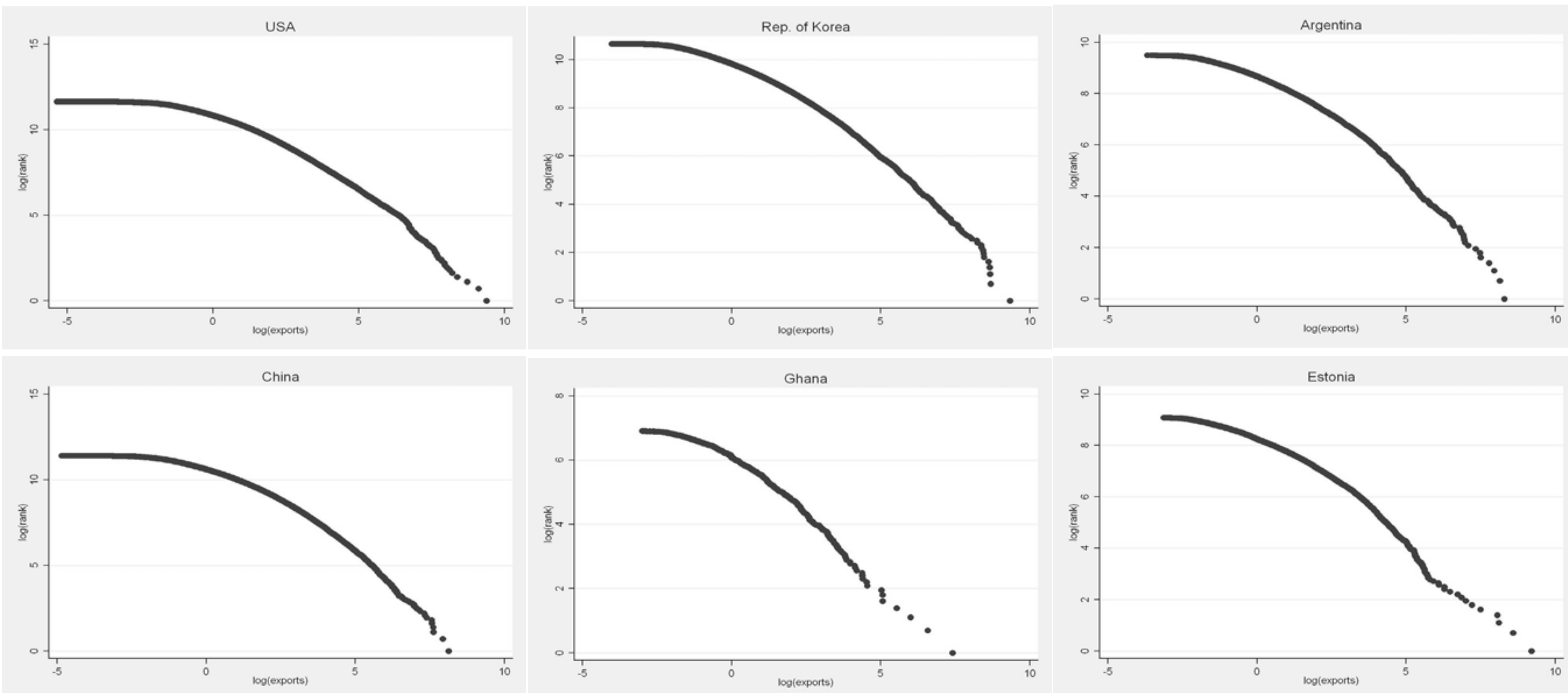
Notes: Each observation is a country. Export Flows is the number of product-destination categories that a country exports. Export Value is the log of export value that a country exports. Source: U.N., Comtrade.

Figure 4: Export Success and Product-Destination Flows, Conditional on Size and Income



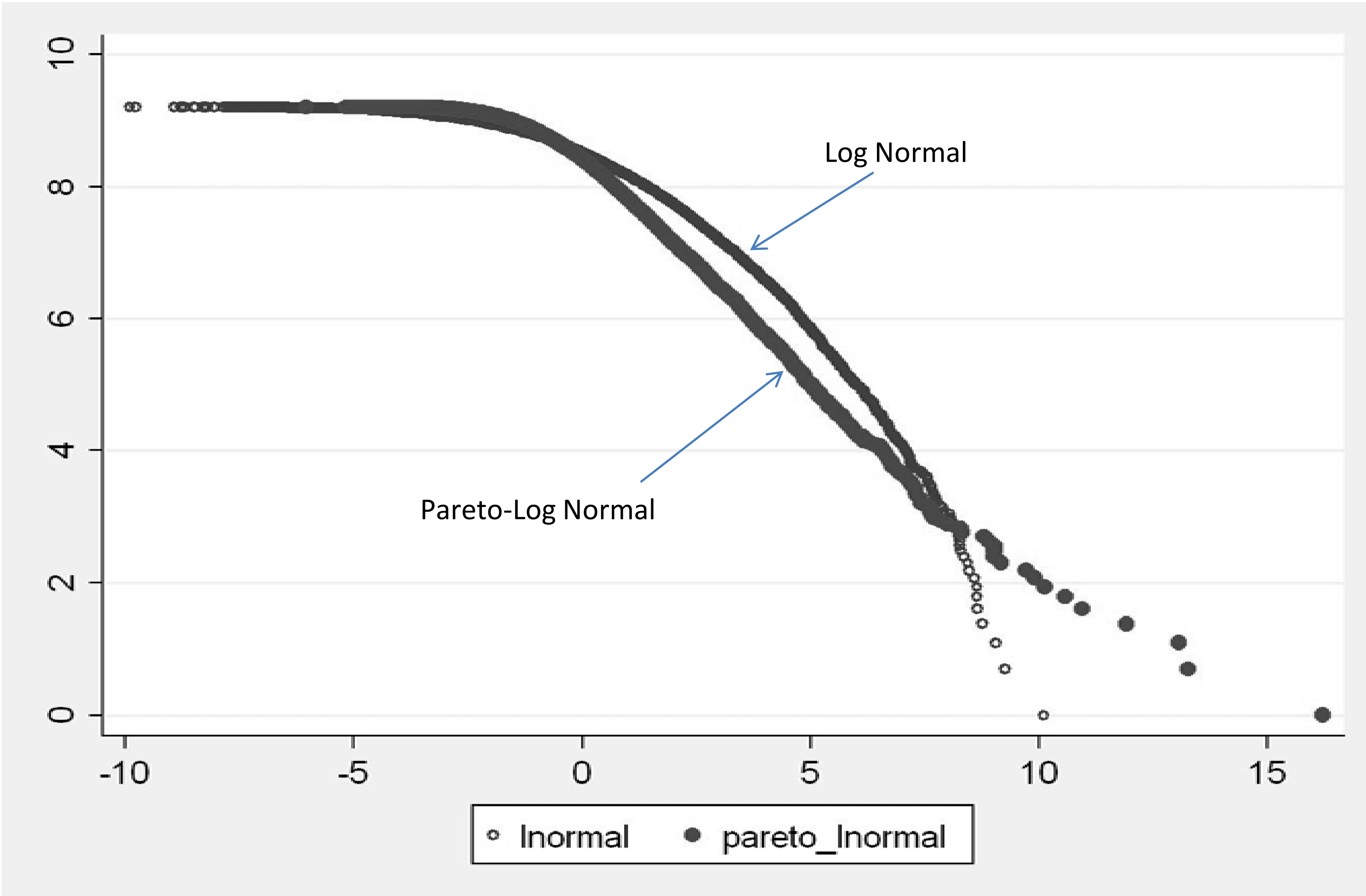
Notes: Each observation is a country. Export Flows is the number of product-destination categories that a country exports. Export Value is the log of export value that a country exports. The data are residulas from regressions on log GDP and log GDP per capita, both corrected for PPP. Source: U.N., Comtrade, World Bank, World Development Indicators.

Figure 5: Log Export Rank and Log Export Value



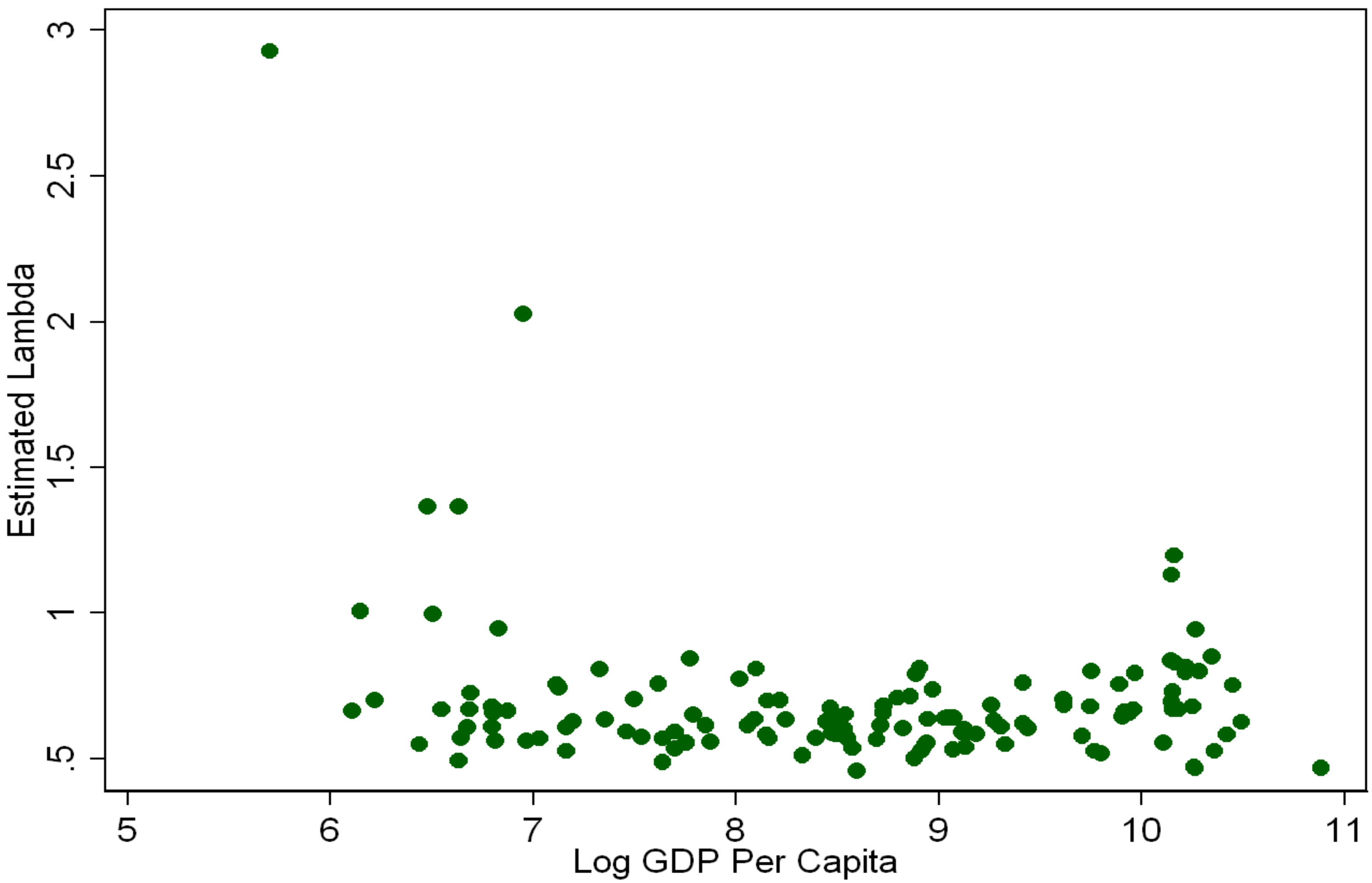
Notes: log(exports) is the log of bilateral product-destination export value. Log(rank) is the log of the rank of the product-destination export value.
Source: U.N. Comtrade.

Figure 6: Simulated Rank Graphs for Log Normal and mixed Pareto-Log Normal



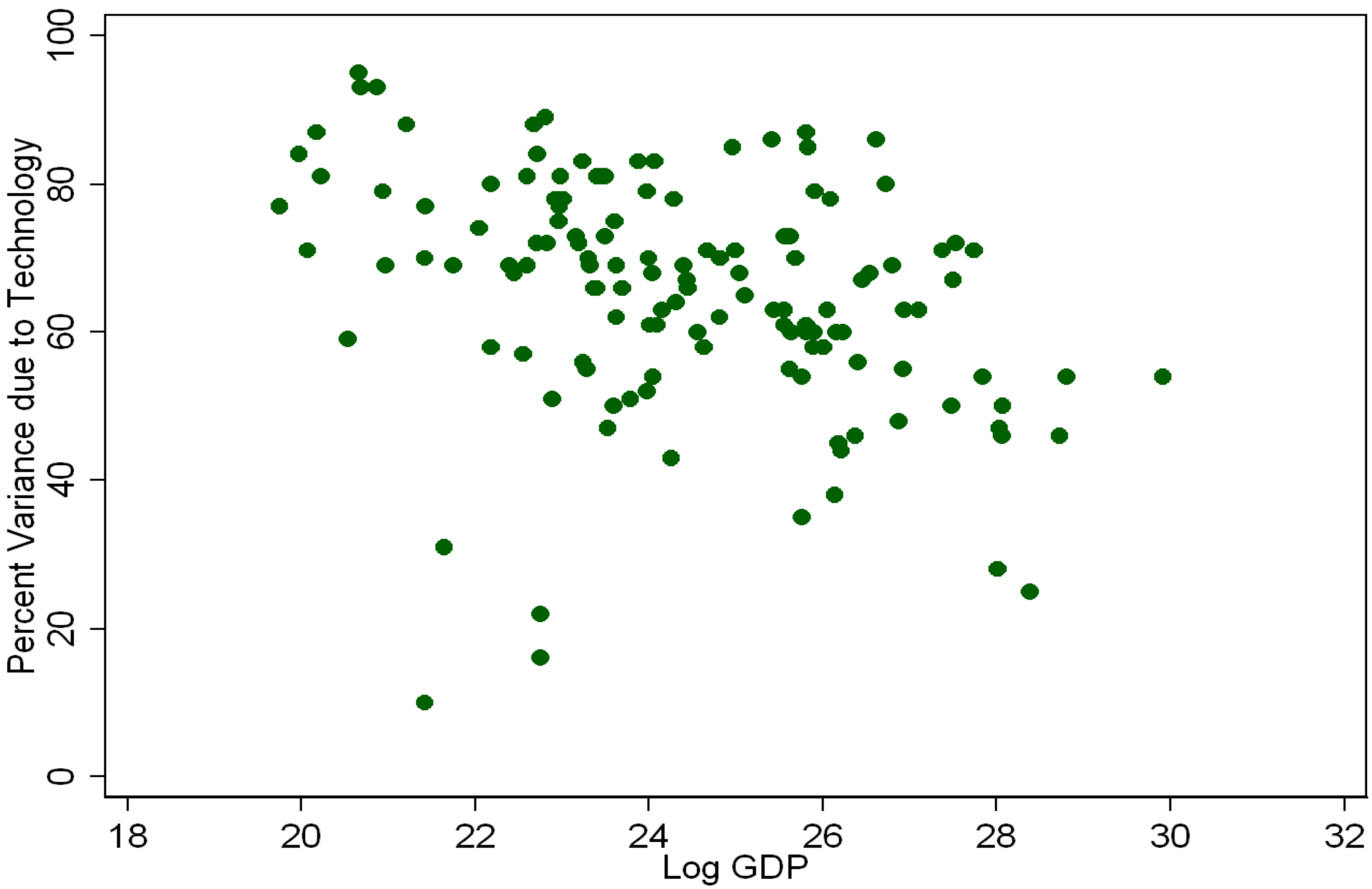
Notes: The simulation for the log normal uses the empirical standard deviation of export values averaged over all 151 countries. The distribution of the mixed Pareto-log normal is defined in the text. The simulation uses the average estimated coefficients and standard deviations for all 151 countries from the estimation results below.

Figure 7: Estimates of λ and Log GDP per Capita



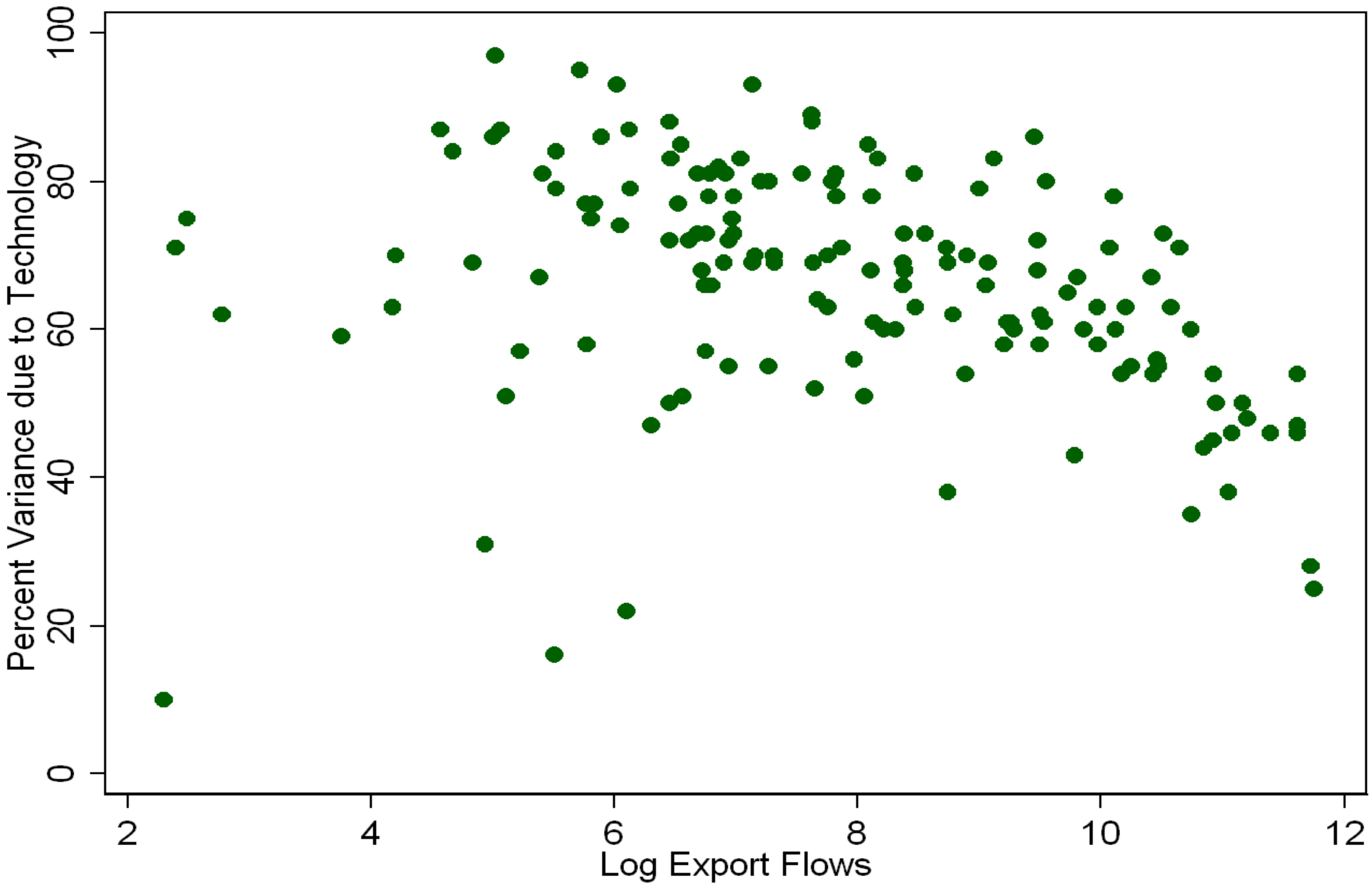
Notes: Each observation is a country. Lambda is the parameter that governs the distribution of the technological component in export revenues. GDP per capita is corrected for purchasing power parity.

Figure 8: Percent Variation due to Technology and Log GDP



Notes: Each observation is a country. Percent Variance due to Technology is the percent of variance of export values that is accounted for by productivity variation. GDP is corrected for purchasing power parity.

Figure 9: Percent Variation due to Technology and Number of Destinations



Notes: Each observation is a country. Percent Variance due to Technology is the percent of variance of export values that is accounted for by productivity variation. Export Flows is the number of product-destination categories that a country exports.