DEPARTMENT OF TRANSPORT AND REGIONAL ECONOMICS

Linear and non linear growth models using mixed modeling: An application on European Import volumes

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**Linear and non linear growth models using mixed modeling:
An application on European Import volumes**

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The purpose of this paper is the identification of appropriate growth models for trade volumes as a policy tool. The methodology utilized is based on linear and nonlinear mixed modeling. The specifications tested are the linear, the exponential, the logarithmic and the logistic model. The focus lies on the imports of Europe from the world. We present two pilot cases corresponding to different levels of aggregation in terms of country groups and product categories, thus emphasizing the differences between aggregate and disaggregate approaches. The core econometric finding suggests that no clear superiority can be attributed to a single growth model specification on either level of aggregation. Therefore, the implications of each specification on policy decision making is discussed and a recommendation on the use of such models for policy making is made. The growth models are further employed for the purpose of trend extrapolation, to initiate a discussion on the role and responsibility of transport policies implemented today based on alternative future scenarios 20 years ahead.

KEYWORDS: mixed modeling, growth expectations, policy implications

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Introduction

The objective of this paper is the identification of appropriate growth models of volume flows in order to draw inferences for freight transport policy making. The methodology used is based on linear and nonlinear mixed modeling and the specifications tested are the linear, the exponential, the logarithmic and the logistic model. An investigation is hence made regarding which growth function best describes the observed growth patterns. The assumptions made are that trade and freight flows are subject to variability due to country specific effects while growth patterns vary per product category. Additionally, external effects occurring on a global scale and in particular on the short to medium term disrupt those trends unequally between countries and product categories.

The application in this paper follows a different approach from either the strictly structural, time series techniques or gravity models. The innovative element is the use of mixed models for countries and the application of nonlinear specifications for modeling trade volumes. In particular we use longitudinal data and apply both linear and nonlinear trend models of several growth specifications, namely the linear, exponential, logarithmic and logistic model, estimated in a mixed model setting. The mixed approach in particular is to be preferred because of its ability to realistically capture the variability observed in the cross section units, by in particular allowing the modeling of random effects. The cross section variability is represented in this paper by the trading profiles of European countries, in terms of trade volume and growth rate. Product variability on the other hand is addressed by applications of different growth specifications for different levels of product aggregation.

Mixed modeling applications are usually concentrated in the fields of the medical, biological and social sciences. In particular a lot is found on issues within the field of psychology and mobility patterns. In the broader literature, these types of models are often quoted under different names like hierarchical or multi-level models. Under the latter name the amount of applications is bigger but the spectrum is not necessarily broader. A large part of the literature on mixed modeling focuses on the theoretical background and software advancements. Specifically on longitudinal data analysis, which fits the type of input of this paper, Diggle et al (2002), Verbeke and Molenberghs (2000), Singer and Willet (2003) are standard references in the field. Concerning the theory of nonlinear mixed models, Pinheiro and Bates (1990, 1995) are typically quoted. The field of nonlinear mixed models is less mature and hence there are only a limited amount of applications.

The growth models are further utilized for trade volume forecasting. By applying the trend models of the different specifications, the intention is to reflect considerations regarding the final user. The reason is that the final user, in this case transport decision makers (transport agents or policy makers), are mostly driven by expectation. Such practice, emphasizing on the final user rather than the data or the model, can be compared to the statements made by international organizations in their applications of structural modeling, in which expert opinion is used for the forecasting exercises. The OECD's INTERLINK or the IMF's GEM or the European commission's QUEST models are examples where expert opinion is used. In this sense the different growth models each in their own right reflect a different expectation and somehow substitute the use of experts in adjusting forecasting output.

The structure of the paper is as follows. The appropriateness of the mixed procedure for this research is explained in chapter 2, complemented by a description of the growth specifications. Chapter 3 explains the decisions made in selecting the pilot cases which are interpreted in a transport context. The empirical results of the pilot cases are described in chapter 4. Chapter 5 contains the expectation based projections and chapter 6 a summary of findings. The paper ends with a discussion on the usefulness of the results for transport policy making in chapter 7 and the concluding remarks in chapter 8.

1 Mixed models

The justification for the mixed model choice is a consequence of the data itself where: a) yearly measurements of trade on each country included in the sample are correlated and b) the geographic groups demonstrate variation between the countries in the same geographic group and between geographic groups. The variability between the countries is conformed by graphical analysis of the data and more formally through initial separate estimations of the different specifications (linear, logarithmic, exponential, logistic) per country. For this purpose, the models are estimated without random variables which results show clear variability in the parameters between the countries. Additionally a null model test where all effects are fixed against the model being estimated with mixed effects is performed. The discussion however on whether the fixed instead of the mixed model is more appropriate is quite complex and no clear cut answers are found in the literature. According to Verbeek (2008) the fixed model is intuitively chosen when the individuals in the sample are one of a kind which is the case of countries as in the current study. However fixed effects methods completely ignore the between-country variation and focus only on the within-country variation. Discarding the former can yield standard errors that are considerably higher than those produced by methods that utilize both within- and between-item variation. On the other hand the between country variation may be contaminated by other unmeasured country characteristics which are correlated with the volume of trade. This results in biased estimates. Another practical difficulty is that with a large number of levels in a fixed effects model, like countries in this study, this leads to a huge overhead of parameters, especially since interactions need to be included in the model. Doing so wastes a lot of degrees of freedom. Another reason is that one wants the overall model to be valid irrespective of which countries happen to be included in the study. Bearing the limitations of both approaches in mind and considering the objective of the trend modeling which includes the making of projections the approach for choosing the most suitable model is by means of econometric testing, graphical fit and model comparisons. The comparisons considered are the following:

- Compare the models split in geographic groups (model HW, model HS, model HE) with the model with the geographic groups estimated together (model HWHSHE);
- Compare the disaggregated model HWHSHE of cat 6 (HWHSHE_cat6) with the aggregated model HWHSHE of total trade (HWHSHE_TOTAL);
- Compare covariance structures autoregressive (AR(1)) and unstructured (UN);
- Compare the mixed models with the models with only fixed effects;
- Compare model quality in terms of residuals analysis;
- Compare models when the dataset changes due to the different sources[3] ;
- Compare the different growth specifications for the HWHSHE models.

The anticipation from such an extensive quality control is that appropriate growth models are constructed which reflect true patterns and variability between the European countries and can therefore be used as policy tools which produce high quality trend forecasts.

1.1 Growth specifications

The different specifications include the linear, exponential, logarithmic and logistic functions which correspond to different growth expectations. The conceptual background for each growth model is described below:

- A linear growth is order 0 and characterizes a quantity which grows by the same amount in each time step;
- An exponential growth is order 1 and characterizes a quantity which increases at a fixed rate proportionally to itself;
- A logarithmic growth is not supported by any growth theory. It characterizes a quantity whose growth can be described as a logarithm function of some input. It is the inverse of the exponential growth and is very slow;
- A logistic growth is order 2, characterizes a quantity whose initial stage of growth is approximately exponential and as saturation begins, the growth slows, and at maturity, growth stops.

The reason why these four cases are chosen is firstly due to what is observed by plotting the data. Furthermore and most importantly, because these model specifications are

[3] The problem was identified when comparing databases sourced from the uncomtrade directly or from the World Integrated Trade Solution (WITS) or when sourcing data based on different flow direction i.e. imports of countries as reporters from the world and exports of the world to countries as partners.

interpretable in economic terms which can thus also be used for the making of projections. The consideration of alternative specifications like for example a cubic polynomial would yield more flexible, fitting the data reasonably well, but would lead to nonsensical projections. The reason is that polynomial models, especially of higher order, behave really badly in an extrapolation setting, and hence cannot be used in a trend fitting application.

By fitting a dataset to a particular mathematical specification one opts to explain and understand the historic pattern on the basis of the mathematical properties inherent to the equations themselves. The choice of which model to use from this broad pallet of models is subject to the expectations of the decision maker. The fact that the linear growth pattern is very popular is because of its computational (over)simplicity and because during times of growth it has given good estimates of future outcomes, provided the considered horizon is not that long. This is also true for the logarithmic growth which provides for more moderate estimates of future growth. In the case of the exponential growth, it is typically observed in the initial stage of growth. It is an extreme form of unbounded growth and hence it is of no use for the purpose of long term projections. Nevertheless, it's worth mentioning that given the impressive growth patterns experienced for example by the BRIC countries, projections of their growth using the exponential model in the past would have proven to be very reliable on the short term. With the unbounded growth being the major disadvantage of all previous mentioned growth models, further considerations on other nonlinear specifications led to the consideration of fitting a logistic growth specification. The latter is a sigmoid curve described by an initial stage of growth which initially behaves almost exponential and as saturation begins, the growth slows, and at maturity, growth stops. As such this model is very well suited and regularly used for the description of growth of physical phenomena. Its most well-known applications is in explaining population growth. It is not difficult to show that the option of a logistic type of growth derives from the law of diminishing marginal utility. Metz (2010) describes apparent patterns of saturation in terms of passenger travel (daily travel demand) and discusses the possibility of saturation patterns in freight. The analysis is based on a large database of the National Travel Survey in 2009 where he observes the presence of a plateau type of growth. Concerning freight the main argumentations used explaining saturation are amongst others: diminishing marginal utility, a mix of elements in terms of population growth, scale of sourcing from abroad, the composition of consumer goods and the high level of ownership of durables in the developed world. More specifically, freight growth maturity is primarily discussed by McKinnon (2007) and Osenton (2004) who argue that the process of road freight driven by the concentration of economic activity cannot continue indefinitely, while pointing out that the possibility of saturation of demand for consumer durables needs to be recognized. Therefore unbounded growth models are less suitable.
A parallel discussion among economists, relevant to the discussion of saturation but within a different stream of research, relates to what constrains economic growth. This

research field highlights factors like diminishing returns to capital in production, Research and Development (R&D) technology and saturation of demand. As such technical progress and the addition of new products and industries have been discussed as necessary factors sustaining economic growth (Masanao, 2001; Grossman and Helpman, 1991). Hence, one could argue that while saturation may come to play due to diminishing marginal utilities for existing products, new products can stimulate further growth. In the absence however of new products saturation may occur. In our database however we cannot distinguish between existing and new products since the latter fall under the same headings of existing products. Furthermore it is very complex to define what represents to the consumer a "new" product. It is hence unclear whether we will observe saturation patterns in our investigation.

1.2 Growth models in a mixed context

The aforementioned individual growth models to be used in the modelling application are explained in a mixed context. For each model two cases are considered, the first estimation is made with a single random effect - the intercept - and the second estimation with two random effects - the intercept and the slope -. In the case of the exponential and the logistic growth models the estimations without random variables show that all three parameters – in the case of the exponential being the intercept, the natural parameter space and the initial slope and in the case of the logistic being the intercept, slope and point of inflection - should be classified as random effects. However, for reasons of cross model comparisons, resulting computational load and attribution of clear economic interpretation to the parameters it is decided against estimating the logistic model with three random variables.

The specifications are listed in table 3.1. In all equations (1) until (8) b_0 b_1, b_2 are the fixed effect parameters, u_{i1} , u_{i2} are the random effect parameter assumed to be independent and identically distributed $N(0,\sigma^2_u)$ and e_{ij} are the residual errors assumed to be independent and identically distributed $N(0,\sigma^2_e)$.

Table 1-1: Model Specifications

Linear one random	$y_{it} = (b_0 + u_{i1}) + b_1 \cdot t + e_{it}$	*(1)*
Linear two random	$y_{it} = (b_0 + u_{i1}) + (b_1 + u_{i2}) \cdot t + e_{it}$	*(2)*
Exponential one random	$y_{it} = (b_0 + u_{i1}) + b_1 \cdot \exp b_2 \cdot t + e_{it}$	*(3)*
Exponential two random	$y_{it} = (b_0 + u_{i1}) + b_1 \cdot \exp((b_2 + u_{i2}) \cdot t) + e_{it}$	*(4)*
Logarithmic one random	$y_{it} = (b_0 + u_{i1}) + b_1 \cdot \log t + e_{it}$	*(5)*
Logarithmic two random	$y_{it} = (b_0 + u_{i1}) + (b_1 + u_{i2}) \cdot \log t + e_{it}$	*(6)*

Logistic one random	$y_{it} = \dfrac{(b_0 + u_{i1})}{1 + \exp\left(-\dfrac{(t - b_1)}{b_2}\right)} + e_{it}$	*(7)*
Logistic two random	$y_{it} = \dfrac{(b_0 + u_{i1})}{1 + \exp\left(-\dfrac{(t - b_1)}{b_2 + u_{i2}}\right)} + e_{it}$	*(8)*

Where,

y :	*volume of imports in kg*
i :	*country*
t :	*year*
b_0, b_1 *:*	*fixed effects*
u_{i1}, u_{i2} *:*	*random effects*
e_{it} *:*	*residual errors*

In the linear equation (1) the trajectory for the import volume is a function of the intercept b_0 - the import volume at year 1980 - which is a random variable u_{i1} and the slope b_1 - the growth rate- while in the linear equation (2) the second random effect added is the slope represented by $u_{i2,}$ The same symbolism and logic applies to the logarithmic models in equations (5) and (6) with the difference that the import volume is described as a logarithm function of time. It is the inverse of the exponential growth and is very slow. In the case of the exponential equations (3) and (4) a parameterization is used which has no clear economic interpretation in terms of its b_1 and $b_{2.}$ The parameter b_0 represents the initial volume of imports.. In the logistic equation (7) The specification of the one random effect mixed logistic growth model is borrowed from Pinheiro and Bates (1995) where the import volume is a function of the intercept b_0 which is a random variable u_{i1} the slope b_1 and inflection point b_2. The two random effects specification in the equation (8) is borrowed from Litell et al (2006) with the difference that the second random effect u_{i2} is added for the slope instead of the point of inflection.

The specifications in table 3.1 are re-estimated to account for the crisis year through the addition of dummy variables for the year 2009 (b_4). In each model the dummy takes the values 0 or 1 to indicate the presence of the crisis. This approach addresses the sharp declines observed during the crisis year which would distort the estimations if time series from the year 1980 until 2009 were simply included in the estimation. Hence by the addition of the dummy the pattern of growth before 2009 is estimated without the influence of the crisis, while the period after the crisis will either be covered by existing data in the future or by assumptions on what is believed to be the rate of recovery. The latter is the approach followed in this research due to lack of data for 2010. In some cases the decline for the year 2009 is so severe that it raises question-marks on the reliability of the data. It is for this reason that the data for that year have been double checked and alternative sources have been consulted in order to somehow validate the accuracy of the data. Given the lack of strong evidence against the data of the UNCOMTRADE (and the data compilation/mining performed by the author) the data are kept as originally sourced. The intention is to recheck the data of 2009 for any updates after the release of the data for 2010. In this chapter only the estimations with the dummy variable are reported since these are the models which are going to be updated with newly acquired data in the future, while it is anticipated that the sharp declines in 2009 even if revised upwards will still require the incorporation of a dummy variable. The only exception to the above is the case of the NLD which according to the World Economic Outlook (WEO) of the IMF it did not experience sharper declines than the other countries of Western Europe (see Annex I). The indicator chosen to draw inferences on data quality is the volume of import of goods for the sample countries. Given however the additional proof from that same database of an almost complete recovery the final decision taken is to keep the original data and estimate the models with the dummy for 2009 and a full recovery in 2010 for the forecasts.

The non linear specifications in particular, require an additional step, the setting of initial values. The way this is done is described in box 1 and box 2 in Annex I which describe the process for the models of exponential and logistic growth respectively.

2 Pilot cases and Data

The pilot cases consider different levels of aggregation in terms of product composition. The justification for using disaggregated data on the product level is that valuable information is lost due to the aggregation of product categories. This is observed within the transport and maritime field due to the fact that container freight rates are charged on the basis of market conditions and not on the traditional method of "weight or measurement whichever is the greater"[4] while the type of cargo is an indicator of freight height[5]. Furthermore, supply chain corridors differ according to product type. Concerning trade, empirical research (gravity, demand estimations, etc.) has often shown that aggregated flows mask or distort the estimated impact of the explanatory variables. This can be explained through a demand growth which differs per product category and through patterns of consumption which differ per product category as income level rises and as unit price increases (Siliverstovs and Schumacher, 2008; Anderson and van Wincoop, 2004; Hummels, 1999). In addition to the latter, considerations regarding the quality of the attained dataset and practical reasons – primarily the checking for the

[4] "Weight or measurement whichever is the greater" is a method for defining the freight rate. It means that the cargo is charged according to weight when heavy and volume when volumous.

[5] However during today's times the behavior of the market experiences disruptions in its common workings. This is illustrated through the peculiarities in the charging of freight rates.

presence of outliers by tracing them back in the database and interpreting them accordingly – are additional reasons why the disaggregated approach is considered in this paper. At the same time however the aggregated approach is typically free of volatile patterns, where outliers level off. For the aforementioned reasons two cases of total and disaggregated trade are considered and compared.

The chosen pilot concerning the disaggregated analysis is category six, which is 81% composed of processed industrial supplies, titled "manufactured goods chiefly categorized by material" (see annex 1). It belongs to the broader category of manufactured goods completed by category five "Chemicals and related products", seven "Machinery and transport equipment" and eight "Miscellaneous manufactured articles". In particular categories eight and the pilot case comprise of the category of "other manufactured goods". The reason why it is chosen as a pilot is because it belongs to the category of manufactures, which is a sector largely relocated from Europe to countries with lower labor costs. Interestingly, category six remains a category which is still produced within Europe and hence included in the intra European trade datasets. At the same time - given structural tendencies of relocation of industries in the manufacturing sector in Europe (Rowthorn and Ramaswamy, 1997) - it is seen as representing potential volumes which due to the structural tendencies could ultimately be transported from overseas and hence become relevant to the maritime sector. An example is the imports of category six from China which currently in terms of volumes are less important when compared to intra trade volumes but the exponential growth pattern (see Annex I) shows potential for further growth.

Typically, analyses on trade utilize data in values which are widely available in extensive detail from a number of sources. For this analysis however to make sense for the transport sector the data unit desired is the one of volume. Such data are however scarce and not directly attainable on all levels of product disaggregation. The database utilized in this paper is the result of an extensive data mining exercise performed on the digit 3 level SITC classification from the UNCOMTRADE. All data are checked for their coverage and quality thoroughly and are found suitable for their subsequent use for modeling (Markianidou, in process). In particular the estimations of the disaggregated and aggregated database include the total of 19 countries, listed in table 4-1.

Table 2-1: Country levels

Class Level Information		
Class	**Levels**	**Values**
Partner	19	AUT BGR BLX CHE CYP CZE DEU ESP FRA GRC HUN ITA MLT NLD POL PRT ROM SVK SVN

However, not all countries have complete time series from the 1980's until 2009. For this reason, applications are made twice, the first time with the complete sample of countries and the second including only those countries with complete datasets. The procedure used (proc mixed of SAS) does not delete an entire subject when a single observation is missing and it analyzes all of the data that are present. However, while the proc mixed procedure can accommodate missing values, (which is confirmed in the current application by comparing the estimation results between the two datasets, complete and reduced) the preferred approach in this research is to present the results incorporating only the models estimated without any missing values. The total number of observations hence amounts to 464. In the case where the geographic groups are estimated separately the countries with missing values are included but with a reduced time scale in order to estimate the models without missing values. In particular the latter case corresponds to the geographic group of the Eastern European countries for which the sample includes observations from 1996 until 2009. The main reason for excluding the countries with missing values (when estimating all countries in a single dataset) in the first case and reducing the sample size in the second case (when estimating countries per geographic group) is because the data are not missing at random which invalidates the analysis. This situation occurs when systematic factors lead to missing data. In this case the missing observations for the countries SVN, SVK, CZE, between 1980 and 1996 relate to the political conditions of that time which endured until the year 1990. The final assessment therefore is that the data are not missing at random and it is therefore best to exclude them from the analysis.

The data are sourced for the European countries listed in table 4-2.

Table 2-2: Country groups

Flow	**Groups**	**Countries**
Partner/	HW	AUT BLX CHE DEU FRA NLD
Reporter	HS	CYP ESP GRC ITA MLT PRT
	HE	BGR CSK HUN POL ROM SVN

The criterion for creating the country groups is based on geographical considerations as defined by the United Nations classification. HW includes Western European countries while HS and HE Southern and Eastern countries respectively. Sample countries from Northern Europe are not included given the extreme diversity between the countries in their patterns of trade. The geographic division thus made less sense and it is hence decided to exclude them entirely from the analysis.

3 Growth models in practice

This chapter presents the results of the modeling exercises for both the disaggregated and aggregated datasets and for both the geographic groups separately (HW, HS, HE) and all together in one dataset[6] (HWHSHE) with the addition of examples of country results for BLX, DEU and NLD. The estimations are made with and without a dummy variable, hence with and without the year 2009. The latter are illustrated by means of comparison by reporting on the fit statistics only. The models are estimated with two random variables (the intercept and the slope) except for the linear model which only includes the intercept as random[7]. All estimations are performed in levels and the error analysis is found in Annex III. In each group the candidate models are estimated, evaluated and compared with each other. The final choice on which model(s) best represent(s) the growth pattern is made according to the econometric properties of the models and considerations of model bias and robustness (see chapter 6).

3.1 Disaggregated

The results of the disaggregated estimations are summarized in tables 4-3 until 4-7. The mixed model output is reported including the estimations for the fixed and random variables and the fit statistics.

In the linear applications according to tables 4-3 and 4-4 fixed and covariance parameter estimates for both the linear and logarithmic models are highly significant. The exponential trend is only fitted to the geographic groups HS and HE although only the latter displays a clear exponential growth pattern. According to table 4-5 the parameters for the HS and HE geographic groups of category six are significant. The results of the logistic estimation described in table 4-7 also show that both fixed and random parameters are significant. The insignificant variance estimate does not have an interpretational interest to this paper[8]. Concerning the suitability of the mixed approach (in the case of only the linear models), the covariance structure is significant based on the "null model likelihood ratio test" where the null model (one with only the fixed effects listed in the model) is rejected. In other words the linear and logarithmic models including random effects are superior to the models with only the fixed effects. The type of the error correlation structure specified is the first-order autoregressive correlation. The AR(1) structure is deemed appropriate since it represents a structure which has homogeneous variances and correlations that decline exponentially with distance. It means that two measurements that are right next to each other in time are going to be

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[6] For all groups the data has for the facilitation of the convergence of the models (linear and non linear) been rescaled

[7] Due to convergence issues, which indicate that the slope parameter is probably not random

[8] This is most likely due to numerical and algoritmic issues. Since this variance is estimated as one of the likelihood parameters this can sometimes happen. It however does not mean it is actually zero.

correlated but that as measurements get farther and farther apart they are less correlated (Kincaid, 2005). The choice of the AR(1) structure is intuitive but is complemented by a trial and error approach, by testing with other error structures, in particular the unstructured one which is the most flexible of all. No significant differences were noted between the two structures, indicating that the AR(1) specification is appropriate. In all cases, models with the sample countries in a single dataset are the best performing models compared to the models estimated for the geographic groups separately. This is expected given the larger sample size of the former database and is also established through a comparison of fit statistics (See Annex III). Among the linear models estimated the HE model produces the best fit from the geographic grouped models which is also the case for the logarithmic models. The best performer for the exponential and logistic models is the HS group. Such statistics are influenced by the number of observations and given that each group contained a different number of countries, results should be viewed with caution. Finally a comparison of Mean Absolute Error (MAE) and Mean Squared Error (MSE) is performed with the aim of comparing the model specifications to each other. However, no model showed clear superiority with only very little differences between the calculated values.

Table 3-1: Linear Growth

LINEAR_HWHSHE_CAT6_ dummy					
Covariance Parameter Estimates					
Cov Parm	**Subject**	**Estimate**	**Standard Error**	**Z Value**	**Pr > Z**
Variance	Partner	0.03184	0.01080	2.95	0.0016
AR(1)	Partner	-0.9608	0.03975	-24.17	<.0001
Residual		0.004072	0.000255	15.99	<.0001
Solution for Fixed Effects					
Effect	**Estimate**	**Standard Error**	**DF**	**t Value**	**Pr>|t|**
Intercept	-7.2315	0.6670	17	-10.84	<.0001
Year	0.003679	0.000334	503	11.02	<.0001
year2009	-0.1254	0.04503	17	-2.78	0.0127
Intercept	-7.2315	0.6670	17	-10.84	<.0001
Fit Statistics	**CAT6_ dummy**		**CAT6_ nodummy**		
-2 Log Likelihood	-1041.3		-1006.9		
AIC (smaller is better)	-1029.3		-998.9		
AICC (smaller is better)	-1029.1		-998.8		
BIC (smaller is better)	-1024.6		-995.8		

Table 3-2: Logarithmic growth

LOGARITHMIC_HWHSHE_CAT6_ dummy					
Covariance Parameter Estimates					
Cov Parm	**Subject**	**Estimate**	**Standard Error**	**Z Value**	**Pr > Z**
Variance	Partner	0.01400	0.005018	2.79	0.0026
AR(1)	Partner	-0.7822	0.1049	-7.45	<.0001
Residual		0.003268	0.000220	14.88	<.0001
Solution for Fixed Effects					
Effect	**Estimate**	**Standard Error**	**DF**	**t Value**	**Pr>|t|**
Intercept	-0.1827	0.03294	15	-5.55	<.0001
Lyear	0.1262	0.03001	15	4.20	0.0008
year2009	-0.1831	0.01496	447	-12.24	<.0001
Fit Statistics	**CAT6_ dummy**		**CAT6_ nodummy**		
-2 Log Likelihood	-1260.3		-1389.6		
AIC (smaller is better)	-1248.3		-1379.6		
AICC (smaller is better)	-1248.1		-1379.5		
BIC (smaller is better)	-1024.6		-1375.7		

Table 3-3: Exponential growth

Parameter Estimates HE_CAT6									
Parameter	**Estimate**	**Standard Error**	**DF**	**t Value**	**Pr > |t|**	**Alpha**	**Lower**	**Upper**	**Gradient**
b1	-0.09636	0.02747	3	-3.51	0.0392	0.05	-0.1838	-0.00895	-1.39E-6
b2	0.07377	0.01783	3	4.14	0.0256	0.05	0.01703	0.1305	-7.26E-6
b3	0.07429	0.01162	3	6.40	0.0077	0.05	0.03733	0.1113	-2.16E-6
s2u1	0.000233	0.000344	3	0.68	0.5470	0.05	-0.00086	0.001327	0.000018
s2u2	0.000391	0.000257	3	1.52	0.2262	0.05	-0.00043	0.001210	-0.0003
s2e	0.004460	0.000542	3	8.22	0.0038	0.05	0.002733	0.006186	2.284E-6
Parameter Estimates HS_CAT6									
B1	-0.4599	0.09649	5	-4.77	0.0050	0.05	-0.7079	-0.2119	3.033E-9
B2	0.4854	0.09182	5	5.29	0.0032	0.05	0.2494	0.7215	-137E-12
B3	0.01364	0.005730	5	2.38	0.0631	0.05	-0.00109	0.02837	-5.94E-9
S2u1	0.002962	0.001645	5	1.80	0.1315	0.05	-0.00127	0.007190	2.769E-6
S2u2	0.000206	0.000120	5	1.71	0.1479	0.05	-0.00010	0.000516	0.000058
S2e	0.000957	0.000098	5	9.72	0.0002	0.05	0.000704	0.001210	0.000019

Fit Statistics	HE	HS
-2 Log Likelihood	-346.7	-765.5
AIC (smaller is better)	-334.7	-753.5
AICC (smaller is better)	-334.1	-753.1
BIC (smaller is better)	-337.1	-753.9

Table 3-4: Logistic growth

LOGISTIC_HWHSHE_CAT6_ dummy									
Parameter Estimates									
Parameter	**Estimate**	**Standard Error**	**DF**	**t Value**	**Pr > |t|**	**Alpha**	**Lower**	**Upper**	**Gradient**
b1	0.4292	0.1131	14	3.79	0.0020	0.05	0.1865	0.6718	1.738E-6
b2	1999.12	1.1221	14	1781.60	<.0001	0.05	1996.71	2001.52	-0.00002
b3	10.1747	1.5163	14	6.71	<.0001	0.05	6.9226	13.4267	-0.00003
s2u1	0.1984	0.07146	14	2.78	0.0149	0.05	0.04512	0.3516	-4.16E-6
c12	1.1786	0.6853	14	1.72	0.1075	0.05	-0.2912	2.6485	-0.00007
s2u2	25.7867	10.5419	14	2.45	0.0283	0.05	3.1765	48.3969	-0.00186
s2e	0.001364	0.000093	14	14.70	<.0001	0.05	0.001165	0.001563	-0.00002
Fit Statistics	**CAT6_ dummy**					**CAT6_ nodummy**			
-2 Log Likelihood	-1613					-1601			
AIC (smaller is better)	-1597					-1587			
AICC (smaller is better)	-1596					-1587			
BIC (smaller is better)	-1591					-1582			

3.2 Aggregated

The results of the aggregated estimations are summarized in tables 4-7 until 4-10. The mixed model output is reported including the estimations for the fixed and random variables and the fit statistics. In general equivalent results as for the disaggregated cases are produced.

In the linear applications according to tables 4-7 and 4-8, fixed and covariance parameter estimates for both the linear and logarithmic models are highly significant. The nonlinear exponential trend described in table 4-9 is only fitted to the geographic groups HE and HS. The parameters for the geographic groups are not significant. The results of the logistic estimation described in table 4-10 show that both fixed and random parameters are significant. The insignificant variance estimate does not have an interpretational interest to this paper[9]. Concerning the suitability of the mixed approach (in the case of only the linear models), the covariance structure is significant based on the "null model likelihood ratio test". In other words as for the disaggregated models the

[9] See comment 8.

linear and logarithmic models including random effects are superior to the models with only the fixed effects. In all cases, models with the sample countries in a single dataset are the best performing models compared to the models estimated for the geographic groups separately. Same reasons of sample size confirmed by fit statistic are also valid in the aggregated case. Among the linear models estimated the HW model produces the best fit among the geographic grouped models. Among the logarithmic the best fit is achieved by the HE countries. Finally the HS group produces the best fit from the logistic growth models. Such statistics are influenced by the number of observations and given that each group contained a different number of countries, results should be viewed with caution. Finally the comparison of Mean Absolute Error (MAE) and Mean Squared Error (MSE) positions all model specifications on an equal performance level.

Table 3-5: Linear growth output

LINEAR_HWHSHE_TOTAL_dummy					
Covariance Parameter Estimates					
Cov Parm	**Subject**	**Estimate**	**Standard Error**	**Z Value**	**Pr > Z**
UN(1,1)	Reporter	0.04908	0.01597	3.07	0.0011
Residual		0.003776	0.000238	15.86	<.0001
Solution for Fixed Effects					
Effect	**Estimate**	**Standard Error**	**DF**	**t Value**	**Pr > |t|**
Intercept	-12.8033	0.6849	18	-18.69	<.0001
Year	0.006515	0.000342	501	19.03	<.0001
year2009	-0.07852	0.01513	501	-5.19	<.0001
Intercept	-7.2315	0.6670	17	-10.84	<.0001
Fit Statistics	**TOTAL_ dummy**		**TOTAL_ nodummy**		
-2 Log Likelihood	-1319.5		-1064.5		
AIC (smaller is better)	-1309.5		-1056.5		
AICC (smaller is better)	-1309.4		-1056.4		
BIC (smaller is better)	-1304.8		-1053.7		

Table 3-6: Logarithmic growth output

LOGARITHMIC_HWHSHE_TOTAL_ dummy					
Covariance Parameter Estimates					
Cov Parm	**Subject**	**Estimate**	**Standard Error**	**Z Value**	**Pr > Z**
UN(1,1)	Reporter	0.02358	0.008428	2.80	0.0026
UN(2,1)	Reporter	-0.00743	0.003864	-1.92	0.0545
UN(2,2)	Reporter	0.008196	0.002744	2.99	0.0014
Residual		0.001625	0.000104	15.59	<.0001
Solution for Fixed Effects					
Effect	**Estimate**	**Standard Error**	**DF**	**t Value**	**Pr > |t|**
Intercept	-0.1358	0.03307	18	-4.11	0.0007
Lyear	0.1067	0.02516	18	4.24	0.0005
year2009	-0.04615	0.01096	447	-4.21	<.0001
Fit Statistics	**TOTAL_ dummy**		**TOTAL_ nodummy**		
-2 Log Likelihood	-1412.2		-1400.9		
AIC (smaller is better)	-1398.2		-1390.9		
AICC (smaller is better)	-1397.9		-1390.8		
BIC (smaller is better)	-1393.2		-1387.4		

Table 3-7: Exponential Growth output

Parameter Estimates HE_TOTAL									
Parameter	**Estimate**	**Standard Error**	**DF**	**t Value**	**Pr > |t|**	**Alpha**	**Lower**	**Upper**	**Gradient**
b1	0.04452	0.01098	4	4.06	0.0154	0.05	0.01404	0.07500	*-0.00036*
b2	0.000038	0.000156	4	0.24	0.8192	0.05	-0.00039	0.000470	*-9.86458*
b3	0.2332	0.1431	4	1.63	0.1787	0.05	-0.1642	0.6306	*-0.00882*
s2u1	0.000554	0.000324	4	1.71	0.1623	0.05	-0.00035	0.001454	*-0.00074*
s2u2	0.000225	0.000180	4	1.25	0.2797	0.05	-0.00027	0.000724	*-0.28108*
s2e	0.000047	8.267E-6	4	5.70	0.0047	0.05	0.000024	0.000070	*-0.37915*
Parameter Estimates HS_TOTAL									
B1	-0.01259	0.003989	2	-3.16	0.0875	0.05	-0.02975	0.004575	-0.00001
B2	0.009902	0.001884	2	5.25	0.0344	0.05	0.001794	0.01801	-0.00016
B3	0.09180	0.01189	2	7.72	0.0164	0.05	0.04062	0.1430	8.249E-7
S2u1	0.000017	0.000017	2	0.97	0.4363	0.05	-0.00006	0.000091	-0.392
S2u2	0.000402	0.000289	2	1.39	0.2994	0.05	-0.00084	0.001647	0.000232
S2e	*0.000111*	*0.000015*	*2*	*7.32*	*0.0182*	*0.05*	*0.000046*	*0.000176*	*-0.01772*

Fit Statistics	HE	HS
-2 Log Likelihood	-776.8	-701.3
AIC (smaller is better)	-764.8	-689.3
AICC (smaller is better)	-764.0	-688.5
BIC (smaller is better)	*-768.5*	*-693.0*

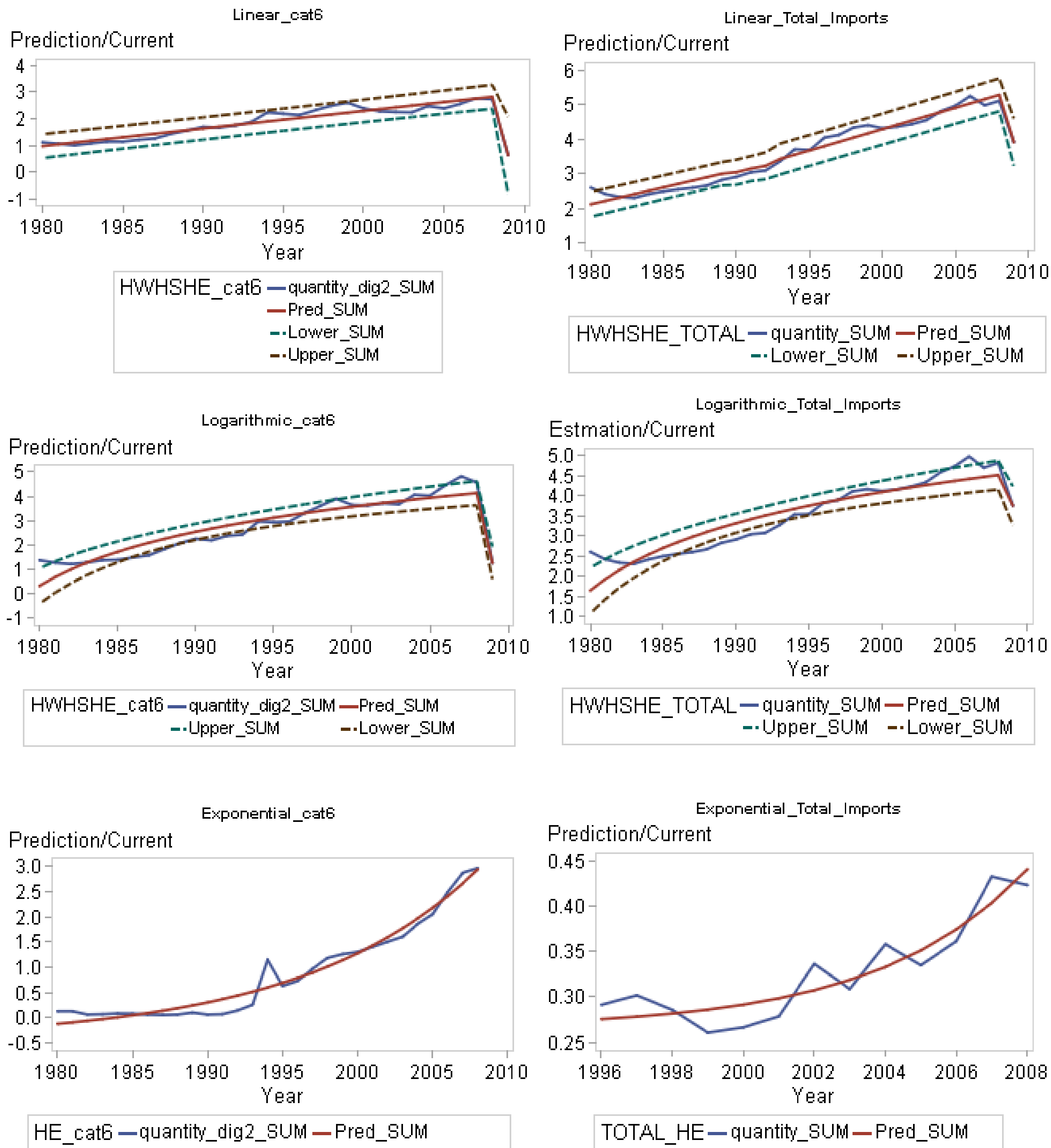
Table 3-8: Logistic Growth Output

LOGISTIC_HWHSHE_TOTAL dummy									
Parameter Estimates									
Parameter	**Estimate**	**Standard Error**	**DF**	**t Value**	**Pr > |t|**	**Alpha**	**Lower**	**Upper**	**Gradient**
b1	0.4734	0.1198	13	3.95	0.0017	0.05	-712E-12	0.4734	0.1198
b2	1994.76	0.7404	13	2694.22	<.0001	0.05	-1.5E-9	1994.76	0.7404
b3	16.9144	2.9073	13	5.82	<.0001	0.05	1.27E-10	16.9144	2.9073
s2u1	10.9782	0.8784	13	12.50	<.0001	0.05	-617E-13	10.9782	0.8784
c12	0.2139	0.07853	13	2.72	0.0174	0.05	1.599E-9	0.2139	0.07853
s2u2	89.4892	35.4977	13	2.52	0.0256	0.05	-658E-13	89.4892	35.4977
s2e	2.1565	1.3898	13	1.55	0.1448	0.05	-137E-13	2.1565	1.3898
Fit Statistics	**TOTAL_ dummy**					**TOTAL_ nodummy**			
-2 Log Likelihood	-1623					-1633			
AIC (smaller is better)	-1607					-1619			
AICC (smaller is better)	-1606					-1619			
BIC (smaller is better)	-1601					-1614			

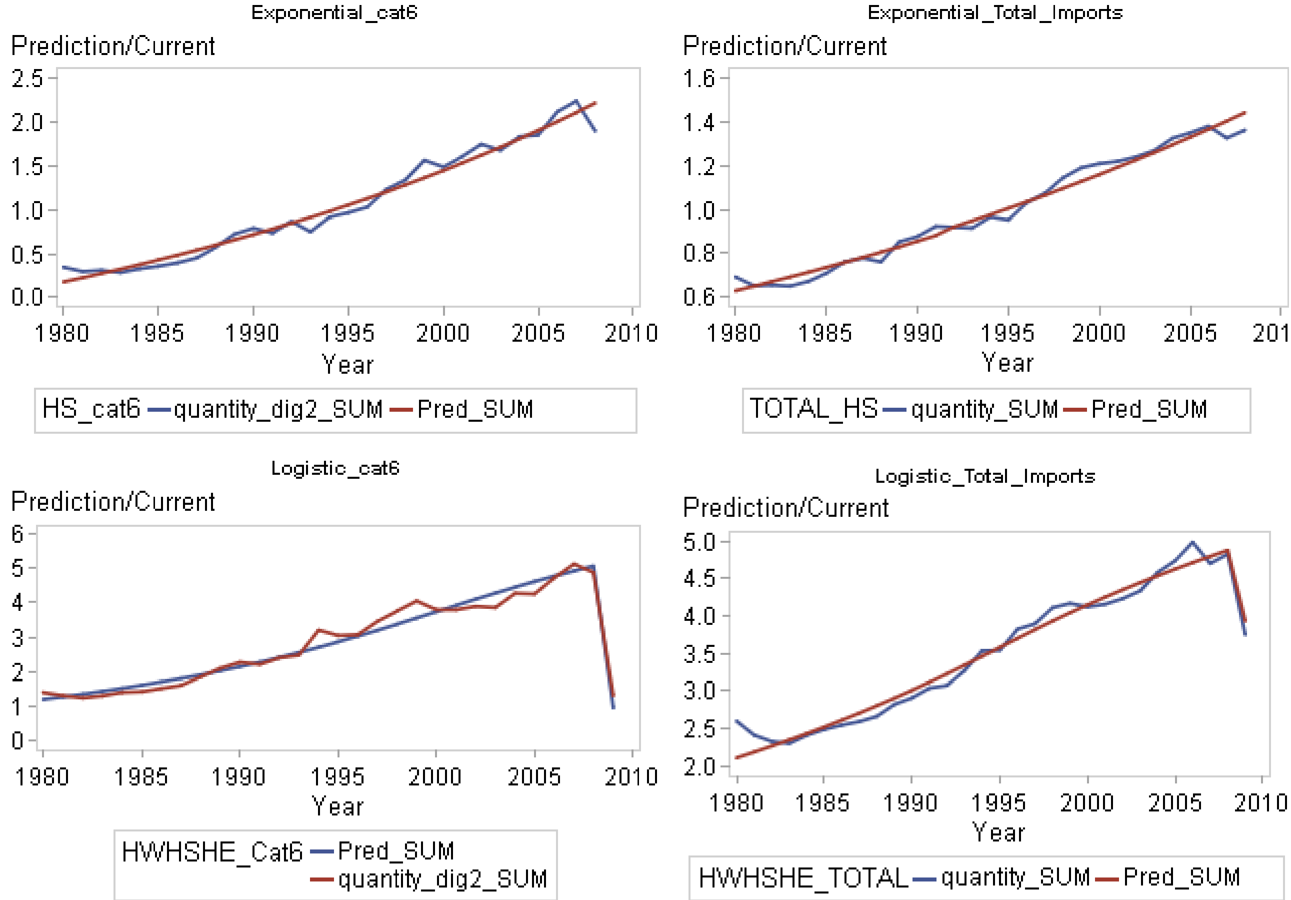
3.3 Graphical assessment of model fit

Using an exclusively graphical approach towards narrowing down the models which fit the data best, inevitably involves some degree of arbitrariness. The fit of the estimated models with the countries in one single dataset aggregated are illustrated in graph 4-1.

Graph 3-1: Fit aggregated - Category 6 & Total



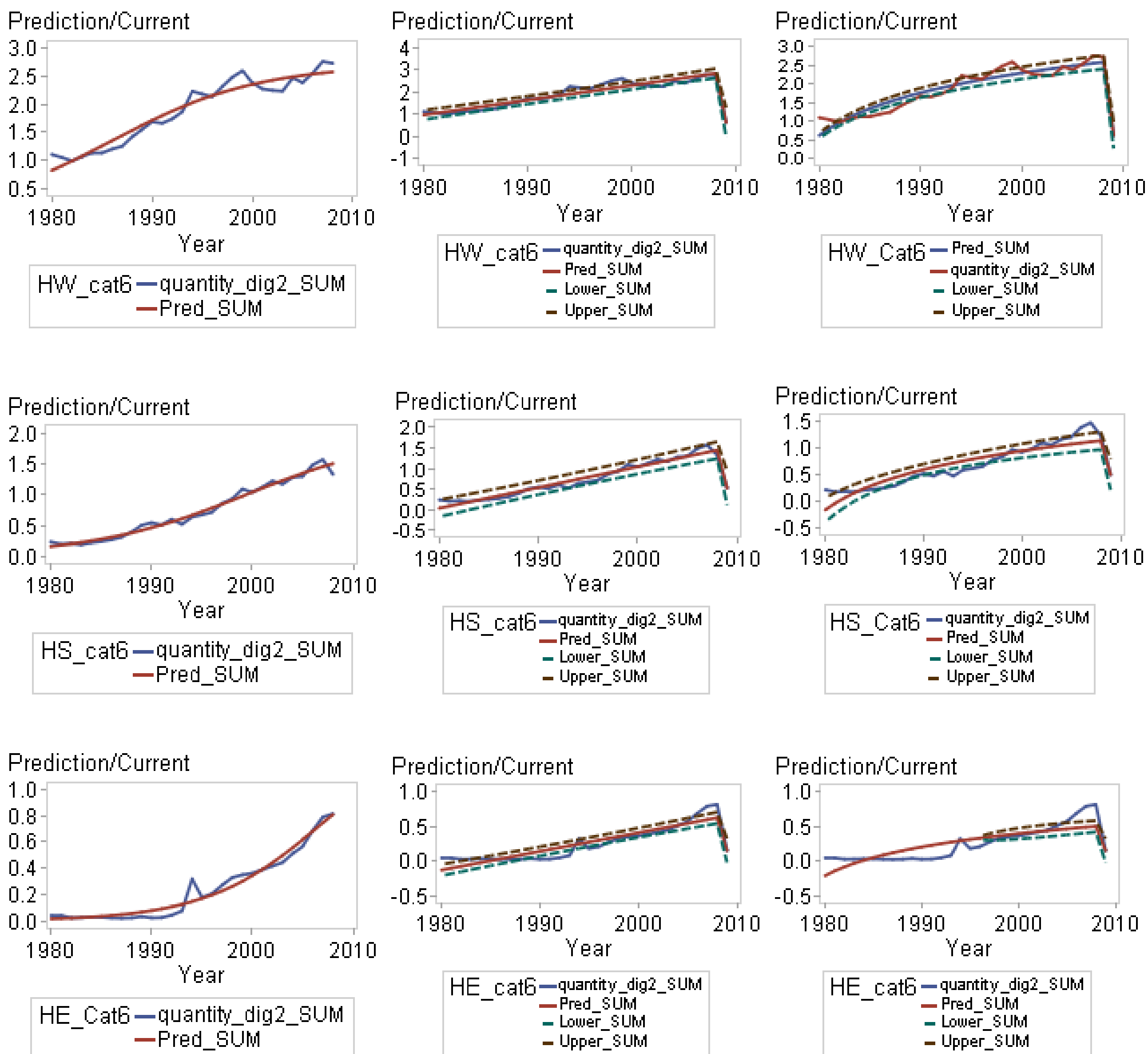
Graph 4-1 (continued): Fit aggregated - Category 6 & Total



The graphical fit for each geographic group and a sample of countries, in particular BLX, DEU and NLD is illustrated in graphs 4-2 and 4-4 for category six and 4-3 and 4-4 for total trade respectively. In the majority of cases more than one specification fits the data well as shown in graph 4-1 too. For example, the logistic growth function provides for a reasonable fit to both hinterland groups and countries. The reason for its graphical performance is due to the initial phase that resembles exponential growth and succeeding slowdown phase, that is almost linear, a pattern observed in many countries in Western Europe. The model is however not yet saturating. The presence of currently saturated flows is therefore rejected for both aggregated and disaggregated applications. Besides the logistic growth model however the linear specification, initially intended as a benchmarking tool, performs reasonably well. The logarithmic model on the contrary does not perform very well. The exponential model clearly also performs very well especially in the applications for Eastern European countries.

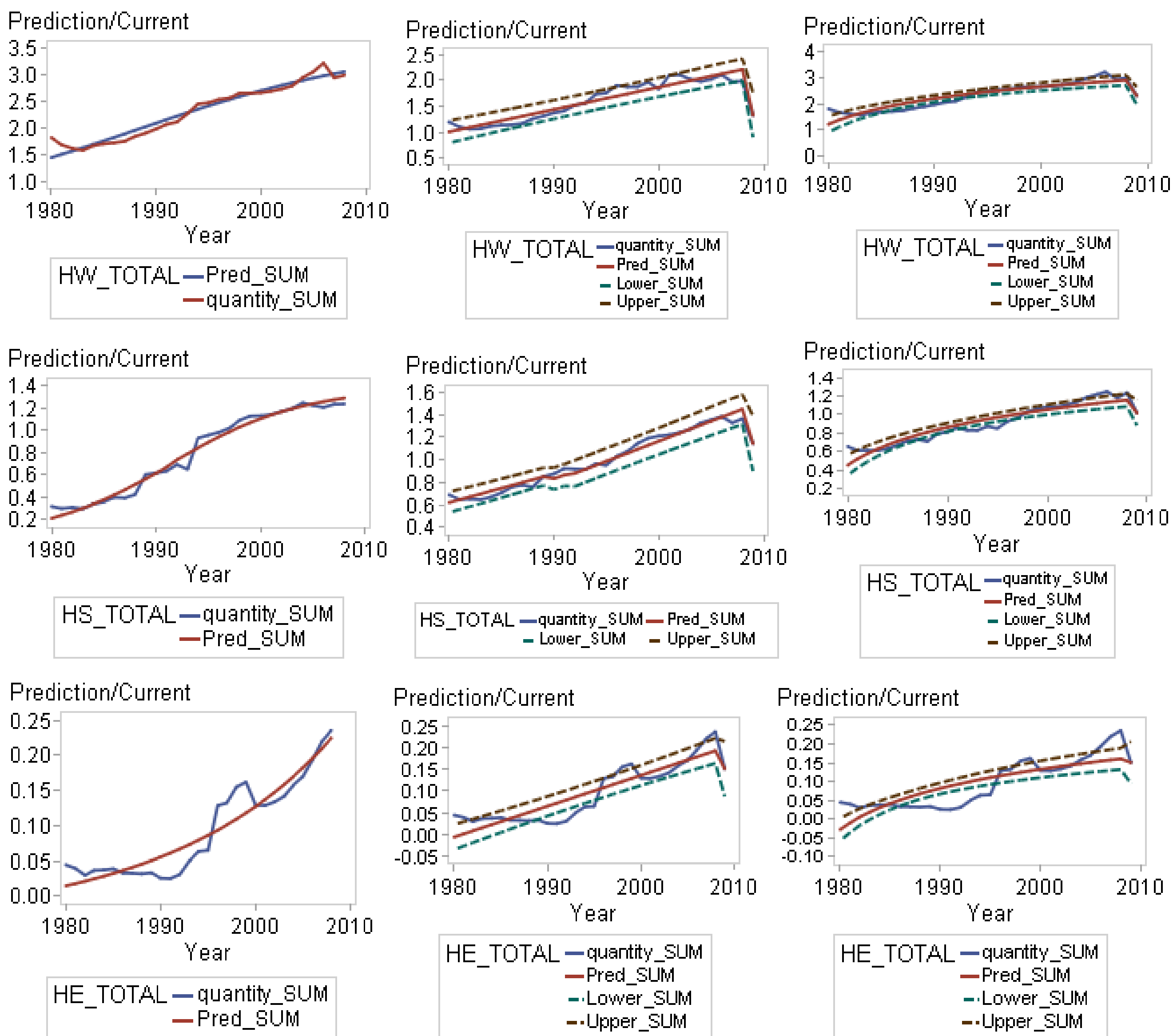
Graph 3-2: Fit per geographic group_category six

Logistic **Linear** **Logarithmic**



Graph 3-3: Fit per geographic group_total

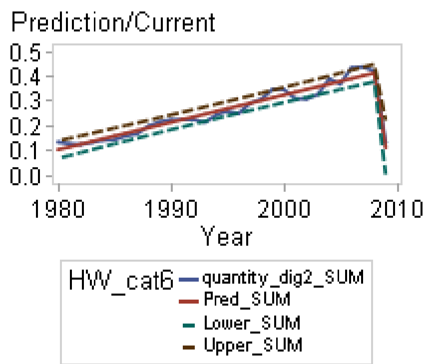
Logistic | **Linear** | **Logarithmic**



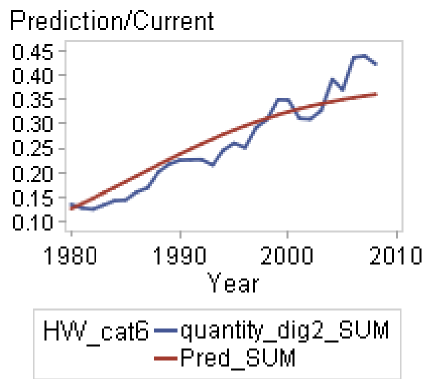
Graph 3-4: Fit per country_category six

Fit_BLX

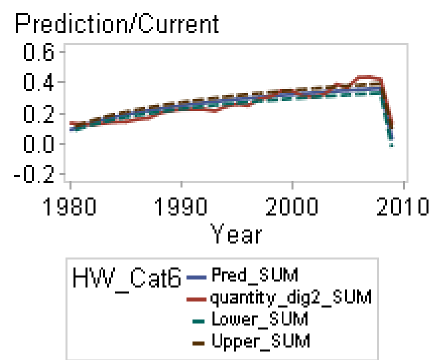
Linear



Logistic/exponential

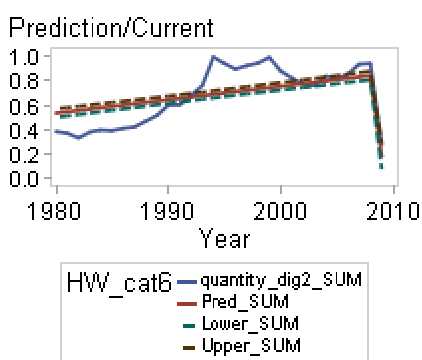


Logarithmic

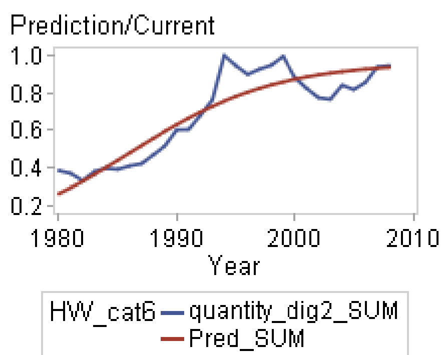


Fit_DEU

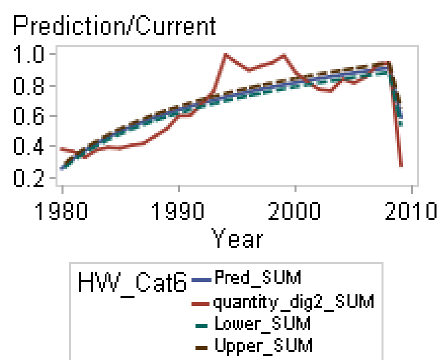
Linear



Logistic/exponential



Logarithmic

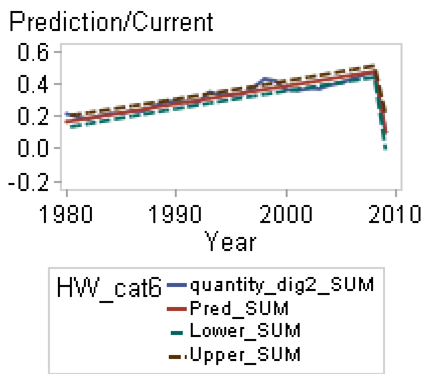


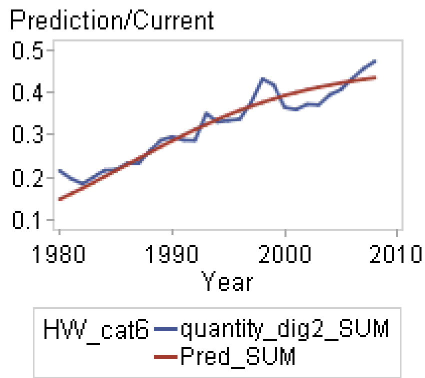
Fit_NLD

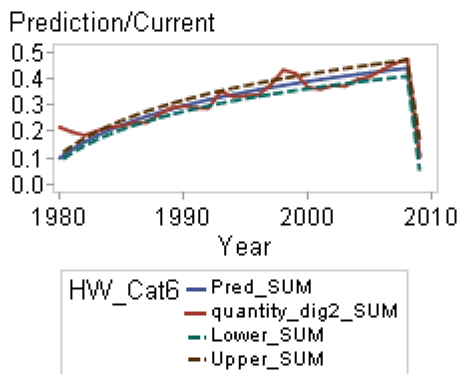
Linear

Logistic/exponential

Logarithmic


Prediction/Current
0.6
0.4
0.2
0.0
-0.2
1980
1990
2000
2010
Year
HW_cat6
quantity_dig2_SUM
Pred_SUM
Lower_SUM
Upper_SUM

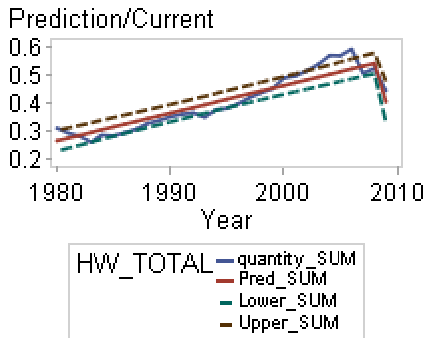

Prediction/Current
0.5
0.4
0.3
0.2
0.1
1980
1990
2000
2010
Year
HW_cat6
quantity_dig2_SUM
Pred_SUM


Prediction/Current
0.5
0.4
0.3
0.2
0.1
0.0
1980
1990
2000
2010
Year
HW_Cat6
Pred_SUM
quantity_dig2_SUM
Lower_SUM
Upper_SUM

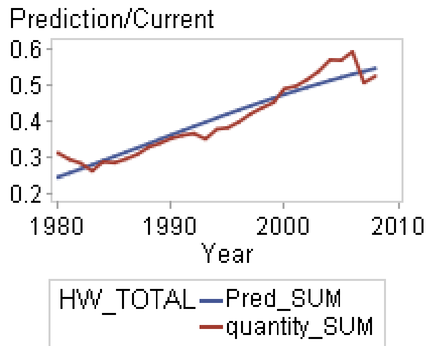
Graph 3-5: Fit per country_total

Fit_BE

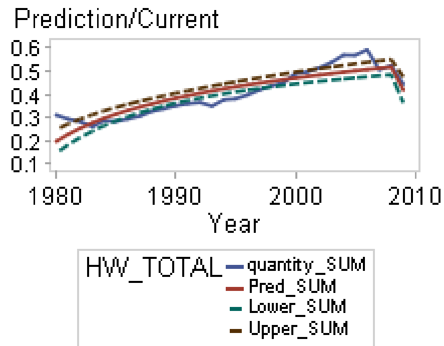
Linear



Logistic/exponential

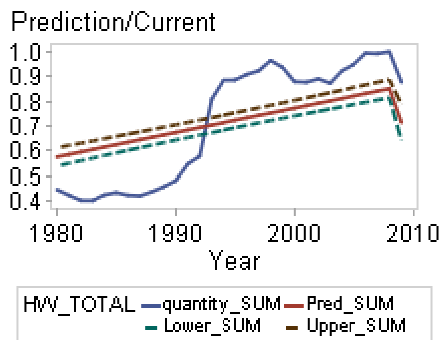


Logarithmic

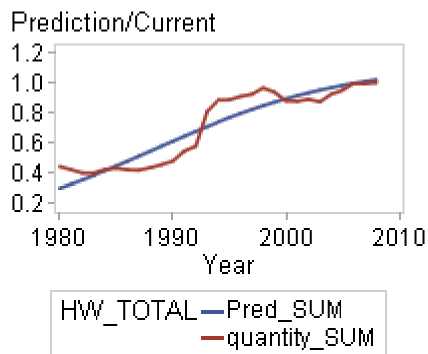


Fit_DEU

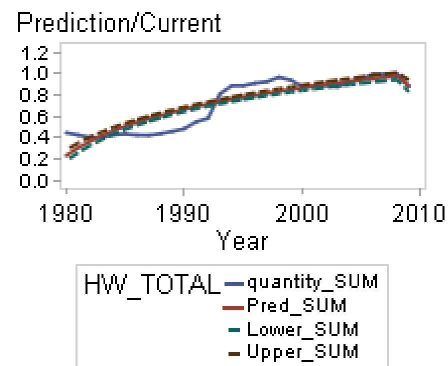
Linear



Logistic/exponential

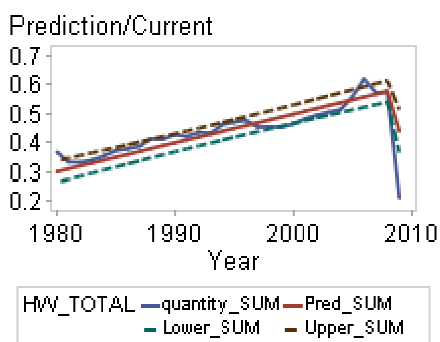


Logarithmic

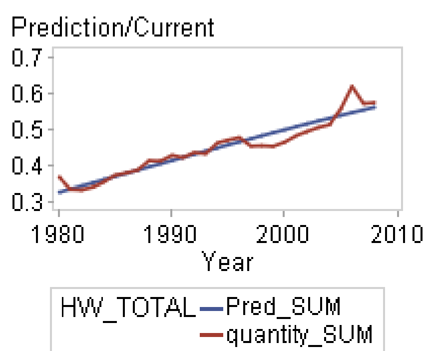


Fit_NLD

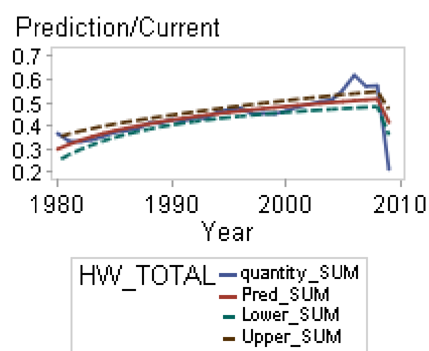
Linear



Logistic/exponential



Logarithmic



An exception to the latter commentary on saturated flows is the case of the DEU, where the pattern appears to follow a complete S shaped curve. The growth pattern of DEU is historically explained by the unification of Eastern and Western Germany in 1990 and the 2003 "Agenda 2010" measures which intended to make Germany a more competitive economy. The overall pattern of growth is often explained by the German economic model of an export driven economy which stimulates its competitiveness by restricting wage growth and domestic demand as quoted and systematically indicated by the press (Financial times, 2011; 2010; 2008; 2005).

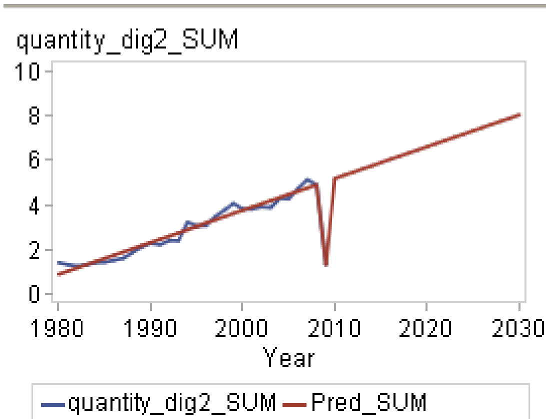
4 Trend extrapolation

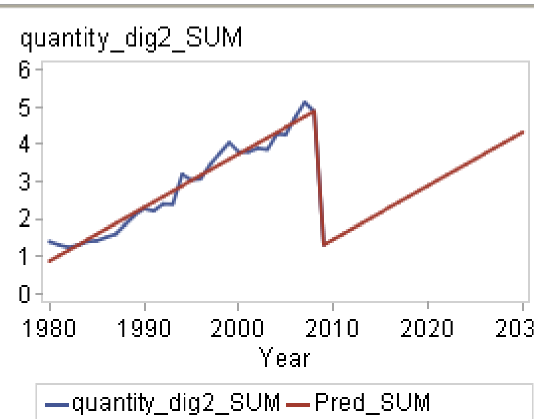
The trend models are extended in their use for the making of future projections. In this case the model specifications are viewed as corresponding to growth expectations of transport stakeholders. The scenarios illustrated graphically reflect two alternatives. The first scenario represents the full recovery of the global economies after the crisis leading to a recovery of the growth pattern for trade in 2010. Under this assumption the underlying dynamics forming the global economy are based on sustainable foundations which have additionally not been fundamentally altered by the global economic crisis. The second scenario represents the case of a pertaining crisis effect, by specifying the dummy as an increasing linear function of time after 2009. For this scenario to be more insightful however the data for 2010 are of crucial importance. A third scenario of imposing a predefined number of time lags before full recovery was considered but has been meanwhile abandoned given the signals from the IMF's WEO of an almost complete recovery of the flows for 2010 (see annex I). While the first scenario represents according to early data on 2010 the most realistic one the assumption of sustainable foundations of the growth patterns is uncertain.

The projections use trend extrapolations based on the growth models estimated in chapter 4. The models include the year 2009 as a dummy. In the case of the non linear applications they are only estimated with either the total database with the year 2009 included or for the geographic groups separately but without the year 2009. The reduced number of observations within the geographic groups is identified as the cause for the non conversion of those models.

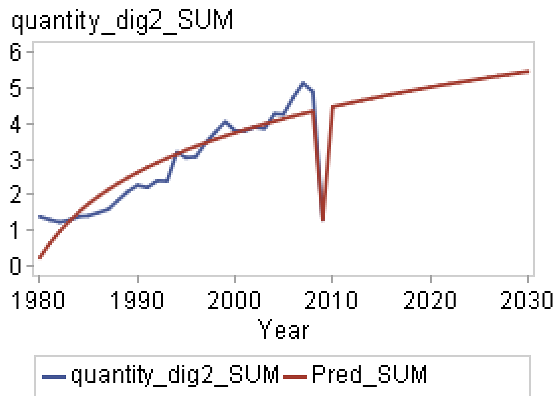
Graph 4-1: Trend Extrapolation – imports cat_6

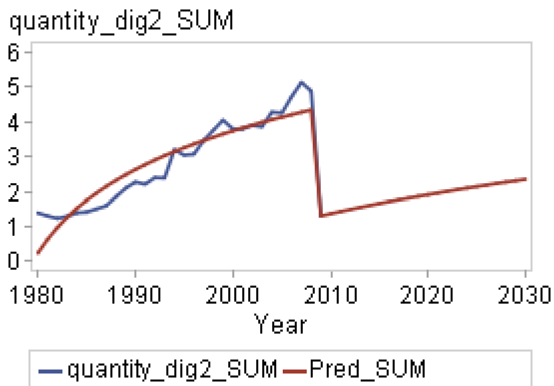
Linear_HWHSHE



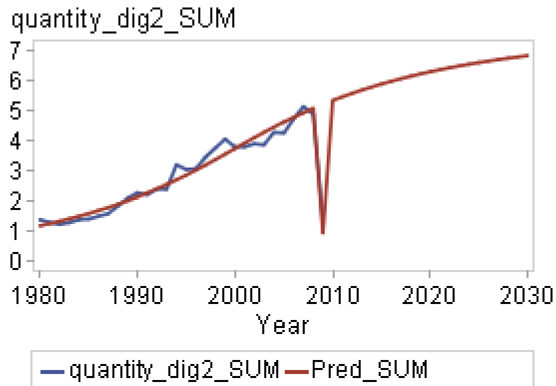


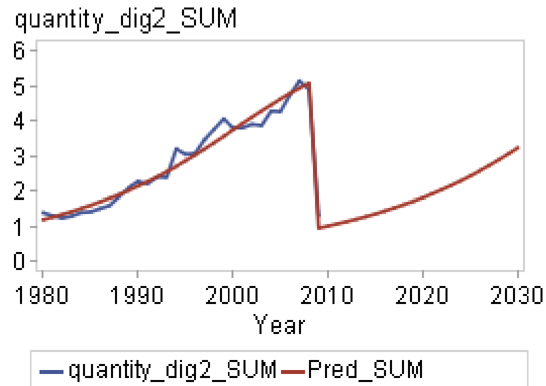
Logarithmic_HWHSHE





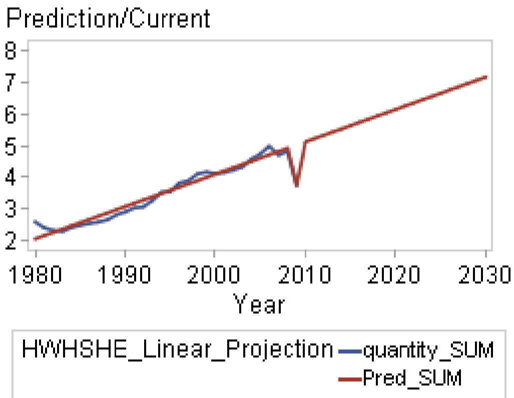
Logistic_HWHSHE

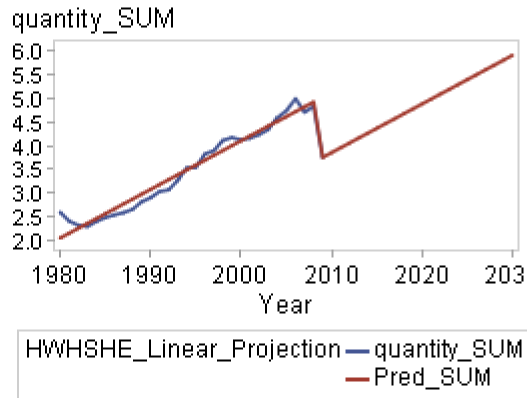




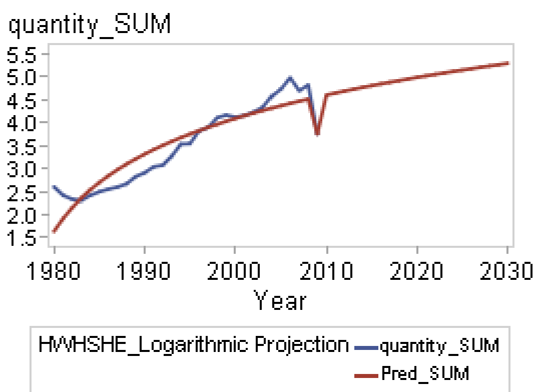
Graph 4-2: Trend Extrapolation - Total Imports

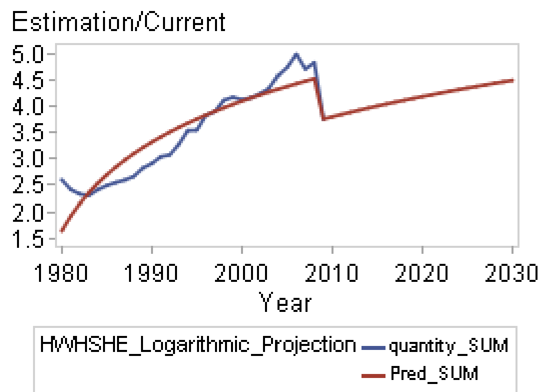
Linear_HWHSHE



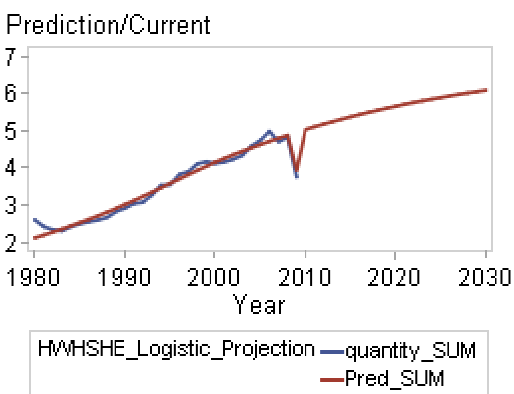


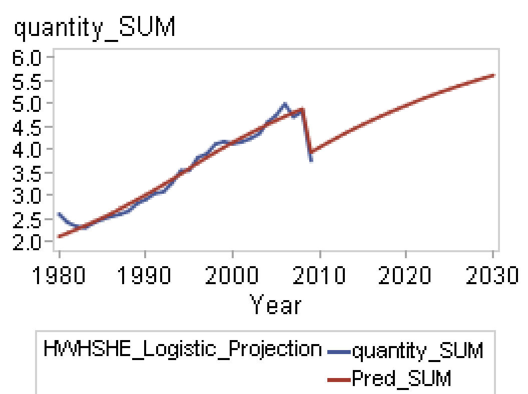
Logarithmic_HWHSHE





Logistic_HWHSHE





The findings from the forecasts of total trade with the one year as intervention point are summarized in table 5.2. The growths are calculated with 2008 as the basis with 2020 and 2030 being the forecast target.

Table 4-1: Forecasts

AGGREGATION LEVEL	GROWTH MODEL	MARKET CONFIDENCE	**FORECASTS_TOTAL PRE CRISIS % GROWTH**	
			2020	**2030**
Total Trade HWHSHE	Linear	Median-high	**25%**	**46%**
	Logarithmic	Median-low	**11%**	**19%**
	Logistic	Low	**16%**	**25%**

AGGREGATION LEVEL	GROWTH MODEL	MARKET CONFIDENCE	**FORECASTS_CAT_6 PRE CRISIS % GROWTH**	
			2020	**2030**
Total Trade HWHSHE	Linear	Median-high	**35%**	**65%**
	Logarithmic	Median-low	**16%**	**26%**
	Logistic	Low	**24%**	**34%**

The forecasts assume no structural effects resulting from the crisis year of 2009 which reflects the scenario of recovery in the year 2010. By definition the linear and logarithmic unbounded growth models produce positive growth forecasts. Additionally the forecasts from the logistic growth model give no indication of import saturation on the total level of either total import flows or the import flows of category six. On the contrary, when using trend extrapolation having fitted a logistic growth function, imports continue to grow for at least another 20 years.

5 Summary of findings and Comparisons

The growth model findings are explained by means of comparison through a summary of main findings for total trade which are contrasted by the main findings for the trade of category six. In this way the overall conclusions are described while highlighting the advantages and disadvantages of the two approaches, disaggregated and aggregated.

The findings for total trade are that:

- Mixed models are superior to the fixed models because they account for between-country variation;
- The specifications with two random effects are in general superior to the ones with only one random effect. The variability hence lies in both volume and growth rate between the European Countries;

- The fixed effect and random effect parameters are significant in all the model applications. Especially for the random effects this is to be expected given the differences across European countries in terms of their volume and the growth of imports;
- When estimating the models under the different specifications with the countries in one dataset the resulting models are always superior to the models of the geographic groups HW, HW, HE estimated separately on the grounds of fit statistics due to the increased number of observations in the former case;
- The model best describing the trend for the single database is inconclusive with the linear, the logistic and the logarithmic specification showing no clear econometric superiority.
- Based on graphical inspection, the best fit is achieved by the linear and the logistic specification.
- The logistic model performs well. There is however at present, no indication of saturation;
- No indication of future import saturation on the aggregated European country level exists, for at least another 20 years. Nevertheless, the more disaggregated the analysis is, the more likely it becomes that saturated patterns of growth may be found like in the case of DEU;
- The growth pattern for the HE countries is graphically best described by the exponential model. The growth patterns for the HW and HS countries are econometrically inconclusive though graphics suggest it is best described by in this case too the logistic growth model for the HS countries and the linear growth model for the HW countries.
- Despite the criticism on the linear model it remains a model worthy of consideration and can be used as a benchmarking tool.
- The error analysis showed that in the majority of the models the errors are homoscedastic and normally distributed;
- Serial correlation is addressed by defining the correlation structure. Typically the AR(1) is preferred but the most appropriate structure is chosen on the basis of trial and error and comparison of the AIC and BIC values. The alternative structure tested is the unstructured which is also the most flexible one. Serial correlation does not bias the estimators. Furthermore it does not influence the projections since the trend extrapolations are independent of time. For this reason a full correlation elimination approach is not further pursued.

The main findings when compared to the disaggregated approach:

- In the estimation of the model of category six for the equivalent applications as for total trade the model best describing the trend is also inconclusive. None of the logistic, the logarithmic or the linear specification show clear econometric superiority. Hence in the case of category six, the disaggregated approach did not provide for clearer indications of best fit. Such cases could be possible when disaggregating category six further in its sub-products;

- The growth pattern for the HS and HE countries is best described by the exponential model. The growth pattern for the HW countries is inconclusive as in the case of the total trade model. Nevertheless, the logistic growth model performs best based on graphical inspection;
- No indication of current or future saturation of import flows on the aggregated level is established.

Given the limitations in attributing clear superiority to just one growth specification it is more appropriate to focus on the illustration of advantages and disadvantages from the use of either one of the specifications estimated. This discussion is important for the final model choice when the purpose is forecasting. The commentary involves model reliability in terms of model bias and robustness.

Advantages:

- The linear models – linear and logarithmic- are robust. This means that they are insensitive to small departures from the idealized assumptions. This is proven through the testing with the different covariance structures. Additionally, the testing with the different datasets resulting from the different sources confirmed the stability of the estimators;
- The nonlinear models - exponential and logistic - fit the data best. This means that the difference between this estimator's expected value and the true value of the parameter being estimated is small leading to unbiased estimators;

Disadvantages:

- The linear models have the poorest fit. This means that they do not predict well the current trend leading to biased estimators;
- Both linear and nonlinear models are subject to robustness issues in the presence of outliers. This means that by changing one point the reliability of the models is questioned. This could lead to misleading results in the case of outliers present in for example the third phase of the logistic growth model.

The aforementioned econometric findings and the discussion on graphical fit are exclusively based on the empirical output. The choice on the most appropriate growth model for the making of trend extrapolations is however a different discussion. As mentioned in chapter 5, market confidence plays a crucial role which goes beyond statistics. For this reason, empirical output now has to be translated into insights for transport research.

6 Discussion on mixed growth model suitability and impact on the transport sector

The understanding of the pattern of growth and the variability of this pattern between the countries represents high added value knowledge to transport stakeholders. Since we cannot definitively single out a particular specification, one should treat the different specifications as different scenarios of future behavior. The suggested approach in today's extraordinary times of high uncertainty is to use all growth models and draft strategies on the basis of expectation assumptions. What is hence recommended is the reliance on all specifications for the provision of a spectrum of possible future outcomes in this case possible volumes of goods. Each specification in particular has different implications on policy decisions and in particular on investment decisions and on concerns about sustainability. In fact, while the challenges defined in the White paper for Transport remain, adjustments in funding priorities and the implementation mix of short and long term solutions might differ per growth expectation. For example the logistic growth specification when used for forecasting presupposes asymptotically zero growth. Hence, on the basis of the belief of diminishing marginal utility and no new products entering the market it would indicate that growth asymptotically comes to a halt. This can be a very informative scenario in instances where a natural limit to growth is assumed as argued also by Metz (2011). On the other hand a linear or exponential growth based forecast puts immediately pressure on investment decisions and at the same time inflates concerns about sustainability. Transport infrastructure and current supply chain systems would thus need to appropriately and rapidly tackle, what could be called a growing green demand, without compromising economic growth and the successful adherence to the 2020/2030/2050 emission targets. Assuming logarithmic growth while not supported by any growth theory it represents a scenario of slow growth. As such, necessary policy implementations would not be exposed to the pressure and risk assumed by the linear or particularly an exponential pattern of growth.

7 Conclusions

In this paper we applied linear and non linear longitudinal mixed models to model trade growth. The unit of trade volume used for the applications was a result of an extensive data mining exercise from the three digit SITC classification of the UNCOMTRADE. Aggregated and disaggregated product flows were considered which tested four different growth specifications the linear, exponential, logarithmic and logistic, for the three geographic groups (HW, HS and HE) separately and in a single dataset. The growth models estimated in the mixed context were superior to the fixed models because they accounted for between-country variation in terms of (in most cases) both the rate of growth and the volume of import flow. The models were used for trend extrapolations with the purpose of reflecting future growth expectations as expressed by the mathematical properties inherent in the specifications. Policy implications for transport were discussed on the grounds of the projected positive growth of future trade volumes.

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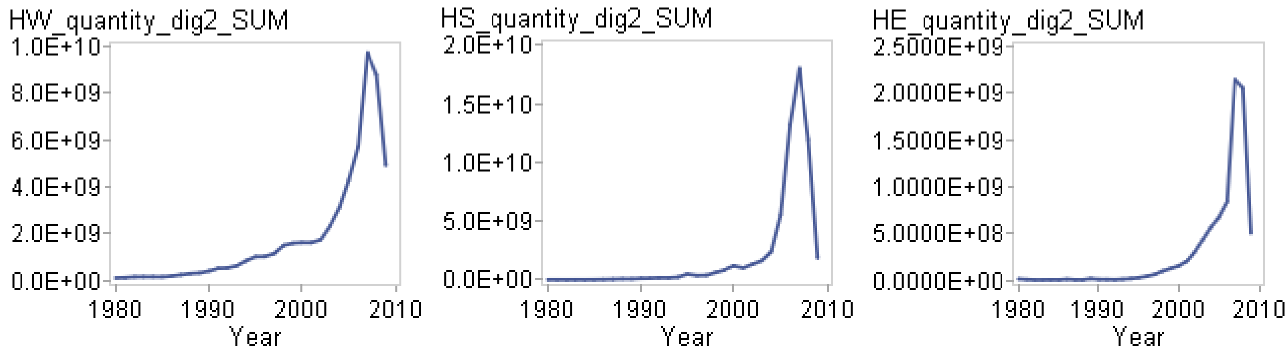
Annex I

Annex Graph 1.1: Chinese imports growth pattern



Source: own calculations based on UNCOMTRADE data

Annex table 1.1: Category 6

Code 6	**Manufactured goods classified chiefly by material**
61	Leather, leather manufactures, n.e.s., and dressed furskins
62	Rubber manufactures, n.e.s.
63	Cork and wood manufactures (excluding furniture)
64	Paper, paperboard and articles of paper pulp, of paper or of paperboard
65	Textile yarn, fabrics, made-up articles, n.e.s., and related products
66	Non-metallic mineral manufactures, n.e.s.
67	Iron and steel
68	Non-ferrous metals
69	Manufactures of metals, n.e.s.

Annex Table 1.2: Crisis data quality check

Countries	**Import volume of goods (Percent change)**		**Estimates start after**
	2009	**2010**	
AUT	-15	10	2010
BGR	-26	-6	2010
BLX	-10	10	2010
CHE	-8	9	2010
CZE	-15	19	2010
CYP	n.a	n.a	2010
DEU	-10	13	2010
ESP	-19	6	2010
FRA	-11	8	2010
GRC	-18	-15	2010
HUN	-14	11	2010
ITA	-18	7	2009
NLD	-10	12	2010
POL	-12	10	2010
PRT	-14	-5	2010

Source: IMF /WEO, 2011

Annex II

Box 1: Exponential growth model initial values-some clarification notes

The specification of the initial values b_1, b_2, b_3 for the fixed parameters was made with the help of three equations each representing basic features of the exponential model and graphically based information. The latter were taken from the aggregated graph. The calculations were made in a maple worksheet.

The necessary inputs to calculate b_1, b_2, b_3 included the initial year and the last year, the highest and the lowest observed values and the initial slope. After defining the necessary inputs the following equations were estimated:

- For b1: f(first_year)=lowest_observed_value,
- For b2: f(last_year)=highest_observed_value
- For b3 the derivative of the formula (df) with b1, b2, b3 was initially calculated. The equation estimated then was df(first_year)=initial_slope.

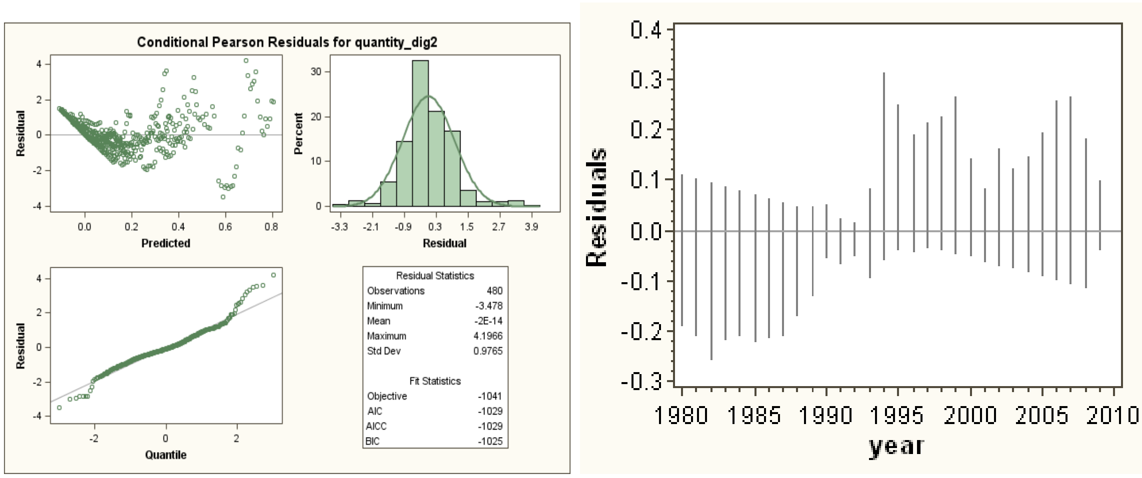
For the specification of initial values for the random effects the aforementioned process was replicated for each of the countries separately. By calculating the variance of b1 and b3 it was possible to get an estimate for the u_{i1} and u_{i2}.

Box 2: Logistic growth model initial values-some clarification notes

The specification of initial values for the fixed parameters was mainly based on graphical information. In particular: 1) b_1 was based on the upper intercept, 2) b_2 on the point of inflection and 3) b_3 which represents the slope was calculated in maple. This was done by solving the mixed logistic growth formula for b_3. The random variable u_{i1} was estimated by calculating the variance of b_1 for the year 2008. In the case of u_{i2} being placed as the random variable of the point of inflection it was estimated by calculating the variance of b_2. The random variable u_{i3} represents the variance in the slope between the countries and it was estimated by calculating the variance of the b_3's of each country.

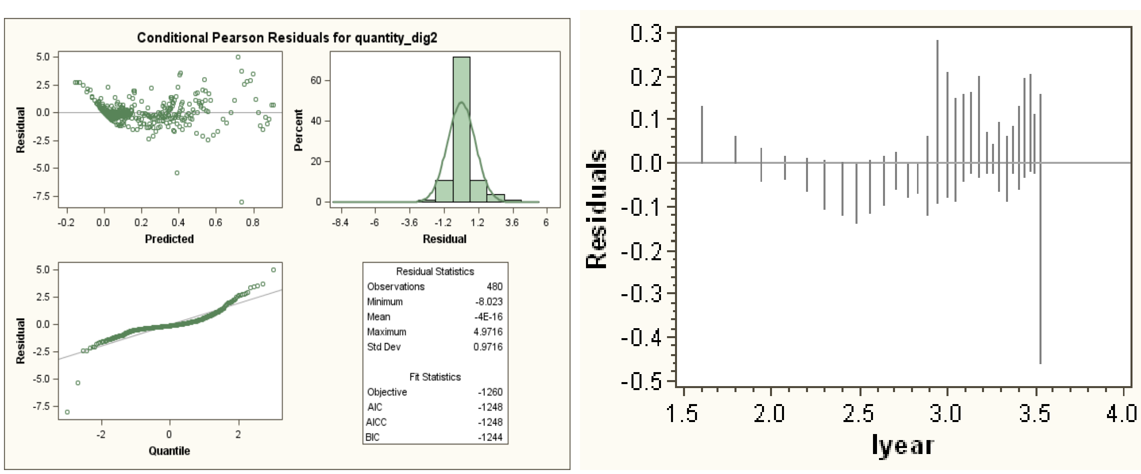
Annex III - Growth models disaggregated

Annex figure 3.1: Linear growth model tests



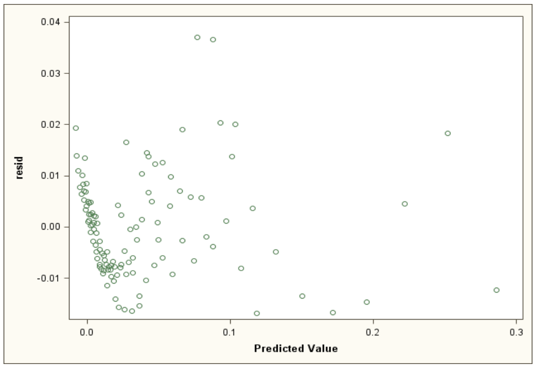
Fit Statistics LINEAR	HW_TOTAL	HS_TOTAL	HE_TOTAL
-2 Log Likelihood	-365.3	-455.3	-553.3
AIC (smaller is better)	-353.3	-445.3	-543.3
AICC (smaller is better)	-352.8	-445.1	-542.9
BIC (smaller is better)	-354.5	-445.6	-545.2

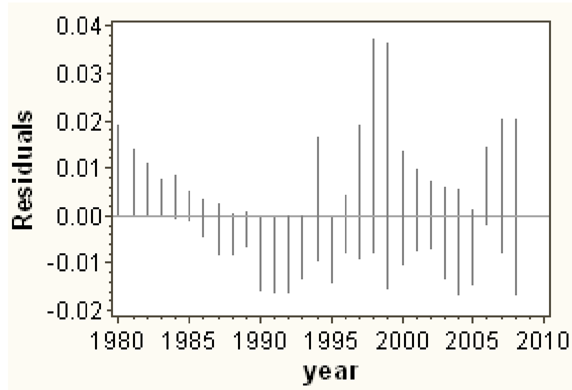
Annex figure 3.2: Logarithmic growth model tests



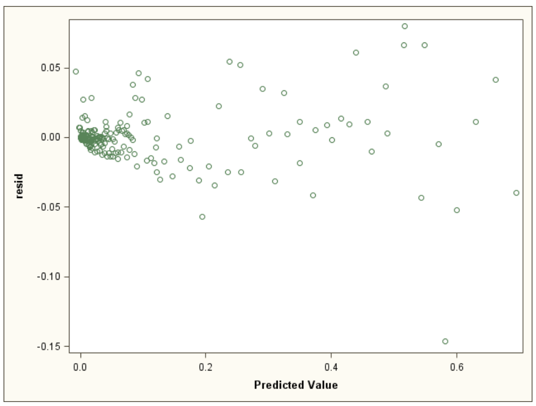
Fit Statistics LOGARITHMIC	HW_TOTAL	HS_TOTAL	HE_TOTAL
-2 Log Likelihood	-437.6	-529.7	-562.9
AIC (smaller is better)	-423.6	-515.7	-548.9
AICC (smaller is better)	-423.0	-515.0	-548.1
BIC (smaller is better)	-425.1	-517.1	-551.6

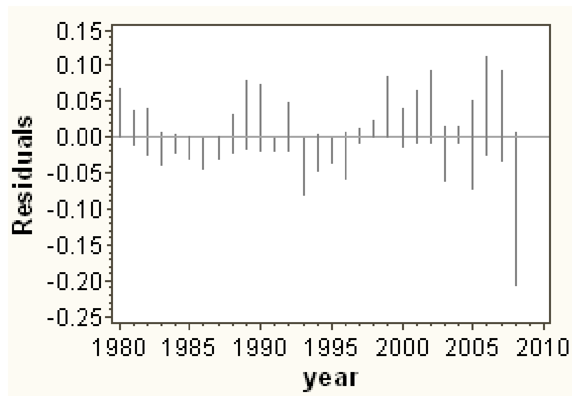
Annex figure 3.3 (a): Exponential HE growth model tests



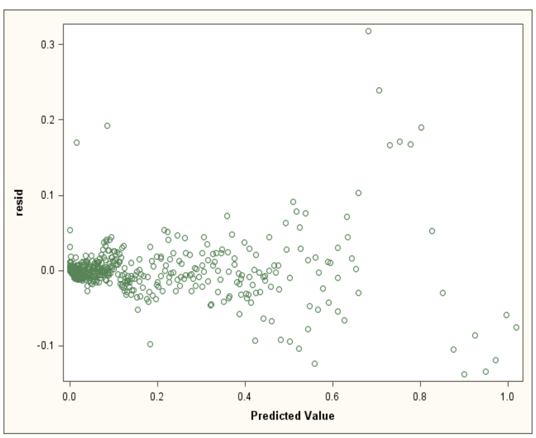


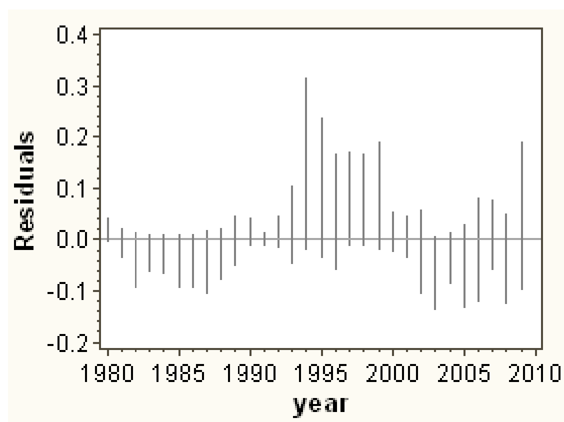
Annex figure 3.3 (b): Exponential HS growth model tests





Annex figure 3.4: Logistic growth model tests

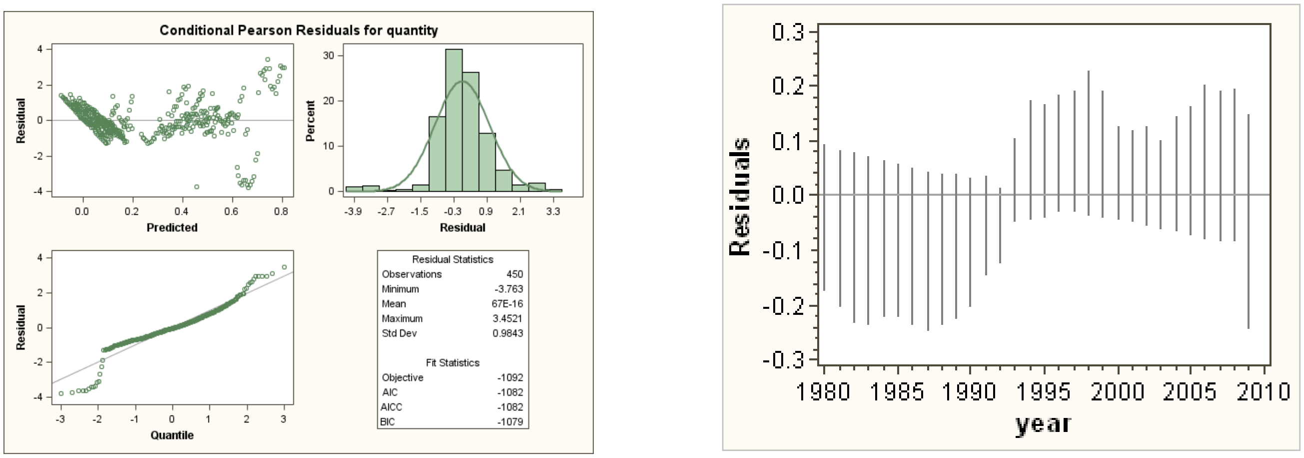




Fit Statistics LOGISTIC	HW_TOTAL	HS_TOTAL	HE_TOTAL
-2 Log Likelihood	-531.6	-948.9	-734.8
AIC (smaller is better)	-517.6	-934.9	-720.8
AICC (smaller is better)	-516.9	-934.3	-720.0
BIC (smaller is better)	-519.1	-935.2	-723.6

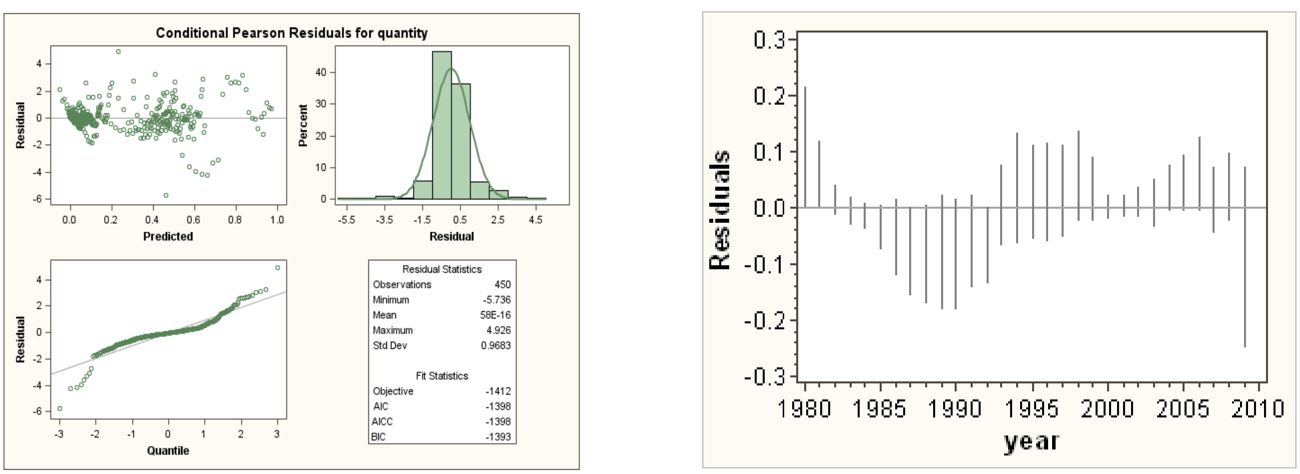
Annex III (continued) - Growth models: aggregated

Annex figure 3.5: Linear growth model tests



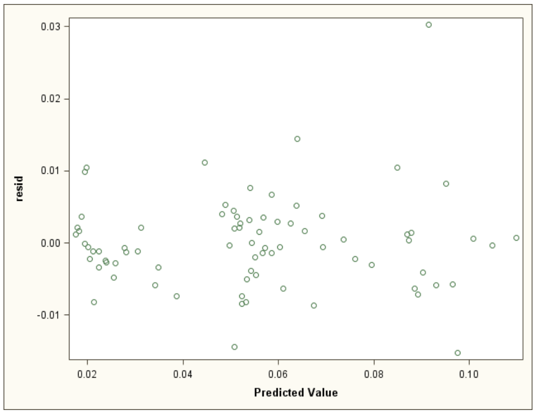
Fit Statistics LINEAR	HWHSHE_cat6	HW_TOTAL	HS_TOTAL	HE_TOTAL
-2 Log Likelihood	-1333.3	-349.1	-616.2	-651.0
AIC (smaller is better)	-1321.3	-339.1	-606.2	-641.0
AICC (smaller is better)	-1321.2	-338.8	-605.9	-640.5
BIC (smaller is better)	-1316.0	-340.2	-606.5	-644.1

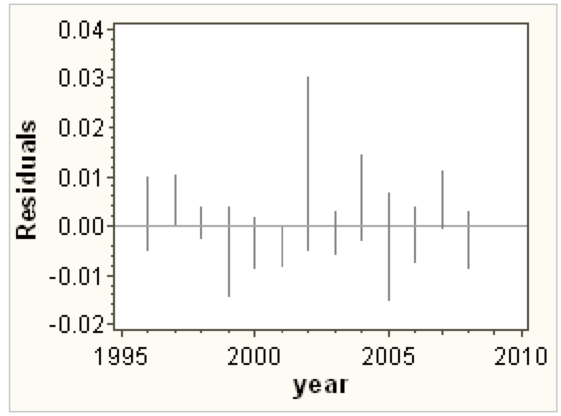
Annex figure 3.6: Logarithmic growth model tests



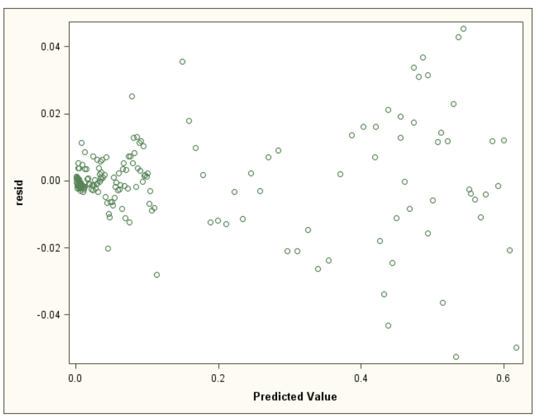
Fit Statistics LOGARITHMIC	HWHSHE_cat6	HW_TOTAL	HS_TOTAL	HE_TOTAL
-2 Log Likelihood	-1453.7	-463.4	-455.8	-691.3
AIC (smaller is better)	-1439.7	-449.4	-441.8	-677.3
AICC (smaller is better)	-1439.5	-448.7	-440.8	-676.3
BIC (smaller is better)	-1433.5	-450.9	-446.1	-681.6

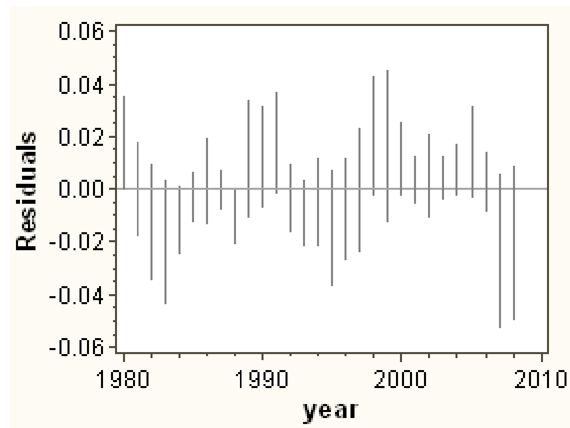
Annex figure 3.7 (a): Exponential growth model tests





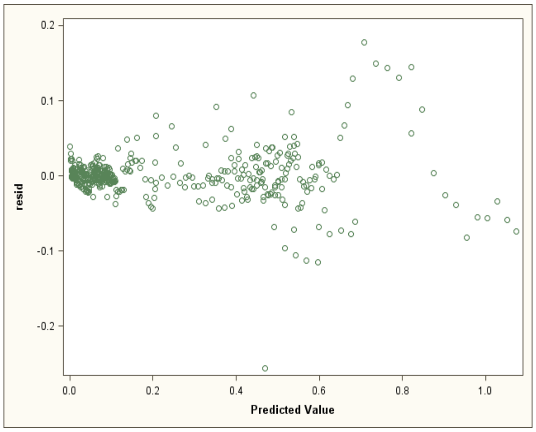
Annex figure 3.7 (b): Exponential growth model tests

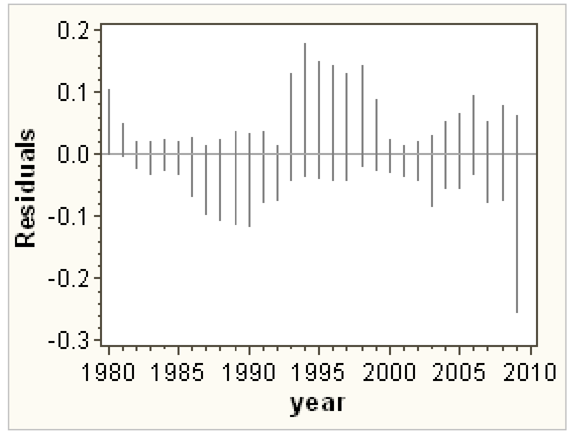




Null Model Likelihood Ratio			
Model	**DF**	**Chi-Square**	**Pr > ChiSq**
linear_dummy_6	2	858.89	<.0001
logarithmic_dummy_6	2	1082.91	<.0001
logarithmic_dummy_total	3	1395.35	<.0001
Linear_dummy_total	1	1277.80	<.0001

Annex figure 3.8: Logistic growth model tests





Fit Statistics LOGISTIC	HWHSHE TOTAL	HWHSHE cat6	HW TOTAL	HS TOTAL
-2 Log Likelihood	-1623	-1853	-547.8	-673.2
AIC (smaller is better)	-1607	-1837	-533.8	-659.2
AICC (smaller is better)	-1606	-1837	-533.2	-658.5
BIC (smaller is better)	-1601	-1830	-535.3	-660.7