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Margins, Gravity, and Causality: Export Diversification and Income Levels Reconsidered

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Abstract

The paper shows that the relationship between GDP per capita and levels of specialization can be predicted differently depending on whether the intensive or the extensive margin is considered. It shows that at the extensive margin countries continuously diversify their exports and that cross-sectional patterns can be captured well by a gravity equation. Prior studies documenting nonmonotone patterns with respecialization appear to have obtained their results from sample-selection bias, the omitted log-transformation of the income variable, and the neglect of control variables. Furthermore, results from dynamic panel analyses (system GMM) suggest that causality goes in both directions, with income having a contemporaneous impact on diversification, while the feedback effect of diversification on GDP per capita may be delayed. This pattern fits into theoretical rationales that view diversification as driven by technology or efficiency and where diversification generates additional revenues as it proves to be persistent.

Keywords: diversification, extensive margin, international trade, technology, gravity equation

JEL classification: F11, F14, F43, O40, O11

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Article Outline

1 Introduction

The relationship between GDP per capita and levels of diversification in economic activity is expected to be positive.[1] Growth theories – for example, those of Grossman and Helpman (1991, 1993) – emphasize the role of research and development (R&D) in generating a continuous increase in the range of goods an economy can produce and sell. Countries in the early stage of economic development are not directly involved in the process of innovation at the

1 I am grateful to Erich Gundlach for his valuable suggestions and support in writing this paper. I also want to thank Michael Funke and the participants at the 16th Göttinger Workshop: Internationale Wirtschaftsbeziehungen for their comments.

technology frontier. Instead, they gradually take over new activities that they have acquired the technological knowledge to perform. For them, diversification is thus a consequence of investments in new activities, of which some prove to be fruitful and foster economic development (Acemoglu and Zilibotti 1997; Hausmann and Rodrik 2003).

It is surprising, then, that recent empirical studies have identified a pattern that suggests respecialization among economically advanced economies. Imbs and Wacziarg (2003) were the first to document such a pattern based on statistical measures of concentration in employment and production, which they correlated with GDP per capita. Their findings are drawn from nonparametric techniques and quadratic polynomials applied to panel data encompassing a heterogeneous group of countries over several decades. An almost identical pattern has been identified by Cadot, Carrère, and Strauss-Kahn (2011) for exports. Their findings suggest that respecialization holds as a general pattern as countries approach income levels that are comparable to Ireland's in the 1990s. Cadot et al. have also used nonparametric techniques (that is, locally weighted scatterplot smoothing, LOWESS) and quadratic polynomials to analyze panel data. Their specialization indices rely on much more disaggregated trade data, and they use Theil's (1972) entropy measure to identify the extensive margin as the relevant dimension where diversification and respecialization occurs.[2]

Skepticism concerning the robustness of these patterns is raised in the studies of Benedictis, Gallegati, and Tamberi (2009) and Parteka (2010). They extend the nonparametric approach by implementing country-fixed effects into their analysis and find that, depending on which measure is used, respecialization can no longer be observed. The focus of their studies, however, is the distinction of absolute diversification (as the deviation from a normal distribution) and relative diversification in comparison to other countries (Benedictis et al. 2009), and the co-movement of specialization patterns in exports and employment (Parteka 2010). Because the case of respecialization is weakened mostly for relative diversification measures, this could suggest that aggregate time-specific effects have generated Imbs and Wacziarg's and Cadot et al.'s findings.

Another problem could be that GDP per capita is the only explanatory variable that is used in the studies mentioned so far. Benedictis et al. (2009) leave this question open for future work, but Parteka and Tamberi (2013) explore numerous covariates that may potentially explain the diversification levels observed across countries. This paper follows up on their suspicion that a country's size and geography are important determinants of specialization and uses Eaton and Kortum's (2002) theoretical framework to formalize export diversification at the extensive margin. The resulting gravity equation is estimated using alternative data sets and samples that cover at least 88 countries. The results suggest that cross-sectional patterns of diversification are mainly explained by GDP per capita. Size and geography im-

2 The extensive margin refers to the range of goods a country produces or exports. It is distinguished from the intensive margin, where the range of products remains constant but relative output and factor allocations change.

prove the predictive power of the empirical model, but leaving them out does not bias the coefficient for the income variable. The interpretation of the results using Eaton and Kortum's theoretical framework suggests that richer countries export more goods because their superior production techniques endow them with an absolute advantage in global markets. Large countries can compensate for a lower level of fundamental productivity with lower factor costs. A great geographic distance to large markets – that is, remoteness – impedes diversification because the exporter has to compensate for high trade costs.[3]

In addition to highlighting the relationship of diversification to the gravity equation of a competitive multicountry model, this paper also addresses methodological issues concerning measurement and analysis using panel data. Measurement issues are addressed in the first section of the paper, where the possibilities of alternative diversification paths are discussed using Lerner (1952) diagrams. The diagrams are especially useful for distinguishing the extensive from the intensive margin – that is, predicted patterns within and across cones of specialization. When focusing on the extensive margin, the only appropriate measure should be the counted number of goods a country sells, which, naturally, requires a sufficient level of detail in the data. The scaling of variables is also important, depending on which unit of measurement is used and how it is distributed in the data. Clarifying which margin one would like to analyze makes the selection of measures less arbitrary.[4] The paper then illustrates graphically, in Section 3, how sample selection and a simple log-transformation turn the U-shaped pattern of Cadot et al.'s Theil index into a relationship with a linear negative slope. A comparable pattern with an almost linear positive slope is also obtained for the number of exported goods classified in the six-digit Harmonized System (HS6). Econometric analyses based on the gravity framework confirm the linearity of counted exported goods at different levels of aggregation.

While the gravity framework explains cross-sectional patterns well, the inclusion of country-fixed effects lets coefficients for income and geography become insignificant. The paper therefore also adopts a dynamic specification to infer the long-term relationship between GDP per capita and export diversification and to make inferences on the direction of causality. Using system GMM with alternative lag structures suggests the existence of a contemporaneous effect of GDP per capita on the number of goods a country exports. GDP per capita is revealed as weakly exogenous, and testing for reverse causality and potential feedback effects suggests that diversification levels also impact GDP per capita. Despite reassuring test statistics, these results are taken as suggestive evidence only, because the system GMM estimator can produce misleading results in the way that invalid instruments sometimes influence the usual test statistics with which their validity is inspected (Roodman

3 The role of size, distances, and remoteness for different types of trade models is discussed in Baldwin and Harrigan (2011).

4 Previous papers have used alternative measures mainly to ensure the robustness of their results. This paper's appendix suggests that measures can be chosen based on how aggregated or disaggregated the data is.

2009). The high correlation between lagged dependent variables included in the right-hand side and other regressors may raise multicollinearity issues. Nevertheless, causality in both directions is plausible: countries must achieve a certain level of efficiency to export a wider range of goods, while selling them successfully for some time increases income.

The paper begins by discussing alternative diversification scenarios that emphasize the distinction between intensive and extensive margins (Section 2). It reviews the rationales proposed by Imbs and Wacziarg and Cadot et al. and highlights the difficulty of explaining respecialization at the extensive margin as an equilibrium outcome. Section 3 presents descriptive evidence and shows how the U-shaped specialization path is dissolved in a few steps. Concerning the extensive product margin, data characteristics and their implications for econometric analysis are discussed. Section 4 then uses the Eaton and Kortum model to identify an estimation equation for diversification. In addition to GDP per capita, size and geography complement the model, which is estimated in alternative versions and focuses firstly on cross-sectional patterns. Robustness checks and specification tests present results for alternative time periods and levels of aggregation, as well as static and dynamic panel methods. Section 5 discusses the findings and concludes the paper.

2 Diversification in Classical Trade Models

Diversification paths during the process of economic development can be viewed from different perspectives. This section discusses alternative scenarios and their relation to the case of respecialization identified by Imbs and Wacziarg and Cadot et al. The discussion is guided by an analysis of the Lerner (1952) diagram, which depicts a two-factor model and allows for the identification of structural differences across countries with different capital–labor ratios. An important assumption made in this paper is that the capital–labor ratio of a country is proportional to its GDP per capita.[5] That is, income differences are reflected by different relative factor endowments. The Lerner diagrams can then be used to illustrate the distinction between the intensive and the extensive margin.

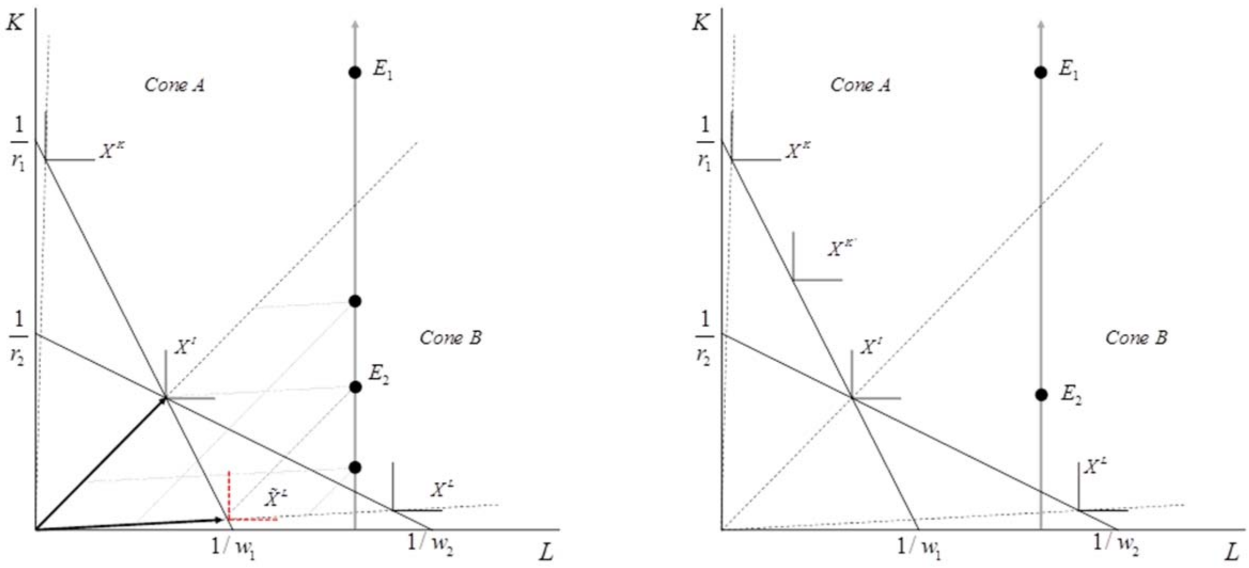
2.1 Margins, Protectionism, and Innovation

The diagrams shown in Figure 1 depict different goods $\left\{X^L, X^I, X^K\right\}$ with their unit-value isoquants. The position of the unit-value isoquants in the $K-L$ space indicates the relative input requirements of capital (K) and labor (L) to produce a value of output that equals one unit of exchange. It also confines the cone of diversification, as shown by the straight lines through the origin. Isocost lines, tangent to the unit-value isoquants, indicate the factor price ratio prevalent in the respective cone of diversification. Countries inhabiting Cone A,

5 Empirical support for this assumption is presented in most standard textbooks on growth theory.

confined by X^I and X^K, have a higher level of capital per worker than countries in Cone B, which is confined by X^L and X^I. With constant L, a country's GDP per capita is higher the farther away its endowment point is from the horizontal axis.

Figure 1: Lerner Diagrams and Diversification



(a) Both cones have two goods (b) Cone A has three goods

The three endowment points (countries) depicted in Cone B of Panel (a) rationalize a pattern of initial diversification and subsequent respecialization. Inside the cone, factor price equalization (FPE) holds and countries allocate resources so as to produce the two goods X^L and X^I. Drawing parallelograms between origin and endowment points indicates the respective output vectors for the two goods as shown for country E_2. As drawn here, E_2 produces good X^L and X^I in equal share, while the two other countries have a more concentrated production structure. Because income differences are indicated by the vertical position of the countries relative to each other, the framework suggests a U-shaped specialization path along with increasing GDP per capita. In Cone A in Panel (a), the high-income country E_1 is characterized by a different product mix consisting of X^I and X^K. The country's relative production structure can be derived in the same way as was done before, but the model does not yield predictions on the degree of specialization relative to countries inhabiting Cone B. In other words, the prediction of an inverted U-shaped diversification path is constrained to countries residing inside the same cone of diversification. Inside a cone, the model requires FPE to hold, and a constant set of products implies a diversification pattern at the intensive margin. Another implication of Panel (a) is that there is no difference in the degree of diversification at the extensive margin: at any point (inside a cone of diversification) countries produce two goods and trade one good, independent of their stage of development.

Based on this approach, Cadot et al. rationalize their identification of a nonmonotone diversification path with the assumption that countries, as they develop, travel from one cone to another while protecting the industries in which they have lost their comparative advantage. For instance, suppose that country E_1 initially resided in the low-income Cone B, where it produced X^L and X^I. As it has become rich, it has found itself in the high-income Cone A, where it can no longer produce X^L. It nevertheless continues to do so by raising the domestic price (for example, by imposing a tariff or import quota). This is shown by an inward shift of the unit-value isoquant to $\tilde{X}^L$. As also discussed in Bernard, Jensen, and Schott (2006), such protectionist measures enable the country to achieve a higher level of diversification at the extensive margin, producing X^K, and X^I, and $\tilde{X}^L$. The country respecializes in the moment when the trade barriers are removed.

The implication of such a mechanism for the general pattern described in Imbs and Wacziarg and Cadot et al. would be that almost all countries protect their traditional industries during the process of economic development, and that only very few have removed protectionist barriers. Along these lines, Rodrik (2007) raises concerns about the policy implications of increasing levels of diversification among countries that are growing out of poverty. Pro-trade policy arguments based on gains from specialization seem to lose their power if countries are observed to engage in increasing ranges of activities until they reach per capita income levels of approximately 22,000 USD (in 2005 purchasing power parity (PPP)).[6] An alternative explanation can be obtained by relaxing the assumption that cones of diversification host an equal number of goods. Theories which propose that higher income levels are reached through (local or global) innovation and product differentiation suggest a positive correlation between diversification at the extensive margin and levels of GDP per capita (Acemoglu and Zilibotti 1997; Grossman and Helpman 1991). This is shown in Panel (b) of Figure 1, where Cone A now hosts an additional good, $X^{K'}$, that can be produced only by rich countries. Diversification now conforms to gains-from-trade arguments because countries in Cone A specialize in capital-intensive goods, while countries in Cone B produce labor-intensive goods. Nevertheless, high-income countries produce a wider range of goods.

2.2 *Implications*

Imbs and Wacziarg address the implications of the scenario in Panel (b) in their discussion of the nonmonotone pattern they identify for production and employment: an inverted U-shaped diversification path contradicts standard theories.[7] Their rationalization is based on the existence of nontraded goods that become tradable at late stages of economic develop-

6 This is approximately the turning point, estimated by Cadot et al., where countries begin to respecialize.

7 Although they do not refer to the Lerner diagram or cones of diversification, they emphasize the fact that diversification requires sufficient resources in order to overcome capital indivisibilities (Acemoglu and Zilibotti 1997).

ment. That is, while the process of innovation and investment into new activities continuously expands the range of the goods produced, countries begin, at some point, to improve their infrastructure technology. This lowers the cost of trading goods and induces the relocation of their production to other countries. In countries where respecialization can be observed, the rate at which nontradable goods become tradable must be higher than the rate at which new goods are invented and produced.

It is correct to argue that an improved trade infrastructure, like trade liberalization, works as a driver of specialization. This argument is also related to an extensive literature on foreign outsourcing (see, e.g., Feenstra 2010, for an overview). The outsourcing or relocation of production might even accelerate the diversification process in those (poorer) countries that "receive" production stages and tasks through this channel.[8] However, the tradability argument is vulnerable in two respects. First, it does not bear up against the implication, stemming from a steady-state growth rate, that continuous respecialization requires the rate of trade-facilitating technological progress to permanently exceed the rate of product discovery and diversification. Unless this is the case, the pattern of respecialization identified by Imbs and Wacziarg and Cadot et al. is a temporary phenomenon during a period of global trade integration rather than a general pattern.[9] Second, permanence implies that all goods will be tradable at some point. This brings us back the scenario, depicted in Panel (b) of Figure 1, where, all other things being equal, high-income countries are strictly more diversified than low-income countries. To conclude, unless innovation comes to a halt or income differences vanish so that all countries inhabit the same cone of diversification, countries continue to diversify.

This last statement is the motivation to revisit the empirical evidence, which expects that diversification at the extensive margin increases monotonically with higher GDP per capita. The analysis in this paper concentrates on diversification in exports because the available data is more detailed than employment and production data with comparable country and time coverage. The empirical patterns and theoretical implications revealed by the analysis are assumed to carry over to production and employment.[10]

8 An example is the importance of processing trade for the increase in the skill content of China's exports (Amiti and Freund 2010).

9 Note that this is also supported by De Benedictis et al.'s (2009) and Parteka's (2010) findings of continuous diversification when they use relative measures of specialization because they incorporate time effects by construction.

10 Although Parteka (2010) finds that concentrations in production and employment do not necessarily move together, this must be the true for the extensive margin, where relative quantities are neglected and production requires at least a small unit of labor.

3 Data and Measurement Issues

This section reproduces Cadot et al.'s descriptive analysis and illustrates how their data can lead to a different conclusion about the diversification–income nexus. Methodological issues concerning scaling and measurement are discussed alongside this analysis, and a roadmap with suggestions for the econometric analysis is presented at the end of the section.

The Cadot et al. data has a panel dimension and reports export-concentration indices calculated at the country level based on detailed information from the UN Comtrade database.[11] The original data from Cadot et al. covers the years 1988 through 2006 and is used in the first part of this section. Comparable trade data from the Centre d'Études Prospectives et d'Informations Internationales, the CEPII BACI96 data set (Gaulier and Zignano 2010), covers the years from 1998 through 2009 and is used in the second part. Both data sets are also applied in the econometric analysis, with the aim of comparing results across different time periods.

3.1 Sampling and Scaling

The diversification literature uses alternative concentration measures such as the Gini, Herfindahl, or Theil (1972) indices, mainly to show that the results are robust. This subsection focuses on the Theil index because it demonstrates the best distributional properties in disaggregated export data, while its qualitative interpretation is equal to other measures.[12] Cadot et al. also used it, both to motivate a quadratic parameterization and to identify the extensive margin as the relevant dimension of diversification. Panel (a) of Figure 2 reproduces the diversification path that Cadot et al. show for the Theil index; this is indicated by the two U-shaped lines. The solid line represents the predicted pattern of a nonparametric estimation (locally weighted scatterplot smoothing; LOWESS),[13] while the broken line reproduces the prediction of a quadratic polynomial. Both lines suggest a path of initial diversification (i.e., decreasing concentration) and subsequent respecialization. The scatterplot shows the underlying sample with all its country–year observations up to an income level of 60,000 USD (PPP 2005).[14]

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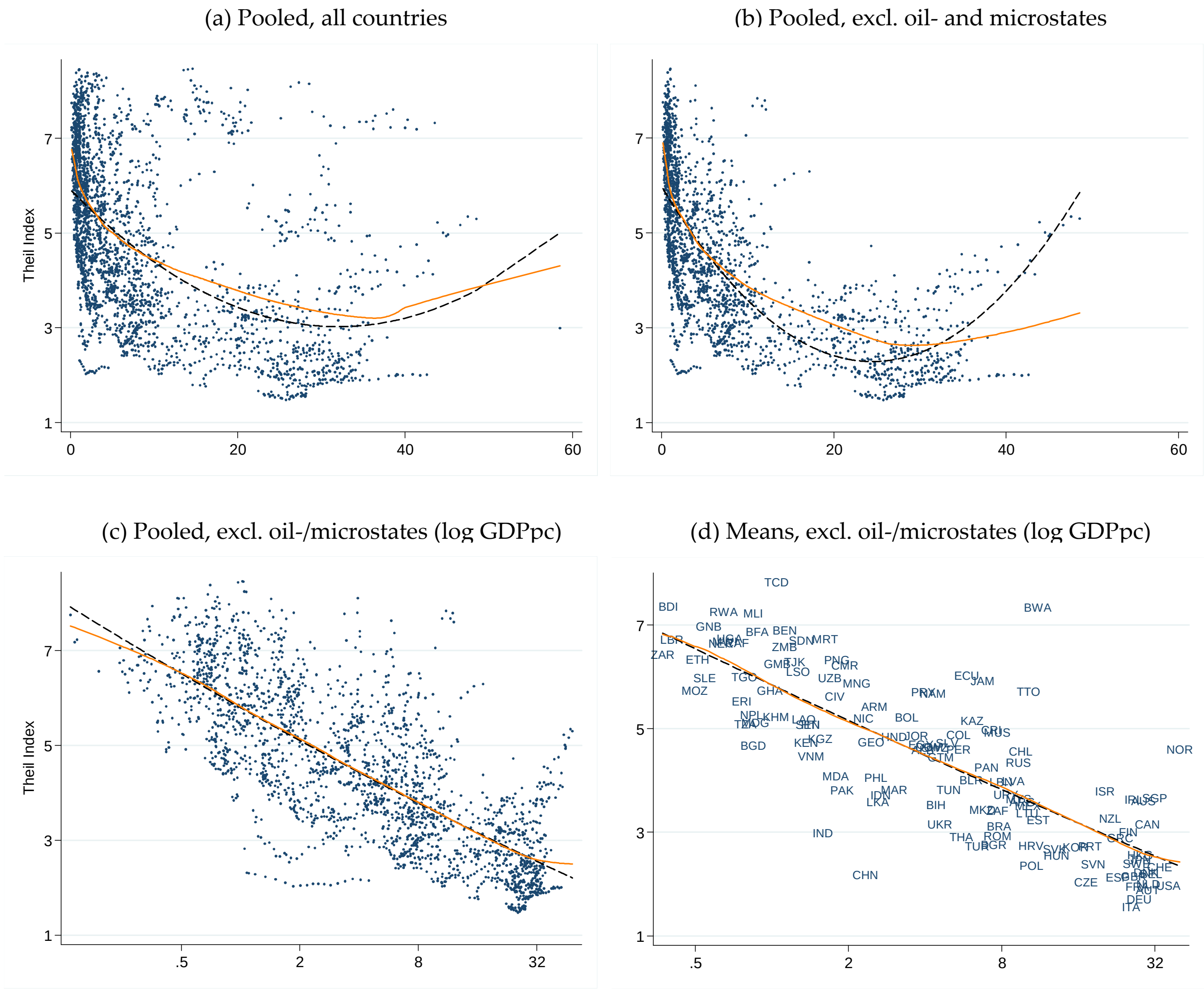
11 At the highest level of disaggregation, the UN Comtrade database reports trade flows in about five thousand product categories using six-digit codes from the Harmonized System (HS6).

12 A high index always implies high concentration and a low index always implies low concentration. See Appendix A for a discussion of the Gini, Herfindahl, and Theil indices in the present context.

13 This method is described in greater detail by Imbs and Wacziarg, who apply a modified version of it.

14 In the figure, as in Cadot et al., the sample is censored at a GDP per capita level of 60,000 USD (PPP 2005). Censoring applies only in the graphical representation of the figures, not for the estimations used to obtain predicted values. This practice follows Cadot et al. and ensures that the predicted path shown here looks the same as theirs.

Figure 2: Theil Index and GDP Per Capita, 1988–2006



Note*:* Data used is from Cadot et al. (2011). GDP per capita stated in 1,000 international dollars (PPP 2005). Dashed line: predicted values from quadratic OLS; solid line: LOWESS. Each point represents a country-year observation; ISO codes represent country averages (1988–2006). Micro-states defined as average population below one million. Oil exporters defined as average export shares in HS chapters 26 and 27 equal to or greater than 50 percent.

Panel (b) of Figure 2 reestimates the parametric and nonparametric curves after removing countries with populations below one million and those with oil-export shares greater than or equal to 50 percent, on average.[15] LOWESS still predicts respecialization, but the quadratic polynomial is now much more skewed and deviates substantially from the nonparametric curve. The fact that most of the observations are located near the vertical axis raises the concern that the quadratic parameterization obtains its pronounced U-shape from the high variation of export concentration in the very first percentiles of the income distribution. Panels (c) and (d) illustrate the power of a logarithmic transformation. Applied on the horizontal axis that denotes GDP per capita, it stretches the scale among the lower values. Reestimating

15 Oil exports are defined as exports in HS chapters 26 and 27.

the quadratic polynomial and LOWESS with log GDP per capita produces a linear fit on export concentration. The similarity of the patterns in panels (c) and (d) suggests that the functional form obtained from the pooled sample resembles cross-country differences – that is, a static pattern.

Figure 2 illustrates the sensitivity of Cadot et al.'s results with respect to sample selection and scaling. The downward trend of export concentration at higher stages of economic development and the low number of outliers in panel (d) support the prediction of continuous diversification discussed in the previous section. The distinction that remains to be made is that between the intensive and the extensive margin. While the Theil index, like all other concentration measures, contains information on the shape of a distribution, diversification at the extensive margin is concerned only with its range. In order to stick to this distinction, the remainder of the paper measures diversification by counting the number of HS6 products a country exports. This is the same as analyzing diversification at the extensive margin.

3.2 The Counting Goods Measure and Its Limits

Table 1 shows the average number of goods exported by countries from five different income groups between 1998 and 2009.[16] The groups vary in size, with most of the observations coming from low-income and lower-middle-income countries. The figures in brackets indicate the number of countries that have been removed from the sample because of their small population or high oil-export shares. The columns reporting the number of exported goods by the mean and the median country of a group indicate higher diversification levels for richer countries. The columns "Max." and "Std. Dev." (standard deviation) suggest heterogeneity inside the groups. Four of the five countries that export almost everything are large economies (China, India, South Africa, and the United States). Singapore, the most diversified economy among the high-income non-OECD countries, may have reached the high-diversification level through its role as a trade hub for other economies.[17] The table does not contradict the pattern of continuous diversification, but it does reveal potentially important covariates such as a country's size and geography.
A similar picture is shown in Figure 3, which suggests a continuous diversification path alongside economic development. As in Figure 2, pooled and cross-sectional data have the same functional form, independent of whether parametric or nonparametric techniques are used. However, the left panel (a) of Figure 3 reveals an aspect that literally points to the limits of counting goods. The highest level of diversification a country can achieve is, by definition, exporting all the 5,111 product categories included in the HS6 classification. For coun tries near

16 The grouping is based on an adjacent file to the CEPII BACI96 data set.

17 A similar level of diversification can be expected for Hong Kong, which reexports many goods from and to China (Feenstra and Hanson 2004).

Table 1: Number of Exported HS6 Products across Income Groups, 1998–2009

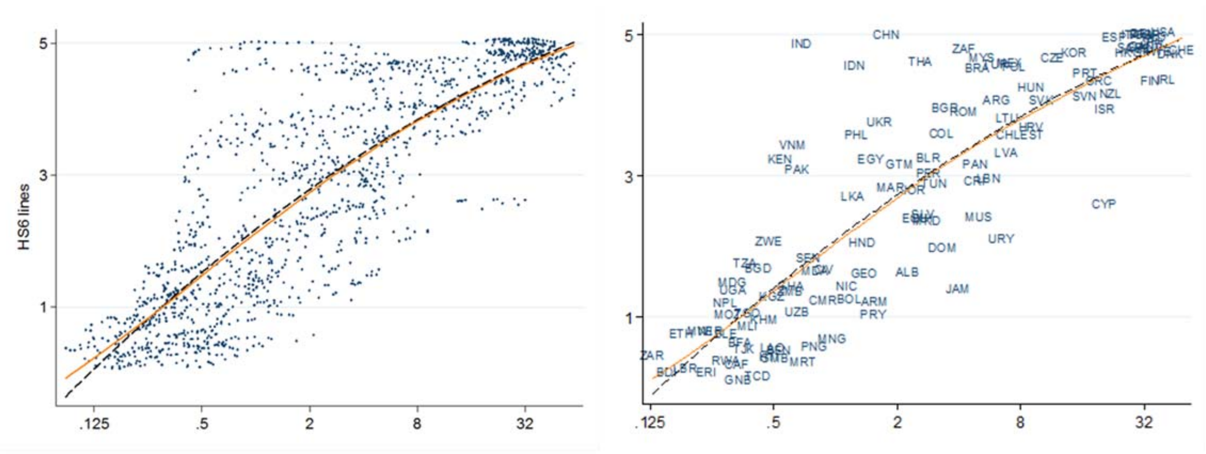
Income	# Countries		Mean	Median	Max.	Std. Dev.	Most diversified
High OECD	22	[2]	4,598	4,791	5,037	657	United States
High Other	17	[12]	2,386	1,885	4,810	1,588	Singapore
Upper Middle	36	[16]	2,606	2,947	4,792	1,659	South Africa
Lower Middle	51	[20]	1,957	1,661	5,003	1,386	China
Low	48	[7]	1,070	784	4,874	963	India
Total	174	[57]	2,211	1,732	1,672	1,672	

Note: The data is drawn from the CEPII BACI96 and represents country averages for 1998–2009. The sample identifies a total of 5,111 HS6 product categories. Numbers in brackets indicate the number of countries with a population below one million or oil exports equal to or more than 50 percent of total exports, on average. Income groups are presented as documented in the CEPII BACI96 adjacent file.

this limit (practically all the high-income countries as well as China, India, and Indonesia), it is impossible to diversify further. Ignoring this limit can lead to downward-biased estimates observations for India and China in the upper left of the point cloud in Panel (a) of Figure 3.

Figure 3: Exported HS6 Lines and GDP Per Capita, 1998–2009

(a) Pooled, excl. oil-/microstates (log GDPpc) (b) Means, excl. oil-/microstates (log GDPpc)



Note: GDP per capita stated in 1,000 international dollars (PPP 2005); number of active HS6 lines in 1,000. Dashed line shows predicted values from quadratic OLS. Solid line shows fitted lines from LOWESS. Each point represents a country-year observation; ISO codes represent country averages (1988–2006). Microstates defined as average population below one million. Oil exporters defined as average export shares in HS chapters 26 and 27 equal to or greater than 50 percent of total exports (1998–2009).

Their levels of diversification do not change much despite outstanding growth in the period shown. Relating these observations to GDP per capita reveals a coefficient close to zero, while fitting the whole sample suggests a strong positive relationship. Tobin (1958) suggests censoring those observations that are close to the limit. In the present context this would imply removing exactly those observations where it is claimed that countries are respecializing. Hence, it is useful to have another way to investigate the case of respecialization.

3.3 *Theory, Empirics, and a Roadmap*

The previous subsections presented descriptive evidence for continuous diversification at the extensive margin. They challenged the case of respecialization and attributed its emergence to methodological aspects related to the handling of panel data, the distributions of variable values, and the detail and limits of measurement. In order to obtain an econometric model that both includes a theoretical rationale and takes into account the data characteristics described in this section, a roadmap for the analysis in Section 4 is briefly outlined here.

Omitted variables: Parteka and Tamberi (2013) explore several covariates of export diversification in addition to income per capita. Among other things, they find significant effects related to exporters' size and the distance to their markets, as Benedictis et al. (2009) have suggested. In order to obtain the narrow set of variables needed for the econometric analysis, it is necessary to derive the gravity equation inherent to the Eaton and Kortum model. When aggregated to the total exports of a country and related to the extensive margin, its implementation is analogous to Baldwin and Harrigan's (2011) assessment of export zeros and unit values across space.

Sample selection: An assumption of the comparative statics analyzed in Section 2 is that countries differ only in their level of capital per worker and are otherwise symmetric. The gravity equation accounts for asymmetries arising from differences in country size and geography. However, policy barriers – another important determinant of diversification – can be manifold and are difficult to control for (Anderson and Van Wincoop 2004). To cope with this, this paper uses a subsample of open economies based on Wacziarg and Welch's (2008) classification for comparison. Oil exporters and small countries always remain outside the sample.

Limited dependent variables: The upper limit in the HS6 data leads to the observation that many countries stop diversifying, which may wrongly suggest a turning point (especially when the log-transformation of GDP per capita is omitted). Censoring observations near the upper limit helps to avoid potential estimation bias but also removes those observations for which this paper claims that respecialization does not occur. Evidence on US import data from Feenstra, Romalis and Schott (2002) is thus used to back up the results obtained from using the HS6 data. The US data includes a much richer set of products and encompasses more than 10,000 categories. Although examining exports to the United States narrows the scope of the analysis to a single export destination, this approach provides an increased level of detail and no country reaches the upper limit within the period under study.[18]

4 Econometric Analysis

This section extends the analysis undertaken in Section 2 and presents the theoretical framework upon which the econometric analysis is based.

The framework relies on the Eaton and Kortum model to derive a gravity equation for diversification. This equation is used in the empirical analysis in the second part of this section. Alternative levels of aggregation and time periods are considered in order to check the robustness of the results. Dynamic methods are then applied to infer the direction of causality.

4.1 *Export Diversification and Technology Differences*

The Eaton and Kortum model features an arbitrary number of countries $i=1,\ldots,N$ and goods $j=1,\ldots,J$. Consumers in country n decide to purchase good j at the lowest available price $p_n(j)=\min\{p_{ni}(j);i=1,\ldots,N\}$. The setup is as follows:

Prices include unit production costs, (c/z), and trade costs, d,

$$p_{ni}(j)=\left(\frac{c_i}{z_i(j)}\right)d_{ni},$$

where $d_{ni}>1$ and $d_{nn}=1$. Unit production costs fall with productivity $z_i(j)$, which is randomly drawn from a cumulative distribution function (CDF). The shape of this distribution is governed by a parameter, θ, that quantifies gains from trade that result from comparative advantage. The location of the CDF – or the average $z_i(j)$ – is indicated by T_i and denotes a country's overall technological development.[19] When comparing two countries, the one with a higher T is likely to also have a higher $z_i(j)$, hence it has an absolute advantage.

The probability π that a country i can successfully export to n – that is, offer the lowest price – is a function of its technology, its factor costs c_i, and transportation costs between the two countries, relative to the rest of the world:

18 Only six of 144 countries exported more than 10,000 goods to the United States during the sample period 1989–2006. In descending order, with the number of observations in parentheses: Canada (16), Germany and the United Kingdom (12), Italy (8), China (7), and Japan (1).

19 Technology can also include broader concepts such as infrastructure, institutions, and other non-sector-related determinants of efficiency.

(1.1) $$\pi_{ni} = \frac{T_i (c_i d_{ni})^{-\theta}}{\sum_{k=1}^{N} T_k (c_k d_{nk})^{-\theta}}.$$

Eaton and Kortum show that this expression is equivalent to i's share of the total expenditure of country n, (X_{ni} / X_n), so that

(1.2) $$X_{ni} = \frac{T_i \left(c_i d_{ni}\right)^{-\theta} X_n}{\Phi_\mathrm{n}},$$

where $\Phi_n \equiv \sum_{k=1}^{N} T_k (c_k d_{nk})^{-\theta} = (p_n / \gamma)^{-\theta}$ resembles the denominator of the previous equation and also determines the price level in the destination market. That is, if the rest of the world has a low level of technology or high factor prices and delivery costs, the price level in country n will be high, making it easier for country i to offer the lowest price.

Substituting terms and summing over all destinations yields the total sales of country i as a function of its technology, factor costs, and a term that summarizes the interaction between (deflated) delivery costs and market size:

(1.3) $$X_i = \sum_{n=1}^{N} X_{ni} = T_i c_i^{-\theta} \underbrace{\sum_{n=1}^{N} \left(\frac{d_{ni}}{p_n / \gamma} \right)^{-\theta} X_n}_{\equiv R_i^{-1}}.$$

In empirical adaptations, the sum of partners' GDP-weighted distances is interpreted as the remoteness of a country, R_i, which (inversely) indicates proximity to large markets. In other words, the more remote a country is, the farther it is from large markets and the lower its probability of being a successful exporter to any country. Dividing the last equation by an analogous expression for country k and taking logs states the log-linear gravity equation for countries' relative exports.

(1.4) $$\ln\left(\frac{X_i}{X_k}\right) = \ln\left(\frac{T_i}{T_k}\right) - \theta \ln\left(\frac{c_i}{c_k}\right) - \ln\left(\frac{R_i}{R_k}\right)$$

The comparative expression emphasizes that when a time dimension is added to all variables, a country can improve its technology but still export less if other countries have experienced greater technological growth. Likewise, if technology improves in all countries at an equal pace, relative exports remain unchanged. This aspect has to be borne in mind when the equation is applied to panel data.[20] An implication of the model can be quoted directly from Eaton and Kortum (2002: 1748) in order to emphasize the relation of their model to the this paper's argument: "A source with a higher state of technology, lower input cost [*sic*], or lower barriers exploits its advantage by selling a wider range of goods." Hence, the model not only yields a gravity equation (which can also be obtained from other theories) but also pre-

20 In a cross-section this problem does not arise because absolute and relative technology differences cannot be distinguished with only one observation per country.

dicts that countries diversify at the extensive margin because $(X_i / X_k) > 1$ always implies that i should export a wider range of goods than k.[21]

4.2 Baseline Estimation

The estimation equation takes the following form:

$$\frac{N_{it}^{HS6}}{\overline{N}_t^{HS6}} = \alpha + \beta_1 \ln\left(\frac{y_{it}}{\overline{y}_t}\right) + \beta_2 \ln\left(\frac{y_{it}}{\overline{y}_t}\right)^2 + \beta_3 \ln\left(\frac{L_{it}}{\overline{L}_t}\right) + \beta_4 \ln\left(\frac{R_i}{\overline{R}_t}\right) + \varepsilon_{it} \tag{1.5}$$

Compared to (1.4), variables vary over time, t, and time averages replace the benchmark country k, with $\overline{x}_t \equiv \sum x_{it} / N$. The dependent variable is not logged because its distribution is not as extreme as the income per capita data (it is similar to that in Figure 3). The variables of the Eaton and Kortum model are interpreted in the same way as in Baldwin and Harrigan's (2011) analysis of US export zeros and unit values across space.[22] They are proxied with GDP per capita, y, population size, L, and a measure for remoteness, R. GDP per capita reflects the level of technology and its squared term is included to see if there are nonlinearities beyond the asymptotics internalized by taking logs. Population proxies factor costs, which are lower in large countries due to the internal factor competition.[23] Remoteness is calculated as in Baldwin and Harrigan (2011), capturing the size-weighted distance from destination markets.[24] The expected qualitative results are $\hat{\beta}_1 > 0$, $\hat{\beta}_2 = 0$, $\hat{\beta}_3 > 0$, and $\hat{\beta}_4 < 0$.

Given the similarity of pooled and cross-sectional patterns documented in the previous section, the baseline estimates use both ordinary least squares (OLS) and the between effects (BE) estimator as a starting point. The latter is used instead of a single cross-section for an arbitrary year and takes country averages for the entire sample period. Using the BE estimator in disaggregated trade data has the advantage that it averages out unstable export spells that would otherwise be fully included in a single year. The resulting year-selection bias (which has the same attenuating effect as measurement error) can be meaningful, especially among low- and middle-income countries, which frequently engage in trade relationships that do not survive longer than one or two years (i.e., high churning rates; Besedes and Prusa 2006;

21 Eaton and Kortum note this property as a key difference from other models. With monopolistic competition, adjustments take place at the intensive margin because consumers will always generate demand for all goods.

22 Note that they are interested in the destination market's characteristics and particularly in the effect of distance. As shown in the previous subsection, this variable becomes part of the exporter's remoteness when bilateral exports are aggregated to total exports.

23 Baldwin and Harrigan (2011) argue that large countries have a higher level of domestic competition because they must sell a great deal and are therefore often their own lowest-cost suppliers.

24 E.g. $R_i \equiv \left[\sum_{n=1}^{N} \frac{GDP_n}{distance_{ni}}\right]^{-1}$. Note that in my data, values are $R_i \times 1bn$ because the GDP data used for calculation was scaled in 1-USD units.

Eaton, Eslava, Kugler, and Tybout 2007). As discussed at the end of Section 3, alternative samples are also estimated to see how robust the results are. Additionally, a reduced model with only GDP per capita as the explanatory variable is estimated: $\left(N_{it}^{HS6} / \bar{N}_{t}^{HS6}\right) = \alpha + \beta_1 \ln\left(y_{it} / \bar{y}_t\right) + \beta_2 \ln\left(y_{it} / \bar{y}_t\right)^2 + \varepsilon_{it}$. The next subsection proceeds with further specification tests.

Main results: Table 2 presents the BE results in two panels. The first panel, columns (1) to (3), reports the results of the reduced model, while the second panel, columns (4) to (6), shows results for the full model as stated in (1.5). The first column of each panel uses the full range of data (except oil-exporting countries and microstates); censored samples in columns (2) and (5) use only observations up to a limit of 4,500 goods; and columns (3) and (6) are further restricted to open economies. As expected, censoring affects the results in that the squared GDP per capita variable becomes insignificant. All other coefficients reveal the expected signs, although remoteness is significant only in the censored samples. The full model produces a higher *R-squared* than the reduced model, but the inclusion of population and

Table 2: Active HS6 Lines and GDP Per Capita, 1998–2009; BE Estimation

	Reduced model			Full model		
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Full	Censored	Cens./Open	Full	Censored	Cens./Open
(log) GDPpc	0.255**	0.227**	0.251**	0.228**	0.277**	0.257**
	(0.030)	(0.049)	(0.047)	(0.023)	(0.032)	(0.032)
(log) GDPpc2	-0.0222a	-0.0245	-0.0305a	-0.0285**	-0.00976	-0.0143
	(0.012)	(0.015)	(0.018)	(0.007)	(0.009)	(0.011)
(log) Population				0.177**	0.200**	0.173**
				(0.013)	(0.016)	(0.023)
(log) Remoteness				-0.0550	-0.148**	-0.170**
				(0.045)	(0.053)	(0.057)
Observations	1,404	1,082	475	1,404	1,082	475
R^2 (between)	0.730	0.676	0.810	0.897	0.879	0.925
	Comparison with OLS coefficients					
Hausman: $\Pr > \chi^2$	0.962	0.635	0.728	0.994	0.937	0.992

Source: The table shows estimation results using data drawn from the CEPII BACI96 and CEPII Gravity dataset, and the World Development Indicators database. Standard errors in parentheses; [a] $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. All variables are normalized by their annual means. Sample excludes oil exporters and microstates. Observations with exported HS6 lines equal to or greater than 4,500 have been censored in columns (2), (3), (5), and (6).

remoteness does not suggest that the coefficients for GDP per capita are biased.[25] Because the present and the following tables in this subsection show results only for the between estimator, their last line shows the *p-values* of the Hausman (1978) test. Note that in the present context the test does not provide any guidance about the correct specification of the empirical model. The only thing it does here is compare the coefficients obtained from estimating pooled OLS (not shown here) with those of the BE estimator for their statistical equivalence. As the table shows, they confirm that the pooled and cross-sectional patterns are similar.

Different time period: To see if the same results are obtained using an alternative sample, the estimation is also carried out using Cadot et al.'s original data. The difference between this data and the CEPII BACI96 data is that it is based on a different generation of HS6 classifications (encompassing a slightly smaller range of goods) and that it covers the years 1988 through 2006. Table 3 shows that the results are quite different. The coefficients for GDP per capita are more than twice as great, GDP per capita squared is positive and significant, and OLS produces different results than the BE whenever censoring is applied. This suggests that income differences had greater "effects" on export diversification in the years 1988–2006

Table 3: Active HS6 Lines and GDP Per Capita, 1988–2006; BE Estimation

	Reduced model			Full model		
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Full	Censored	Cens./Open	Full	Censored	Cens./Open
(log) GDPpc	0.553**	0.721**	0.786**	0.544**	0.720**	0.706**
	(0.046)	(0.069)	(0.070)	(0.035)	(0.051)	(0.068)
(log) GDPpc2	0.0575*	0.114**	0.129**	0.0651**	0.130**	0.134**
	(0.023)	(0.032)	(0.040)	(0.014)	(0.020)	(0.032)
(log) Population				0.224**	0.297**	0.255**
				(0.015)	(0.023)	(0.045)
(log) Remoteness				-0.0172	-0.187*	-0.225*
				(0.053)	(0.082)	(0.104)
Observations	1,843	1,506	702	1,843	1,506	702
R^2 (between)	0.750	0.674	0.799	0.925	0.893	0.893
	Comparison with OLS coefficients					
Hausman: Pr $> \chi^2$	0.949	0.045	0.008	0.987	0.001	0.027

Source: The table shows estimation results using data drawn from the CEPII BACI96 and CEPII Gravity dataset, and the World Development Indicators database. Standard errors in parentheses; [a] $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. All variables are normalized by their annual means. Sample excludes oil exporters and microstates. Observations with exported HS6 lines equal to or greater than 4,500 have been censored in columns (2), (3), (5), and (6).

25 This would have been expected if the omitted variables were correlated with income per capita. For population and remoteness this is not the case.

than in 1998–2009. In addition, these effects are convex, which suggests that countries do not respecialize but rather diversify at an increasing pace.

One explanation of this result could be that global trade had a lower average product coverage in the late 1980s and early 1990s than in later years, and that trade participation in the early years revealed a larger gap between poor and rich countries. This would resemble the effect of an increase in global trade activity in the late twentieth century and the increasing participation of relatively poor countries in trade, which is also documented by Hanson (2012). If this argument holds, the convexity should appear only during the early years of the Cadot et al. data. To test this, data from the years prior to 1992 and 1998 was dropped incrementally. The results are shown in tables 4 and 5. As expected, the coefficients become smaller and GDP per capita squared becomes insignificant as the sample concentrates more on observations starting in the late 1990s. If the linearity mostly reflects diversification during the period 2000–2006, it implies that the upper limit of the HS6 classification was less relevant in earlier years and that the respecialization identified by Cadot et al. emerged from the omitted log-transformation rather than from neglect of the upper variable limit.

Table 4: Active HS6 Lines and GDP Per Capita, 1992–2006; BE Estimation

	Reduced model			Full model		
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Full	Censored	Cens./Open	Full	Censored	Cens./Open
(log) GDPpc	0.459**	0.499**	0.509**	0.466**	0.578**	0.542**
	(0.042)	(0.071)	(0.068)	(0.034)	(0.040)	(0.048)
(log) GDPpc2	0.0268	0.0414	0.0317	0.0374**	0.0766**	0.0651**
	(0.020)	(0.028)	(0.033)	(0.013)	(0.015)	(0.023)
(log) Population				0.201**	0.248**	0.217**
				(0.015)	(0.018)	(0.034)
(log) Remoteness				0.0212	-0.0380	-0.0520
				(0.052)	(0.065)	(0.078)
Observations	1,440	1,135	510	1,440	1,135	510
R^2 (between)	0.743	0.646	0.793	0.913	0.900	0.912
	Comparison with OLS coefficients					
Hausman: Pr $> \chi^2$	0.985	0.684	0.541	0.999	0.479	0.645

Source: The table shows estimation results using data drawn from the CEPII BACI96 and CEPII Gravity dataset, and the World Development Indicators database. Standard errors in parentheses; [a] $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. All variables are normalized by their annual means. Sample excludes oil exporters and microstates. Observations with exported HS6 lines equal to or greater than 4,500 have been censored in columns (2), (3), (5), and (6).

Table 5: Active HS6 Lines and GDP Per Capita, 1998–2006; BE Estimation

	Reduced model			Full model		
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Full	Censored	Cens./Open	Full	Censored	Cens./Open
(log) GDPpc	0.378**	0.382**	0.359**	0.395**	0.466**	0.420**
	(0.039)	(0.067)	(0.072)	(0.032)	(0.043)	(0.053)
(log) GDPpc2	0.00545	0.0100	-0.0126	0.0193	0.0434**	0.0286
	(0.018)	(0.025)	(0.032)	(0.012)	(0.015)	(0.023)
(log) Population				0.186**	0.217**	0.205**
				(0.015)	(0.019)	(0.031)
(log) Remoteness				0.0351	-0.00434	-0.0566
				(0.050)	(0.066)	(0.081)
Observations	846	650	299	846	650	299
R^2 (between)	0.733	0.655	0.747	0.906	0.884	0.896
	Comparison with OLS coefficients					
Hausman: Pr $> \chi^2$	0.998	0.834	0.897	1.000	0.924	0.914

Source: The table shows estimation results using data drawn from the CEPII BACI96 and CEPII Gravity dataset, and the World Development Indicators database. Standard errors in parentheses; [a] $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. All variables are normalized by their annual means. Sample excludes oil exporters and microstates. Observations with exported HS6 lines equal to or greater than 4,500 have been censored in columns (2), (3), (5), and (6).

More disaggregated data: The baseline results showed that diversification is linear to log GDP per capita when the data is censored. In the Cadot et al. data the results suggested a convexity in export diversification, which is probably an artifact of a lower trade activity in the early years of their sample and the characteristics of the classification scheme that is used to identify the extensive margin. The last robustness check makes use of a more disaggregated data set on US imports. A first version of this data set is documented in Feenstra et al. (2002), and an updated version spanning the years 1989–2006 can be downloaded at the Center for International Data at the University of California, Davis.[26] In contrast to the data sets used here so far, the classification scheme in the US data uses 10-digit codes and distinguishes between 15,000 product categories. Inspection of the data reveals that no country ever exported the entire range of goods to the United States during this period, and that only five countries went beyond the 10,000-product threshold (Canada, China, Germany, Italy, Japan, and the United Kingdom). The distribution is also much more skewed, with only a few countries exporting a large range of products; most exhibit relatively low levels of diversification.

For the econometric analysis, the estimation equation is different in three respects: (i) the model is estimated in fully log-linear form; (ii) the remoteness of the exporter is replaced by

26 <http://cid.econ.ucdavis.edu/usix.html>.

the exporter's distance to the US; and (iii) a $NAFTA_t$ dummy is included for Canada and Mexico in the years since 1994. The parameter δ_t is equivalent to the demeaning applied in (1.5) and captures aggregate time effects:

$$\ln N_{it}^{U.S.} = \alpha + \delta_t + \beta_1 \ln y_{it} + \beta_2 \ln y_{it}{}^2 + \beta_3 \ln L_{it} + \beta_4 \ln d_i^{U.S.} + \varepsilon_{it} \quad (1.6)$$

Table 6 also confirms the absence of nonlinearities and shows that the regressions produce robust point estimates for GDP per capita around unity. NAFTA membership matters when other variables are not controlled for, but it is absorbed when the full model is estimated as shown in column (6). Size and distance show the expected signs, although distance becomes insignificant when the sample is reduced to the subsample of open economies. As was the case in the previous estimates, the BE produces a very high *R-squared* and the coefficients are statistically the same as those obtained with standard OLS. Altogether, the results presented in this subsection clearly reject the case of respecialization. They also reveal the high predictive power of the gravity equation for cross-sectional patterns of diversification at the extensive margin.

Table 6: Active HS10 Lines to US and GDP Per Capita, 1989–2006; BE Estimation

	Reduced model			Full model		
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Full	Open	Open/NAFTA	Full	Open	Open/NAFTA
(log) GDPpc	1.089**	1.104**	1.081**	1.113**	1.030**	1.029**
	(0.147)	(0.123)	(0.120)	(0.096)	(0.080)	(0.081)
(log) GDPpc2	-0.0934	-0.0557	-0.0552	-0.0197	-0.0168	-0.0179
	(0.076)	(0.076)	(0.073)	(0.050)	(0.050)	(0.051)
NAFTA dummy			1.608*			0.111
			(0.779)			(0.691)
(log) Population				0.673**	0.549**	0.546**
				(0.061)	(0.068)	(0.072)
(log) Remoteness				-0.342*	-0.215	-0.198
				(0.157)	(0.133)	(0.171)
Observations	1,674	900	900	1,674	900	900
R^2 (between)	0.675	0.783	0.801	0.865	0.913	0.913
	Comparison with OLS coefficients					
Hausman: Pr $> \chi^2$	0.964	0.984	0.945	0.991	1.000	1.000

Source: The table shows estimation results using data drawn from the CEPII BACI96 and CEPII Gravity dataset, and the World Development Indicators database. Standard errors in parentheses; [a] $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. All variables are normalized by their annual means. Sample excludes oil exporters and microstates.

4.3 Specification Tests

This subsection presents the results from standard specification tests for panel data. These tests focus on the detection of unobserved effects and the need for dynamic specification. The sample analyzed henceforth uses CEPII BACI96, censored at 4,500 goods and without the years following 2006. A balanced panel is constructed by removing all those countries where only partial information on their diversification path during the remaining period, 1998–2006, is available. This censoring minimizes the potential for distortions associated with the global financial crisis and provides a full record of information so that dynamic specifications are not forced to consider different samples for alternating lag structures.

Unobserved effects: Table 7 shows the results obtained from OLS, BE, random effects (RE), and fixed effects (FE). Alternative test statistics for the presence of unobserved effects and for choosing between FE and RE are presented at the bottom of the table. It is noteworthy that the estimated coefficient for GDP per capita falls from approximately 0.4 to below

Table 7: Active HS6 Lines, 1998–2006; Specification Tests

Estimator	OLS	BE	RE	FE
	(1)	(2)	(3)	(4)
(log) GDPpc	0.394**	0.402**	0.157**	0.0569
	(0.020)	(0.023)	(0.035)	(0.044)
(log) Population	0.252**	0.253**	0.245**	0.691**
	(0.025)	(0.025)	(0.040)	(0.191)
(log) Remoteness	-0.223**	-0.213**	-0.419**	-0.127
	(0.069)	(0.071)	(0.127)	(0.200)
Observations	1,056	1,056	1,056	1,056
R^2	0.831	0.863		0.0854
Specification tests				
Unobserved effects:				
Serial correlation:		$\hat{\rho} = 0.92$		$S.E. = 0.010$
Breusch-Pagan LM test:		$\overline{\chi}(1) = 3505.25$		$\Pr > \overline{\chi} = 0.000$
Fixed vs. random effects:				
Hausman test:		$\chi^2(3) = 245.11$		$\Pr > \chi^2 = 0.000$
Gould (2001)	$\ln y$	$F(1,87) = 10.11$		$\Pr > F = 0.002$
	$\ln L$	$F(1,87) = 8.59$		$\Pr > F = 0.004$
	$\ln R$	$F(1,87) = 0.01$		$\Pr > F = 0.919$

Source: The table shows estimation results using data drawn from the CEPII BACI96 and CEPII Gravity dataset, and the World Development Indicators database. Robust standard errors in parentheses; [a] $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. All variables are normalized by their annual means. Sample excludes oil exporters and microstates. Observations with exported HS6 lines equal to or greater than 4,500 and years after 2006 have been censored. Strongly balanced panel with 9 observations per country.

0.06. It also loses statistical significance when errors are clustered at the country level and country-fixed effects are included in column (4). Generally, OLS is not an appropriate estimator in the presence of any unobserved effects because these generate serially correlated errors (Wooldridge 2002). Unobserved effects can be tested for by regressing $\hat{\varepsilon}_{it}^{POLS} = \rho\hat{\varepsilon}_{it-1}^{POLS} + \nu_t$ and seeing if $\hat{\rho} \neq 0$. As shown in the table, $\hat{\rho} = 0.92$ and is highly significant. Additionally, the Lagrange-Multiplier test of whether variance components are zero is rejected, as is the absence of unobserved effects that would allow for the estimation of the pooled OLS model (Breusch and Pagan 1980; Baltagi 1981).

The next question is whether these unobserved effects are correlated with the regressors already included in the model. When this is not the case, the RE estimator delivers consistent and efficient results (Wooldridge 2002). Conversely, if unobserved effects correlate with the regressors, their coefficients will be biased. As the two bottom rows of the table show, both the Hausman (1978) specification test and the FE-versus-BE coefficient test suggested by Gould (2001) indicate the presence of country-specific time-invariant effects. The coefficient test suggests that the estimated coefficients for GDP per capita and population size were biased and that they change considerably when fixed effects are included.

A comparison of columns (2) and (4) suggests that GDP per capita and diversification correlate in the long run but not in the shorter time span of the nine-year period under study. This is a disappointing result because it suggests that the correlation observed in the cross-section may be entirely spurious and that almost everything is explained by unobserved country-specific characteristics. However, the missing link in column (4) could also be the result of an inappropriate static specification. To find out if GDP per capita has any effect on diversification and in which direction causality goes, the remainder of this section considers dynamic panel specifications.

Dynamic panel estimation: A mutually dynamic relationship between GDP per capita and the level of diversification at the extensive margin would imply that causality goes in both directions. This can be rationalized with theory: as the literature mentioned at the beginning of this paper suggests (e.g. Acemoglu and Zilibotti 1997), undertaking investments into new fields of activity is associated with uncertainty about future outcomes and potentially also with sunk costs that cannot be recovered in the event of failure. Capital indivisibilities require a minimum stock of capital in order to make such investments possible at all, which means that larger countries with a higher income per capita have more opportunities to start risky projects. If these projects prove to be fruitful, revenues grow quickly as further investments follow and the newly discovered sector increases in size (see, e.g., Hausmann and Rodrik 2003; Eaton et al. 2007; Easterly et al. 2009). In this case diversification has a positive feedback effect on GDP per capita.

To identify an appropriate dynamic specification, the following process is considered:

$$z_{it} = \phi Z_{it-s} + \xi X_{it-r} + \delta_i + \nu_{it}, \tag{1.7}$$

where Z represents a vector of lagged dependent variables, X includes exogenous control variables, δ_i denotes a country-specific intercept, and ν_{it} is an independent and identically distributed (i.i.d.) error term. To estimate such a model, it has become popular to use GMM estimators that handle fixed effects and endogeneity of the regressors while avoiding dynamic panel bias, which is especially meaningful in panels with a large number of individuals (large N) and a relatively small number of time periods (small T). The persistence of the variables used in the present context makes the system GMM estimator most suitable. It uses lagged differences to instrument current levels rather than using lagged levels to instrument current differences (as in the first applications of this estimator – i.e., difference GMM, Holtz-Eakin, Newey and Rosen 1988; Arellano and Bond 1991).

Table 8 presents the results from the system GMM estimator with one lagged dependent variable and alternative assumptions about the degree of exogeneity of GDP per capita. The Windmeijer correction is applied to account for potentially downward-biased two-step standard errors. These often result from imprecise estimates of the optimal weighting matrix in two-step GMM applications, especially when the sample is small (Roodman, 2009). Columns (1) to (3) suggest that GDP per capita has a significant dynamic impact on the level of diversification, but this impact is estimated to be slower moving when the exogeneity assumption is relaxed. At the same time, the coefficient for the lagged dependent variable increases, which could indicate reverse causality and feedback effects. In column (1) the *p*-value of the Hansen *J*-Statistic merely rejects the null of valid instruments at the 10 percent level. Relaxing the exogeneity assumption for GDP per capita pushes the *p*-value up to levels around 0.36, which suggests that the instruments are valid.

The estimated parameter for GDP per capita can be interpreted as the short-run, dynamic effect of income on diversification. The long-run effect is computed by dividing the estimated coefficient for GDP per capita by one minus the coefficient of the lagged dependent variable. This results in 0.0453 / (1–0.885) = 0.394 in column (2) and 0.0289 / (1–0.901) = 0.292 in column (3). Using the result of the BE in Table 7, which has roughly the same coefficient, as a point of reference lends support to the assumption that GDP per capita is at least predetermined.

Despite this consistency, one reason to remain critical regarding this result is that the number of instruments is extremely large. Instrument proliferation can significantly weaken both the Hansen and the difference-in-Hansen tests. Keeping the instrument count below the number of individuals, $j < N$, is an insufficient precaution (Roodman 2009). Columns (4) through (6) reduce the instrument count by collapsing the instrument matrix and reducing lags. In column (4), where full lag length is exploited, the Hansen test rejects the joint validity of the instruments, and the difference-in-Hansen test rejects the validity of the GMM instruments. In column (5) this misspecification is attacked by instrumenting GDP per capita only in the levels equation, while column (6) extends this approach by reducing the lag depth of the instruments to one. The last two steps reduce the instrument count to 6, which mitigates concerns regarding instrument proliferation. The Hansen test produces *p*-values that indicate the validity of the instruments. The parameter for GDP per capita is now larger relative to column (2), which is to be expected from appropriately instrumented variables.[27]

Altogether, these results can be interpreted as evidence that GDP per capita does have an effect on export diversification. This effect seems to be larger than that obtained from a cross-sectional regression using the BE estimator, something which could be the result of feedback effects of diversification on GDP per capita. To investigate this further, a dynamic model with GDP per capita as the dependent variable is estimated. The results shown in Table 9 consider alternative specifications with lag depth restricted to one period and collapsed instruments. The first column wrongly assumes that the number of exported goods is exogenous, which obviously delivers biased coefficients for both variables. Also, the p-values of the Hansen test and the test against second-order autocorrelation indicate misspecification.

Table 8: Active HS6 Lines and GDP Per Capita, 1998–2006; System GMM

	Baseline			Robustness checks		
	(1)	(2)	(3)	(4)	(5)	(6)
Assumption on GDPpc	Exog.	Pred.	Endog.	Pred.	Pred.	Pred.
# HS6 (t-1)	0.830**	0.885**	0.901**	0.813**	0.746**	0.728**
	(0.0617)	(0.0284)	(0.0291)	(0.0685)	(0.123)	(0.112)
(log) GDPpc	0.0568*	0.0453**	0.0289*	0.0916*	0.122*	0.151*
	(0.0254)	(0.0139)	(0.0115)	(0.0460)	(0.0527)	(0.0613)
(log) Population	0.0439**	0.0328**	0.0265**	0.0507*	0.0706*	0.0826*
	(0.0145)	(0.00834)	(0.00737)	(0.0194)	(0.0310)	(0.0317)
(log) Remoteness	-0.0426a	-0.00972	-0.0237a	0.00521	-0.00259	0.0253
	(0.0216)	(0.0132)	(0.0120)	(0.0713)	(0.0843)	(0.0666)
Observations	704	704	704	704	704	704
Groups/Countries	88	88	88	88	88	88
Instruments	39	81	74	20	18	6
AR2 (p-value)	0.0675	0.0693	0.0712	0.0663	0.0625	0.0593
Hansen-J (p-value)	0.0734	0.373	0.350	0.00911	0.292	0.583

Source: The table shows estimation results using data drawn from the CEPII BACI96 and CEPII Gravity dataset, and the World Development Indicators database. Robust, Windmeijer-corrected standard errors in parentheses; [a] $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. All variables are normalized by their annual means. Sample excludes oil exporters and microstates. Observations with exported HS6 lines equal to or greater than 4,500 and years after 2006 have been censored. Strongly balanced panel with 9 observations per country.

Treating export diversification as an endogenous variable produces improved test statistics and a significant contemporaneous impact on the level of GDP per capita. Similar results can

27 Apparently, the deepest lags are less valid instruments. Experimenting with alternative lag structures and collapsing – while allowing GDP per capita to be instrumented in both the difference and the levels equation – revealed that the Hansen test rejects instrument validity only if lag length is greater than five.

be found by including lagged diversification, as shown in column (3). Column (4) suggests that deeper lags of diversification do not add any explanatory content to the model, and column (5) shows that lagged diversification alone generates second-order serial correlation. The table supports the case for reverse causality, and it also suggests that benefits from diversification materialize with only a short delay, almost contemporaneously.

5 Conclusion

Making predictions about the correlation between the level of diversification and GDP per capita across countries requires the researcher to take into account the margin at which diversification is considered. At the extensive margin, the range of goods or activities varies across countries leads to predictions of continuous diversification in line with standard theo ries of economic growth and development. This paper has presented empirical evidence rejecting recently documented patterns of respecialization (Imbs and Wacziarg 2003; Cadot et al. 2011) and confirming continuity. It has also analyzed and illustrated the reasons why respecialization might have been identified in the studies in question.

Table 9: (log) GDP Per Capita, 1998–2006; System GMM

	(1)	(2)	(3)	(4)	(5)
Assumption on # HS6	Exog.	Endogenous, levels equation			
(log) GDPpc (t-1)	1.030**	0.839**	0.891**	0.961**	0.865**
	(0.0348)	(0.0632)	(0.0868)	(0.0321)	(0.0735)
# HS6	-0.0444	0.601**	-0.418	-1.347	
	(0.0622)	(0.172)	(0.395)	(0.847)	
# HS6 (t-1)			0.721*	1.266[a]	0.404*
			(0.281)	(0.719)	(0.201)
# HS6 (t-2)				0.130	
				(0.166)	
Observations	704	704	704	616	704
Groups/Countries	88	88	88	88	88
Instruments	4	4	5	6	4
AR2 (p-value)	0.0271	0.175	0.0945	0.620	0.0268
Hansen-J (p-value)	0.000	0.113	0.646	0.496	0.754

Source: The table shows estimation results using data drawn from the CEPII BACI96 and CEPII Gravity dataset, and the World Development Indicators database. Robust, Windmeijer-corrected standard errors in parentheses; [a] $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. All variables are normalized by their annual means. Sample excludes oil exporters and microstates. Observations with exported HS6 lines equal to or greater than 4,500 and years after 2006 have been censored. Strongly balanced panel with 9 observations per country.

This paper has shown that diversification patterns observable in pooled panel data sets reflect cross-sectional differences across countries. They are well predicted by Eaton and Kortum's (2002) model. Although these authors' theory explicitly considers the extensive margin, it has never been mentioned or applied in prior studies on this topic. The Eaton and Kortum (2002) model also delivers an empirical specification that can be estimated as a gravity equation where the level of GDP per capita proxies the level of the fundamental country-specific technology. In the trade context this corresponds to a country's absolute advantage and also potentially captures a country's institutional framework, geographic or climatic characteristics, and infrastructure.

Specification tests and dynamic panel estimations using system GMM suggest that GDP per capita has a direct positive impact on the level of diversification. There are also signs of reverse causation and feedback effects. The dynamic results are robust in terms of statistically significant parameters, but the analysis here has also shown that the validity of the internally generated instruments can be questioned in some cases. The appropriateness of using system GMM in this context, as well as the appropriateness of quantifications of the mutual dynamics between levels of diversification and GDP per capita, are promising topics for further investigation.

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Appendix A: Diversification Measures

A.1 Active HS6 Lines and Gini, HHI, and Theil

Statistical measures of concentration give a quantitative indication of how much an economy relies on exporting certain products. Inverted, they indicate the degree of diversification. A feature of detailed trade data, besides the large numbers of export zeros, is that export specialization is also extremely high within the set of exported goods (Hausmann and Rodrik, 2003; Easterly et al. 2009; Hanson 2012). Some statistical measures compensate for these distributional features by weighting particular observations. This appendix reviews the properties of the four indicators of export diversification used by Cadot et al. (2011).

Counting Active HS6 Lines: The first and most straightforward way to look at export diversification is the number of HS6-code products each country exports in a particular year. In the present data set the Harmonized System identifies N = 5,11 different goods at the six-digit level. Examples are *HS 847330*: parts and accessories of data processing equipment, not elsewhere specified (i.e., computer parts); *HS 410421*: bovine leather, vegetable pretanned except whole skin; or *HS 293963*: alkaloids of rye ergot and their derivatives.

Despite the descriptions, it is not always possible to understand what goods are actually traded in these categories. The first example, computer parts, was exported by almost every country in every year of the sample. One can easily imagine that a great variety of computer parts exist and are traded in this category. The last example, extracts of a fungus used for pharmaceuticals, names a good that was exported by only seven countries in an average year between 1998 and 2009. Different varieties of such a product are possibly much harder to produce. Bovine leather was exported by half of the countries in the sample.

The kind of diversification measured by counting active HS6 lines in country i's exports reflects its competitiveness in a wide range of different good categories. Different varieties of some goods are easy for every country to produce, irrespective of their technological endowments. Other goods seem to require a minimum level of knowledge and production factors, so that only a few countries are capable of producing them profitably. If, of the three above-mentioned categories, country 1 exports all of them, country 2 exports two of them, and country 3 exports only one of them, then country 1 is more diversified than the others: $N_1 = 3 > N_2 = 2 > N_3 = 1$. Generally, counting goods considers only the extensive margin.

Gini Coefficient: The Gini coefficient, like the other indicators that follow, represents a continuous measure of concentration. Let $s_k = x_k / X$ be the shares of good k in total exports. Sorted in ascending order so that $s_1 < \cdots < s_k \cdots < s_N$, their cumulative sums, $cs_k = \sum_{l=1}^{k} s_l$, weighted by the number of goods, yield the Gini index:

$$G = 1 - \sum_{k=1}^{N} \frac{cs_k + cs_{k-1}}{N}.$$

Besides accounting for the range of goods, the index provides insight on how product shares are distributed within the export basket. If country 1 earns 80 percent of its revenues on product one and 10 percent on goods two and three, respectively, it is more specialized than if it earned one-third of its revenues from each product, but this difference would not be visible if only the number of goods was counted.

The index is normalized to range between zero and one, where a high value reflects a high level of concentration. Because the number of goods N weighs each observation, the Gini index is sensitive to the level of disaggregation. This becomes clear below when it is applied to HS6 trade data. Moreover, depending on how N is chosen, the Gini index, and all other continuous measures, can include information on both the intensive and extensive margin.

Herfindahl-Hirschmann Index (HHI): The normalized Herfindahl index (or Herfindahl-Hirschman Index, HHI) is typically used as a measure of market concentration. It takes a fixed number of the largest competing entities in a market and calculates the sum of their squared market shares:

$$H^* = \frac{\sum_{k=1}^{N} (s_k)^2 - \frac{1}{N}}{1 - \frac{1}{N}}$$

By raising shares to the square, more weight is assigned to observations where the share is relatively high. However, if there are a large number of entities (5,000 HS6 lines), individual shares become extremely small as soon as there is inequality across product categories. Squaring those lets the sum-term and the whole numerator value converge to zero, whereas the denominator stays close to one. With disaggregated exports the HHI is likely to be biased towards zero, implying low export concentration for most countries.

Theil's Entropy Measure: A different weighting of the observations is used in Theil's entropy index. First, instead of shares it considers absolute values x_k. Each observed export flow is weighted by the hypothetical value that would be given in the case of perfect diversification $\mu = X / N$. The obtained deviations from the mean are weighted by the log of this same deviation:

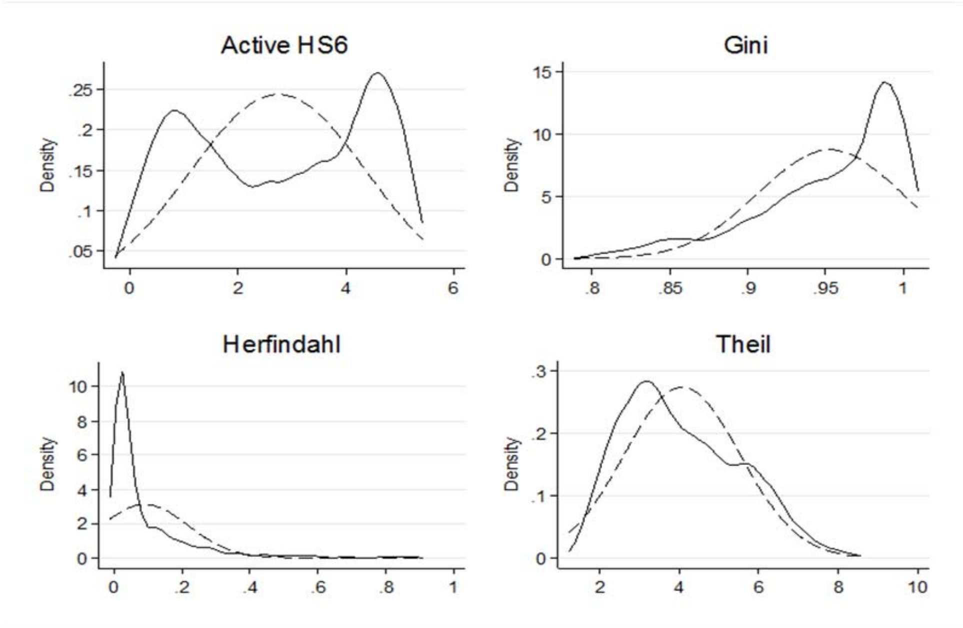
$$T = \frac{1}{N} \sum_{k=1}^{N} \frac{x_k}{\mu} \ln\left(\frac{x_k}{\mu}\right).$$

Because large deviations are given a relatively lower weight, Theil's index operates as a smoother for extremely skewed distributions. In contrast to the Gini and HHI, Theil's index is not bound between zero and one.

A.2 Diversification Patterns

To see how export diversification is documented across the various measures, I consider the 120 countries that remain after small countries and oil exporters (see text for definitions) are removed. Figure A1 shows density estimates from the pooled data of the four measures. The dashed lines indicate a normal distribution.

Figure A1: Distribution of Alternative Concentration Measures, 1998–2009



Note: Data used is from CEPII BACI96. Distributions represent 1,104 country-year observations (117 countries and 12 years). Countries with average population below one million or average oil exports greater than 50 percent of total exports (1998–2009) are excluded.

Each graph looks very different, and the continuous measures seem to reflect their properties from weighting particular observations. An interesting pattern is revealed for the number of active HS6 lines. In contrast to the other measures, this one shows two humps near the two extremes of very high and very low specialization, respectively. That is, there are many countries exporting goods in approximately 1,000 different HS6 categories, and a large number of countries exporting almost everything. Taking the average number of exported goods for each country shows that there are 33 countries exporting in less than 1,350 categories (about 25 percent of the potential product range) and 42 countries that export more than 3,800 products (roughly 75 percent of the reported goods). Apparently, the latter countries concentrate there because the classification system does not leave much room for further diversification, which illustrates the case of limited dependent variables.

The distribution of Gini indices shows that exporting many different goods does not necessarily imply that a country is diversified. Most of the observations reveal indices between 0.9 and 1, which suggests extreme specialization. This may be partly explained by the large number of countries exporting just a few HS6 lines. However, the countries diversifying at the extensive margin do not contribute much to scaling the measure down. The appropriateness of the Gini index for disaggregated trade data appears to be low.

The same holds for the HHI, which suggests an opposite conclusion to the Gini. Instead of most countries being specialized, the HHI says that this is the case for only a handful. On average, 35 countries have an HHI greater than 0.1, and they are all revealed to be at the bottom of the per capita income distribution. Their Gini indexes are consistently larger than 0.98, and except for Ecuador and Côte d'Ivoire, their range of goods does not exceed 1,500.

Theil's index comes closest to a normal distribution. Low levels of export specialization are found for most high-income OECD countries, ranging between 1.6 and 3.0, while most low-income countries reveal higher Theil measures between 4.0 and 7.2. The measure corrects for the apparent hyperspecialization documented in the Gini index without biasing the distribution to the other extreme. In terms of measuring diversification, the Theil index's distributional pattern seems to be most appropriate for analyzing diversification of exports.

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