Forecasting sectoral trade growth under flexible exchange rates

by

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Abstract

A huge body of empirical and theoretical literature has emerged on the relationship between exchange rate uncertainty and international trade. In empirical studies the estimated impacts of exchange rate uncertainty on trade figures are at most weak and often ambiguous with respect to their directions. Almost all empirical contributions on the topic start from the assumption of some linear relationship, the potential of nonlinearity or state dependence of causal links between volatility and trade has been ignored yet. In addition, widely used regression models have not been evaluated in terms of ex-ante forecasting. In this paper we analyze the impact of exchange rate uncertainty on specific categories of exports and imports for 13 industrialized economies towards the rest of the world. Our results support the view that the relationship of interest might be nonlinear and, moreover, lacks of homogeneity across countries, economic sectors and when contrasting imports vs. exports. Parametric threshold models are found to outperform linear regression models in terms of fitting and ex-ante forecasting. In addition, semiparametric models deliver sequences of forecast errors with less dynamic structure than parametric specifications and help to uncover the nature of the nonlinear relation.

Keywords: exchange rate uncertainty, GARCH, forecasting, international trade, nonlinear models
JEL Classification: F14, F17

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1 Introduction

The impact of exchange rate uncertainty on international trade has been generating a huge body of controversial theoretical and empirical literature (e.g. Artus 1983, Brodsky 1984, Demers 1991, Franke 1991, Quian and Varangis 1994, Kumar and Dhawan 1991, Gotur 1985). Following a seminal argument (Ethier 1973) risk averse traders will reduce traded quantities due to costs involved with hedging exchange rate uncertainty. More generally, DeGrauwe (1988) formalizes a positive (negative) impact of exchange rate uncertainty on trade if the exporters' revenues are convex (concave) in the exchange rate. A similar ambiguity is derived in Viane and De Vries (1992) who formally introduce price determination on forward markets. The latter contributions underscore the nature of markets, cost and demand functions etc. as major factors when determining the effect of foreign exchange rate volatility on international trade. These factors, however, may differ across different sectors of the economy, which questions the adequacy of empirical models specified to explain aggregates of international trade. Constraining e.g. the income, price and exchange rate risk elasticities of trade to be identical cross sectors could involve a presumably large aggregation bias (Goldstein and Khan 1985) that might explain why the empirical literature on the topic is inconclusive about the dominating impact of exchange rate uncertainty on trade. In a seminal article Klein (1990) undertakes an empirical investigation for disaggregated US bilateral exports to seven major industrialized economies. Nine categories of traded goods are considered and the case for a sector specific relationship is powerfully underscored. Summarizing the results a stimulating impact of exchange rate volatility on US exports is inferred in five of nine categories.

Two promising directions of empirical work have not been followed yet. Firstly all empirical contributions a-priori postulate a linear relationship between the variables of interest. As Viane and DeVries (1992) conjecture, however, the underlying true relationship might also be nonlinear. This empirical study provides a detailed comparison of linear vs. nonlinear model specifications of sector specific growth rates of trade for 13 industrialized economies towards the rest of the world. Secondly, there is almost no experience with respect to the performance of typical regression models in terms of ex-ante forecasting. One reason why forecasting exercises are ignored yet could be that most existing empirical models characterizing trade patterns fail to pass simple regression diagnostics as, for instance, tests against serial error correlation (Arize 1996). In this paper competing models, linear as well as nonlinear specifications relating trade and exchange rate uncertainty, are compared in terms of in-sample fitting and ex-ante forecasting.

The remainder of the paper is organized as follows: The next section provides some standard approach to modelling the relationship of interest, namely the linear regression model. The latter is generalized in Section 3 where parametric and semiparametric extensions of the linear model are considered. In Section 4 the employed approaches to modelling trade dynamics are compared in terms of their performance in ex-ante forecasting. Apart from providing empirical results methodological issues are briefly addressed in Sections 2 to 4. The paper ends with some conclusions and directions for future research.

2 A common approach: Linear Regression

2.1 Methodology and Data

Numerous empirical approaches to model the impact of exchange rate uncertainty on trade formalize common regression models where current trade or trade growth is determined by the actual activity level of the involved economies, domestic and foreign price levels, the exchange rate and some measure of its (latent) volatility. Along these lines we investigate sector specific import and export patterns measured for 13 economies towards the rest of the world. The following industrial countries are considered: Austria (AT), Canada (CA), Germany (GE), Finland (FI), France (FR), Greece (GR), Italy (IT), Japan (JA) The Netherlands (NL), Norway (NO), Portugal (PO), Sweden (SW) and the United Kingdom (UK). To approximate the economic state of the world we use US-Data on industrial production and prices. We consider the following regression model:

$$\phi_i^{jk}(B)\tilde{y}_{it}^{jk} = \tilde{\mathcal{X}}_t^k \beta_i^{jk} + \tilde{\varepsilon}_{it}^{jk},\ i = 1, 2,\ j = 1, \dots, 5,\ k = 1, \dots, 13,\ t = 1, \dots, T, \tag{1}$$

$$\tilde{\mathcal{X}}_t^k = (\mathbf{1}, \Delta ip_t^k, \Delta ip_t^{US}, \Delta cp_t^k, \Delta cp_{t-1}^k, \Delta cp_t^{US}, \Delta cp_{t-1}^{US}, \Delta e_t^k, \Delta e_{t-1}^k, \tilde{v}_t^k). \tag{2}$$

In (1) and (2) j and k indicate economic sectors and countries, respectively. The index i is used to distinguish imports ($i = 1$) and exports ($i = 2$), i.e. $\tilde{y}_{1t}^{jk} = \Delta m_t^{jk}$, $\tilde{y}_{2t}^{jk} = \Delta x_t^{jk}$, and m_t^{jk} and x_t^{jk} are log imports and log exports (in US Dollar) measured in sector j of country k towards the rest of the world. Moreover, ip_t^{US} (ip_t^k) and cp_t^{US} (cp_t^k) are the US (country k) index of industrial production of manufactural goods and the US (country k) consumer price index (all variables in natural logarithms). B is the so-called lag operator such that $B\tilde{y}_{it} = \tilde{y}_{it-1}$ and $\Delta = (1 - B)$ is short for the first difference operator. The specification of the linear regression in terms of first differences is due to the fact that ADF-tests mostly classify the involved time series as integrated of order one. Detailed results on unit root tests are not given here to economize on space.

The sectors $j = 1, \dots, 5$ are defined according to 1 digit SITC sections as follows:

j	SITC	definition
1	0+1	Food,live animal, beverages and tobacco
2	2+4	Crude materials, inedible, animal and vegetable oils, fats
3	3	Mineral fuels, lubricants and related materials
4	5+6+8+9	Chemicals, manufactured goods
5	7	Machinery and transport equipment

All series are sampled at the monthly frequency. Indices of industrial production are used to approximate the level of economic activity. A more direct measure as, for instance, gross national product is not available at the monthly frequency. For the same reason consumer price indices are used to approximate prices of traded goods.

To complete the set of explanatory variables in (2) e_t is the log price of the US Dollar in terms of country k's currency and $\tilde{v}_t^2$ is an estimated GARCH(1,1) variance process (Engle 1982, Bollerslev 1986) fitted with EViews 3.1 to the corresponding log exchange rate changes (Δe_t). Detailed estimation results for the 13 estimated GARCH specifications are not reported here to economize on space. However, we performed some diagnostic tests indicating significance of volatility clustering for all investigated exchange rate processes. Moreover, the GARCH(1,1) model turned out to deliver standardized residuals that are free of remaining conditional heteroskedasticity.

Being latent in nature other measures of exchange rate uncertainty could also be considered as, for instance, absolute percentage changes (Bailey, Tavlas and Ulan 1986) or moving averages of historical exchange rate variations measured in some past window of time (Koray and Lastrapes 1989, Klein 1990). In favor of the GARCH approach Asseery and Peel (1991) point out that GARCH based risk measures have the advantage to concentrate directly on "economically relevant" conditional second order moments. Moreover, reviewing the empirical literature it is known that the GARCH framework is suitable to capture stylized facts of foreign exchange rate processes such as volatility clustering and leptokurtosis. Finally, under GARCH $\tilde{v}_t^2$ is an unbiased estimator of the conditional expectation $E[(\Delta e_t)^2|\Omega_{t-1}]$ thereby mitigating problems involved with using estimated regressors (Pagan 1984).

Data are sampled from two OECD databases, namely "Monthly Statistics of International Trade" (exports, imports and exchange rates) and "Main Economic Indicators" (indices of industrial production and consumer prices). Since trade processes show a marked seasonal pattern the series are adjusted by the X11(A) procedure implemented in EViews 3.1. Data on industrial production are sampled from the OECD database in seasonally adjusted form. Although less seasonality is observed for price indices these series are also seasonally adjusted.

With respect to the employed explanatory and dependent variables the proposed regression design is analogous to McKenzie and Brooks (1997) analyzing monthly dynamics of aggregate trade flows between the US and Germany. However, the model in (1) and (2) differs from most empirical contributions in two important points. Firstly, to improve the diagnostic properties of the regression model, in particular the autocorrelation pattern of residuals $\tilde{\varepsilon}_{it}^{jk}$, finite order lag polynomials, $\phi_i^{jk}(B) = 1 - \phi_{i1}^{jk}B - \phi_{i2}^{jk}B^2 - \ldots - \phi_{iq}^{jk}B^q$, are introduced allowing for autoregressive dynamics of trade growth. It is worthwhile to mention that poor diagnostic features of empirical trade models are mostly ignored in the literature (Arize 1996). Apart from these a-priori considerations it is important to note that introducing autoregressive dynamics of the dependent variable might affect the coefficient estimates of the exogenous right hand side variables and their significance. Secondly, empirical models similar to (1) and (2) often deliver counterintuitive impacts of prices and exchange rates on trade growth. A possible explanation for these findings are so-called J-curve effects describing lagged adjustment of trade in the sequel of price movements. To account for the potential of such effects lagged price variables augment the set of explanatory variables in (2).

A priori one would expect that foreign and domestic real income affect growth rates of international trade positively. A depreciation of country k's currency ($\Delta e_t^k > 0$) should improve competitiveness of exporting firms in country k whereas some negative effects of $\Delta e_t^k > 0$ are to be expected for import growth. Thus the sum of estimated coefficients of Δe_t^k and Δe_{t-1}^k should be positive (negative) when modeling import growth ($i = 1$) (export growth, $i = 2$). In addition, imports are expected to be increasing (decreasing) in the domestic (foreign) price level. Accordingly when modelling export growth the sum of coefficient estimates of cp_t^k and cp_{t-1}^k (cp_t^{US} and cp_{t-1}^{US}) should be negative (positive).

2.2 Empirical results

Given necessary presample values our sample covers the period October, 1971 to March, 2000 for most economies under investigation. Thus, 342 observations are available to estimate almost all of the 65 (13 countries, 5 sectors) regression models explaining import or export growth. For Greece and Portugal data series were not available over the entire time span. Given presample values the sample period for these two countries is October, 1971 to December, 1997 (315 observations) and March, 1985 to March, 2000 (181 observations), respectively.

Since we investigate regression models like (1) for 13 economies and 5 sectors we will not provide detailed estimation results. Figure 1 displays frequencies of the sign of the partial impacts of the explanatory variables in (2) on trade growth when autoregressive dynamics of the dependent variables are excluded by assumption ($\phi_i^{jk}(B) = 1$). The reported averages are obtained over 65 regression models employed to describe import and export growth, respectively. The black parts of the bars represent the fraction of parameter estimates which are significant at the 5% level. Domestic and US industrial production mostly affect trade growth positively. With respect to domestic industrial production we also have that the majority of parameter estimates is significant at the 5% level. The partial impacts of consumer prices are mostly insignificant. For most regression models explaining import (export) growth we find effects of US (domestic) consumer prices which are at odds with economic intuition. Including lagged consumer prices as explanatory variables does not help to overcome the detected adverse effects (J-curve). The nominal exchange rate affects both import and export growth negatively for the vast majority of empirical models. Note that this finding is in line with intuition merely for import growth. In most cases the latter effects are significant. Lagged exchange rates fail in almost all empirical models to contribute significantly to the explanation of trade growth.

Diagnostic results for the initial empirical specifications excluding autoregressive dynamics ($\phi_i^{jk}(B) = 1$) are shown in Table 1. We display LM-test results (Breusch 1978, Godfrey 1978) against joint autocorrelation up to order j (LM(j)). Alternative values $j = 1, 12$ are selected which are natural when analyzing monthly data. For almost all empirical models the estimated residuals show significant autocorrelation for $j = 1$ and 12. Modelling Portuguese trade delivers the only cases for which not all empirical models fail to pass the autocorrelation test.

To cope with serial error correlation the set of explanatory variables in the regression model (1) is augmented with lagged dependent variables ($\phi_i^{jk}(B) \neq 1$). When introducing autoregressive dynamics the polynomials $\phi_i^{jk}(B)$ are selected such that the autocorrelation function of implied residuals $\hat{\varepsilon}_{it}^{jk}$ does not show any significant estimate up to lag order 13. Preliminary estimates of autoregressive parameters that are not significant at the 5% level are removed from $\hat{\phi}_i^{jk}(B)$. Thus, for most of the 130 regression models the final specification of autoregressive dynamics is some subset model. Note that introducing an autoregressive part to the model changes to some extent the interpretation of the initial model parameters. After introducing lagged dependent variables the remaining model parameters govern the impact of exogenous variables after correcting trade growth for autoregressive dynamics.

Diagnostic LM-tests against serial error correlation obtained from the augmented regression models are displayed in Table 2. Evidently, introducing lagged dependent variables improves considerably the distributional properties of the underlying error terms. The overall number of error processes showing significant autocorrelation reduces to 25 (30) out of 65 when modelling import (export) growth. The latter results may call for further respecification of the employed models. As mentioned, however, autoregressive dynamics of import and export equations ($\phi_i^{jk}(B)$) were specified to delete any significant single lag autocorrelation up to order 13. Moreover, taking results of diagnostic tests on homoskedasticity into account (not reported here) one should not place too much weight on LM-tests which are derived under the assumption that the underlying error processes are homoskedastic.

Figure 2 shows the marginal impacts of industrial production, consumer prices, exchange rates and volatility on trade growth if the empirical model also contains lagged dependent variables. Since the formalization of autoregressive dynamics is regression specific and to facilitate the concentration on the impact of (lagged) exogenous variables estimation results obtained for the autoregressive parameters are not shown. Apparently the adverse effects of some price variables on trade growth which were also found for the initial regression model ($\phi_i^{jk}(B)$) persist. With respect to exchange rate volatility we obtain mostly negative impacts on trade growth but only a few estimates governing this impact are significant at the 5% level.

3 Nonlinear specifications

Summarizing the results obtained from the regression model in (1) and (2) it is apparent that the linear effect of volatility on trade growth is (at most) weak and not unique across countries and economic sectors. The purpose of this section is to evaluate the scope of nonlinear models relating exchange rate uncertainty and trade dynamics. In the first place simple parametric extensions of the linear model are motivated and employed empirically. Since this approach will yield support for nonlinear dependence of trade growth on volatility a semiparametric model is applied as a second device.

3.1 Threshold models

3.1.1 Methodology

To concentrate on the relationship between volatility and trade growth we first adjust both processes by means of partial regression techniques (Greene 1997) for linear impacts of the remaining (regression specific) right hand side variables in (2). Let $\tilde{y}_i^{jk}$ denote the vector of stacked observations on the dependent variables $\tilde{y}_{it}^{jk}$. Moreover, the matrix $\widetilde{\mathcal{Y}}_i^{jk}$ contains regression specific autoregressive variables and $\widetilde{\mathcal{X}}^k$ collects all exogeneous explanatory variables given in (2). Defining a vector of autoregressive parameters, $\underline{\phi}_i^{jk}$, the model in (1) reads compactly as:

$$\begin{aligned} \tilde{y}_i^{jk} &= \widetilde{\mathcal{Y}}_i^{jk}\underline{\phi}_i^{jk} + \widetilde{\mathcal{X}}^k\beta_i^{jk} + \tilde{\varepsilon}_i^{jk} & (3)\\ &= \widetilde{X}_i^{jk}(\underline{\phi}_i^{jk\prime}, \beta_i^{jk\prime})' + \tilde{\varepsilon}_i^{jk}. & (4)\end{aligned}$$

The set of all explanatory variables except the volatility is denoted as $X_i^{jk} = \widetilde{X}_i^{jk} \setminus \tilde{v}^k$. Then, the (partial) linear impact of volatility on trade is obtained from a bivariate regression model

$$y_{it}^{jk} = c_i^{jk} + v_t^k\theta_i^{jk} + \varepsilon_{it}^{jk},\ c_i^{jk} = 0, \tag{5}$$

where

$$y_i^{jk} = (I_T - X_i^{jk}(X_i^{jk\prime}X_i^{jk})^{-1}X_i^{jk\prime})\tilde{y}_i^{jk}, \quad v^k = (I_T - X_i^{jk}(X_i^{jk\prime}X_i^{jk})^{-1}X_i^{jk\prime})\tilde{v}^k \tag{6}$$

and I_T is the $T \times T$ identity matrix. Although the model in (5) is an equivalent representation of the initial regression (1) it might be more intuitive when generalizing the impact of volatility on trade towards nonlinear relationships.

Since volatility clustering is a stylized feature of exchange rate changes one may regard the relation between trade and volatility to differ across states of lower and higher volatility. Such an assumption is straightforward to implement by means of a dummy variable model (Judge, Hill, Griffiths, Lee and Lütkepohl 1988):

$$\text{TM1: } y_{it}^{jk} = c_i^{jk} + v_t^k\theta_i^{jk} + (c_{i1}^{jk} + v_t^k\theta_{i1}^{jk})I_{(v_t^k > \text{med}[v_t^k])} + \varepsilon_{it}^{jk}. \tag{7}$$

In (7) $I_{(.)}$ denotes an indicator variable which is equal to 1 if v_t^k exceeds its median thus characterizing states of high volatility. We regard the median of v_t^k as a robust threshold to separate states of higher and lower exchange rate uncertainty. To detect further deviations from a homogeneous relationship between y_{it}^{jk} and v_t^k the following model is also considered in this study:

$$\text{TM2:} \;\; y_{it}^{jk} = c_i^{jk} + |v_t^k|\theta_i^{jk} + (c_{i2}^{jk} + |v_t^k|\theta_{i2}^{jk}) I_{(v_t^k > \text{med}[v_t^k])} + \varepsilon_{it}^{jk}. \tag{8}$$

If the relationship between volatility and trade growth is stable across alternative states of volatility the parameters governing threshold effects (c_{im}^{jk}, θ_{im}^{jk}, $i, m = 1, 2$) are zero. Thus, significant parameter estimates $\hat{c}_{im}^{jk}$ or $\hat{\theta}_{im}^{jk}$ question the adequacy of a state independent representation in general and, in particular, of the linear model in (5) or (1).

3.1.2 Empirical results

Figure 3 provides graphically the frequencies of estimating positive and negative marginal impacts of explanatory variables obtained from the parametric nonlinear specifications (7) and (8). To facilitate the comparison of the results estimates of the marginal impacts of volatility obtained from linear models are transferred from Figure 2. Apparently, allowing for threshold effects delivers more significant impacts of exchange rate volatility on trade as it is available from the linear regression. For instance, depending on the employed model (TM1 vs. TM2) and the dependent variable (imports vs. exports) the parameter estimate for the threshold variable $I_{(.)}v_t^k$ or $I_{(.)}|v_t^k|$ is significant for 8 to 16 out of 65 empirical models. When modelling import data a shift in the intercept term is significant at the 5% level for 20 empirical models.

Given that the threshold specifications deliver more significant results when explaining trade growth conditional on foreign exchange uncertainty it could be fruitful to apply these models in forecasting trade growth. As it is also available from Figure 3 a uniform impact of explanatory variables in the parametric nonlinear models on trade growth is not available. Moreover, when comparing the two threshold regressions TM1 and TM2 no overall recommendation in favor of a particular model can be made. Regarding the latter arguments it might be sensible to follow a semiparametric approach where the conditional mean $E[y_{it}^{jk}|v_t^k]$ is some unspecified function of volatility.

3.2 A semiparametric model

3.2.1 Methodology

As argued in Section 3.1.2 threshold models outperform linear regression designs when fitting trade growth conditional on exchange rate uncertainty. Considering the performance of parametric nonlinear specifications, however, it appears that nonlinear dynamics are mostly regression specific. A framework which is able to nest a wide range of relations between y_{it}^{jk} and v_t^k is the semiparametric regression model:

$$\begin{aligned} y_{it}^{jk} &= E[y_{it}^{jk}|v = v_t^k] + \epsilon_{it}^{jk} \\ &= a_i^{jk}(v) + \epsilon_{it}^{jk}. \end{aligned} \tag{9}$$

By assumption the error terms in (9) have a conditional mean of zero and finite variance, i.e.

$$E[\epsilon_{it}^{jk}|v_t^k] = 0, \ \mathrm{Var}[\epsilon_{it}^{jk}|v_t^k] = \zeta_i^2(v) < \infty. \tag{10}$$

We evaluate the (unknown) conditional mean $a_i^{jk}(v)$ using the locally linear estimator (Fan 1993, Masry 1996) which is the first component of $a_i^{jk} = (a_{i0}^{jk}, a_{i1}^{jk})'$ solving the minimization problem

$$\min_{a_i^{jk}} Q(v) = \min_{a_{i0}^{jk}, a_{i1}^{jk}} \sum_{t=1}^{T} K\left(\frac{v - v_t^k}{h}\right) [y_{it}^{jk} - a_{i0}^{jk} - a_{i1}^{jk}(v - v_t^k)]^2, \tag{11}$$

where $K(.)$ and h are a symmetric kernel–function and the bandwidth parameter, respectively.

Obviously $\hat{a}_i^{jk}(v)$ solves locally a common least squares problem. Weights associated to sample values y_{it}^{jk} depend on the distance between v_t^k and v, the bandwidth h and the employed kernel function. The locally linear estimation is implemented by means of the Gaussian kernel

$$K(u) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}u^2\right). \tag{12}$$

Due to the large number of empirical models employed for estimation and recursive forecasting a data driven bandwidth selection is infeasible to implement for this empirical study. Therefore a common rule of thumb bandwidth choice is preferred, namely:

$$h = \sigma_v \left(\frac{3}{4T}\right)^{-0.2}, \tag{13}$$

where σ_v is the empirical standard deviation of v_t^k and T is the sample size.

To illustrate the precision of semiparametric estimates pointwise confidence bands for $\hat{a}_i(v)$ could be obtained from quantiles of the Gaussian distribution and some variance estimate $\hat{\zeta}_i^2(v)$ or from resampling techniques as outlined in Neumann and Kreiss (1998). Due to the large number of investigated regression models we refrain from a thorough discussion of significance of semiparametric estimators but characterize sector specific and overall estimation results obtained from aggregates taken over 13 countries. Moreover we employ the semiparametric specification in (9) complementary to parametric models for recursive forecasting exercises.

3.2.2 Empirical results

Figure 4 shows semiparametric estimation results obtained from aggregating over the 13 economies in the sample. The solid curves show semiparametric estimates obtained from overall aggregation across both directions, countries and sectors. Sector specific estimates are also displayed. Figure 4 is also informative with respect to the empirical distribution of alternative states of volatility. The semiparametrically estimated relationship between exchange rate uncertainty and trade growth is obviously nonlinear for both import and export dynamics. In states of very high volatility its impact on trade growth is negative in each sector and therefore indicates a significantly negative overall impact of exchange rate uncertainty on trade growth. Considering the estimated relationship between volatility and export growth it appears that there is hardly any impact of exchange rate uncertainty on international trade in states of low to medium volatility which account for almost 60% of the available sample information. In these states estimates of the conditional mean of sector specific export growth vary around zero. Regarding import growth functions we obtain a different impression. For states of low to medium exchange rate uncertainty it appears that import growth increases with volatility. Since the latter relation comes close to a step function import growth is hardly linear in (lower to medium) exchange rate uncertainty. The displayed semiparametric estimates are indicative for almost 80% of available observations on volatility. We refrain from providing estimation results for the entire empirical support of volatility since the semiparametric estimates become somewhat wiggly in the tails of the explanatory variable. With respect to the estimated import functions we obtain significantly nonzero conditional means of import growth for almost 27% of all available observations on volatility. With respect to export growth the documented negative impact of high volatility states is informative for almost 10% of all available observations on volatility.

Relating semiparametric and parametric results discussed before the former approach could help to explain why parametric specifications deliver only weak causal relationships. Being informative for 30% to 40% of available sample information the average conditional mean of trade growth is zero around the center of sampled volatility. Significant impacts of exchange rate uncertainty are more obvious in the tails of the latter variable. In less frequently observed states of high volatility a (nonlinear) inverted J-type function is detected for both, import and export growth.

4 Evaluation of forecasting models

4.1 Methodology

Forecasting is an important area of applied econometrics which also provides a complementary means for model comparison. To uncover the dependence of trade growth on exchange rate uncertainty, however, forecasting exercises have not been used yet. In the spirit of the concept of Granger causality one would expect some link between the variables of interest if forecasts of trade growth conditional on exchange rate volatility improve competing forecasts with volatility excluded from the conditioning information set. Therefore this section will evaluate the empirical models introduced before in terms of forecasting accuracy.

Ex-ante forecasting exercises are performed for the linear specification (5), the threshold models (7) and (8) and the semiparametric model (9) estimated by means of the local linear estimator (11). Each of these models is applied recursively by increasing the actual sample size from $t^* = 120$ to $t^* = T - 1$ such that 222 forecasts are computed for most data sets. Data limitations leave 195 and 61 one-step-ahead forecasts when analyzing trade growth observed in Greece and Portugal, respectively.

Let $\hat{y}^{jk}_{i,t^*+1}$ denote a one-step-ahead forecast for y^{jk}_{i,t^*+1} conditional on knowledge of explanatory variables in time $t^* + 1$ and some model estimate obtained from the first t^* observations. Then, recursive residuals are defined as

$$\hat{e}^{jk}_{i,t^*+1} = y^{jk}_{i,t^*+1} - \hat{y}^{jk}_{i,t^*+1}.$$

To assess the accuracy of a particular model in forecasting different criteria could be considered. In the first place one may rank competing models by means of the average squared forecast error (ASFE). For the empirical analysis of trade growth, it turned out that this measure is mostly affected by only a few outlying observations y^{jk}_{i,t^*+1} such that the ASFE-criterion is hardly informative for both, causality linking volatility and trade and model comparison. In the second place, forecasting schemes could be evaluated according to randomness of the recursive residuals. A sensible forecasting model should deliver serially uncorrelated one-step-ahead forecast errors $\hat{e}^{jk}_{i,t^*+1}$. Thirdly, to measure forecasting accuracy y^{jk}_{i,t^*+1} and $\hat{y}^{jk}_{i,t^*+1}$ could be regarded as dichotomous random variables. Along these lines a forecasting model is accurate if the distributional properties of the forecasts $\hat{y}^{jk}_{i,t^*+1}$ come close to the corresponding features of the actual quantities y^{jk}_{i,t^*+1}. An intuitively appealing tool to formalize the latter idea contingency tables are often used in applied statistics. As a formal criterion summarizing the information content of a contingency table we consider the so-called Henrikkson Merton statistic (Henrikkson and Merton 1981). Initially proposed to evaluate investment performance this statistic (hm) aggregates the conditional probabilities of forecasting a positive or negative value of the dependent variable, whenever the actual realization in $t^* + 1$ is positive or negative:

$$\begin{aligned} \text{hm} \;=\; & \text{Prob}(\hat{y}_{i,t^*+1} \geq 0 \wedge y_{i,t^*+1} \geq 0 | y_{i,t^*+1} \geq 0) \\ & + \text{Prob}(\hat{y}_{i,t^*+1} < 0 \wedge y_{i,t^*+1} < 0 | y_{i,t^*+1} < 0). \end{aligned} \tag{14}$$

A successful forecasting scheme should deliver hm-statistics larger than unity. Critical values for this test statistic depend on the number of available forecasts and could be obtained from suitable simulation designs. Finally and also related to the distributional properties of y^{jk}_{i,t^*+1} and $\hat{y}^{jk}_{i,t^*+1}$ competing forecasting schemes could also be evaluated by means of a logit model (see e.g. Judge, Hill, Griffiths, Lütkepohl and Lee 1988) where the event of correctly forecasting the direction of trade growth is related to particular features of the employed forecasting scheme. Let

$$P^{jk}_{i,t^*+1} = \begin{cases} 1 & \text{if } (\hat{y}_{i,t^*+1} \geq 0 \wedge y_{i,t^*+1} \geq 0) \text{ or } (\hat{y}_{i,t^*+1} < 0 \wedge y_{i,t^*+1} < 0) \\ 0 & \text{otherwise} \end{cases}$$

The probability of forecasting the sign of future trade growth correctly can then be modelled as:

$$P[P^{jk}_{i,t^*+1} = 1] = \frac{1}{1 + \exp\left(-\alpha - I_{spa}\delta_{spa} - I_{tm1}\delta_{tm1} - I_{tm2}\delta_{tm2} - v^k_{it}\delta_v - I_{v^k_{it} > med[v^k_{it}]}\delta_I\right)}. \quad (15)$$

In (15) indicator variables I_{spa}, I_{tm1}, I_{tm2} are used to indicate if a particular forecast has been generated using the semiparametric model or the competing threshold specifications. Note that with respect to competing forecasting schemes the upper logit model is specified relative to the linear regression. Moreover, the specification in (15) allows forecasting accuracy to depend on the level of volatility and could also indicate if forecasting trade growth is affected when distinguishing states of higher vs. lower exchange rate uncertainty.

4.2 Forecasting results

Forecast error correlation Table 2 shows results for LM-tests against serial correlation of one-step-ahead forecast errors. When forecasting import growth serial forecast error correlation is slightly more often diagnosed as it is for empirical models explaining export growth. The semiparametric model delivers forecast errors which are less affected by serial correlation in comparison to the parametric specifications. Regarding e.g. the LM(12) statistic we find that over all available sequences of forecast errors (65 models for imports and exports) the null hypothesis of no serial correlation is rejected at the 5% significance level in 29, 21, and 23 cases for the linear model, the semiparametric regression, and the threshold models, respectively.

Henrikkson–Merton tests Tables 3 and 4 show country and sector specific hm-test statistics characterizing alternative forecasting schemes for import and export growth, respectively. Almost all test statistics vary around unity and presumably only a few of these indicate significantly good (hm $>$ 1) or bad (hm $<$ 1) forecasting models. However, it appears that linear models deliver on average smaller hm-statistics in comparison to the nonlinear specifications. To be more explicit we consider two more general measures involving the hm-statistic. In the first place both Tables show sector and model specific hm-tests averaged over 13 countries. The standard deviation of these empirical means is used to compute a t-ratio testing the null hypothesis H_0 : hm $= 1$ against H_1 : hm $\neq 1$. Significantly negative t-ratios indicate that particular forecasting schemes deliver systematic errors when predicting the sign of trade growth. Significantly positive t-ratios support the view that conditioning on volatility helps to forecast the direction of trade growth. As a second measure we also provide model and sector specific numbers of hm-statistics exceeding unity. Note that under the assumption of purely random forecasting results the latter quantity should follow a binomial distribution modelling the outcome of 13 draws (countries) from a Bernoulli variable with success probability $p = 0.5$. For both statistics Table 5 provides the corresponding measures aggregated over economic sectors.

With respect to forecasting export growth the latter quantities (Table 5) indicate that overall forecasting performance achieved via a linear forecasting scheme is significantly inferior to a purely random judgement of the sign of trade growth. For the linear model only 26 out of 65 computed hm-statistics exceed unity and at the 5% level the average hm-statistic (0.98) is significantly less than 1. Considering forecasting results for import growth both threshold models outperform the competing approaches significantly. Employing TM1 and TM2 to determine the direction of future trade growth delivers 41 and 44 out of 65 hm-statistics larger than 1, respectively. Although the average hm-statistics are only slightly larger than one (1.02), the obtained measures are significant at the 5% level. Looking at sector specific results for the hm-statistics it is apparent that the efficiency loss involved with the linear forecasting scheme is the largest when export growth in Sector 3 (mineral fuels, lubricants, and related materials) is of interest. Conditioning forecasts of import growth on volatility is particularly fruitful when considering Sector 5 (machinery and transport equipment).

Logit Modelling Estimation results for logit models explaining the empirical probabilities of hitting the correct sign of trade growth are given in Table 6. Specified with an overall intercept term estimates $\hat{\delta}_{spa}, \hat{\delta}_{tm1}, \hat{\delta}_{tm2}$ measure the effectiveness of the nonlinear models relative to the linear forecasting scheme. When investigating forecasting success we obtain throughout negative intercept estimates implying that on average the linear model is outperformed by the nonlinear models. The latter effects, however, are not significant for all cases considered, i.e. import growth forecasts, export growth forecasts and an aggregate of both. The estimated effects of employing a nonlinear model to forecast trade growth are uniformly positive. Whereas these positive impacts are not significant for the semiparametric model significant estimates are obtained for $\hat{\delta}_{tm1}, \hat{\delta}_{tm2}$ when regarding forecasts of import growth and the aggregate over both import and export growth forecasts. Moreover, the level of volatility and the indicator variable $I_{(v_t^k > med[v_t^k])}$ do not significantly contribute to the probability of hitting the correct sign when forecasting trade growth. For this reason we also provide estimates of logit models where forecasting success is merely related to different modelling approaches. Restricting the logit specifications in this way we obtain analogous conclusions with respect to the relative performance of the linear model and its nonlinear competitors. Testing the overall significance of explanatory variables in the restricted logit specification we obtain p-values for the corresponding LR-statistic of .056 and .023 when investigating forecasting accuracy for import growth and the aggregate over both import and export growth forecasts, respectively.

To indicate the performance of rival forecasting models with respect to specific economic sectors Table 7 reports the LR-test against overall significance of explanatory variables in the logit models. When contrasting the LR-statistics for the latter models we obtain for the 4th sector (chemicals, manufactured goods) that the volatility and indicator variable is of predominant importance when assessing the performance of the logit models. For both import and export growth in this sector explanatory variables in the unrestricted logit model are jointly significant at the 5% level but become insignificant when switching to the restricted specification. This implies that knowledge of current volatility is rather useful when predicting the sign of trade growth in this sector. A similar result on the effects of excluding the volatility variable from the logit model is obtained for import growth in the first sector (food, live animal, beverages and tobacco). The choice of a particular forecasting scheme becomes essential if significance of the LR-statistic is almost unaffected when switching from the unrestricted to the restricted logit specification. Such a result is obtained when comparing forecasting accuracy for export growth in the 3rd sector (mineral fuels, lubricants and related materials).

5 Conclusions and Outlook

In this paper we investigate the impact of exchange rate uncertainty on international trade. Distinguishing 5 economic sectors we analyze the dynamics of import- and export-growth for 13 industrialized economies measured towards the rest of the world.

Although causal links operating from exchange rate uncertainty to international trade are mostly week we deliver some evidence that the underlying relationship between these variables is nonlinear, state-dependent, say, in nature. Parametric threshold models improve the fit offered by linear regressions considerably. Estimating a semiparametric regression model we find that the link between exchange rate uncertainty and trade it quite weak in the center of the distribution of empirical volatilities, which accounts for a large fraction of sample information. This might explain why estimated linear relationships are found to be weak. Moreover the provided measures of forecasting performance could also be spoiled by this experience. Nevertheless linear regression schemes are outperformed by threshold specifications in terms of forecasting. In states of higher volatility we find a negative effect of exchange rate volatility on trade which is robust over the considered five economic sectors and, therefore, overall significant.

When implementing nonlinear parametric models we used the median of estimated volatility as a threshold to separate states of lower and higher exchange rate uncertainty. Such a choice is regarded here as a reasonable starting point when investigating the potential of nonlinear models in this area of empirical work. Clearly the ad-hoc choice of a threshold parameter could be overcome via Kalman filtering. As a second direction of future research it is important also to compare alternative approaches with respect to forecasting trade growth conditional on volatility at higher horizons. Considering medium and long term measures of volatility is important as international trading contracts are typically long term in nature and firms generally do the timing of their foreign exchange transactions with certainty. We consider both problems as issues for future research.

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	AT	CA	GE	FI	FR	UK	IT	JP	NL	NO	SW	GR	PR	$\sum$
$\phi_i^{jk}(B) = 1$	Imports													
LM(1)	5	5	5	5	5	5	5	5	5	5	5	5	4	64
LM(12)	5	5	5	5	5	5	5	5	5	5	5	5	4	64
	Exports													
LM(1)	5	5	5	5	5	5	5	5	5	5	5	5	1	61
LM(12)	5	5	5	5	5	5	5	5	5	5	5	5	2	62
$\phi_i^{jk}(B) \neq 1$	Imports													
LM(1)	3	1	1	1	3	1	2	3	0	2	2	1	4	24
LM(12)	2	2	2	2	2	0	1	0	1	3	3	3	4	25
	Exports													
LM(1)	1	3	2	3	1	0	5	1	2	3	4	0	1	26
LM(12)	1	4	1	2	3	3	2	2	1	3	3	1	2	30

Table 1: Lagrange Multiplier tests results (in-sample) (Breusch 1978, Godfrey 1978) against first and twelfth order autocorrelation. Five sectors are modeled for each countries exports and imports first excluding lagged dependent variables (upper panel) and secondly allowing for autoregressive dynamics of the dependent variable (lower panel). The entries give the number of rejecting the white noise hypothesis at the 5% significance level when aggregating over sector specific models, i.e. the maximum entry is 5.

	AT	CA	GE	FI	FR	UK	IT	JP	NL	NO	SW	GR	PR	$\sum$
LIN	Imports													
LM(1)	2	1	0	0	1	1	3	3	1	0	1	2	1	16
LM(12)	1	3	0	2	0	0	2	3	1	2	1	2	1	18
SPA														
LM(1)	2	0	0	0	1	1	3	2	1	0	0	0	1	11
LM(12)	0	3	0	1	0	0	2	2	1	2	1	0	1	13
TM1														
LM(1)	2	0	0	0	1	1	3	3	1	0	1	2	1	15
LM(12)	0	3	0	1	0	0	2	3	1	2	0	1	1	14
TM2														
LM(1)	2	0	0	0	1	1	3	3	1	0	1	2	1	15
LM(12)	0	3	0	1	0	0	2	3	1	2	0	1	1	14
LIN	Exports													
LM(1)	1	1	0	3	1	3	1	2	0	0	2	0	0	14
LM(12)	0	1	1	1	0	2	0	2	0	2	2	0	0	11
SPA														
LM(1)	0	1	0	3	1	3	1	3	0	0	0	0	0	12
LM(12)	0	1	1	1	0	2	0	1	0	0	1	1	0	8
TM1														
LM(1)	1	1	0	2	1	3	1	2	0	1	2	0	0	14
LM(12)	0	1	1	1	0	2	0	1	0	1	2	0	0	9
TM2														
LM(1)	1	1	0	2	1	3	1	2	0	1	2	0	0	14
LM(12)	0	1	1	1	0	2	0	1	0	1	2	0	0	9

Table 2: Lagrange Multiplier test results (out-of-sample) (Breusch 1978, Godfrey 1978) against first and twelfth order autocorrelation. As in Table 1 the entries give the number of rejecting the white noise hypothesis at the 5% significance level when aggregating over sector specific models, i.e. the maximum entry is 5. Four forecasting models are considered: linear regression (LIN), a semiparametric model (SPA) and two threshold specifications (TM1,TM2).

Sec		AT	CA	GE	FI	FR	UK	IT	JP	NL	NO	SW	GR	PR	$\overline{\text{hm}}$	t_{hm}	#hm	Bin
1	LIN	1.020	0.947	1.044	1.110	0.994	0.877	1.028	0.973	1.044	0.951	0.929	1.019	0.821	0.981	−0.903	6	0.71
	SPA	1.053	1.004	1.005	1.005	0.974	1.060	1.028	0.949	0.936	0.913	1.031	1.070	0.938	0.997	−0.189	8	0.29
	TM1	1.076	0.954	1.125	1.075	1.023	1.061	1.043	0.962	1.028	0.965	1.003	1.098	0.930	1.026	1.568	9	0.13
	TM2	1.085	0.986	1.125	1.056	1.035	1.070	1.016	0.966	1.028	0.965	1.027	1.098	0.930	1.030	1.874	9	0.13
2	LIN	1.052	1.037	1.025	1.050	0.956	0.937	0.998	0.856	0.928	1.075	0.989	0.904	0.964	0.982	−0.966	5	0.87
	SPA	1.008	1.098	1.027	0.883	0.906	0.976	0.928	0.951	0.948	1.021	0.905	1.168	0.895	0.978	−0.934	5	0.87
	TM1	1.000	1.095	1.019	0.926	1.009	0.913	0.899	0.976	0.975	1.029	0.893	1.087	1.072	0.992	−0.427	7	0.50
	TM2	1.000	1.097	1.019	0.907	1.009	0.914	0.890	0.983	0.975	1.037	0.877	1.076	1.045	0.987	−0.663	7	0.50
3	LIN	1.103	0.974	0.914	1.044	0.941	1.026	0.930	1.012	0.97	0.955	0.983	0.885	1.203	0.995	−0.193	5	0.87
	SPA	1.035	0.905	1.069	1.037	1.002	1.080	0.926	1.033	0.946	1.037	0.927	0.966	0.969	0.995	−0.326	7	0.50
	TM1	1.040	1.024	1.055	1.065	1.035	0.991	1.052	1.026	0.929	1.062	0.814	0.857	0.967	0.994	−0.283	8	0.29
	TM2	1.040	1.034	1.055	1.102	1.035	1.029	1.047	1.029	0.929	1.053	0.781	0.867	0.942	0.996	−0.177	9	0.13
4	LIN	0.962	0.964	0.942	1.103	0.893	0.949	0.922	0.969	0.976	1.077	0.926	0.933	1.101	0.978	−1.120	3	0.99
	SPA	1.202	0.978	1.062	0.991	0.967	1.061	1.145	0.958	0.908	0.969	0.934	1.036	1.021	1.018	0.768	6	0.71
	TM1	1.220	1.133	1.017	1.002	1.062	1.064	1.070	0.976	0.929	1.027	0.966	0.905	0.962	1.026	1.077	8	0.29
	TM2	1.212	1.151	1.017	0.984	1.062	1.073	1.041	1.022	0.929	1.034	0.966	0.917	0.932	1.026	1.093	8	0.29
5	LIN	0.899	0.949	1.092	1.088	1.054	1.036	1.043	1.131	1.133	1.101	0.951	1.003	1.072	1.042	2.084	10	0.05
	SPA	1.016	0.955	1.103	1.039	1.095	1.005	0.981	1.109	1.101	0.991	1.074	0.964	1.138	1.044	2.528	9	0.13
	TM1	1.029	0.996	1.089	1.040	1.052	1.054	0.987	1.141	1.130	1.047	0.953	0.979	1.219	1.055	2.652	9	0.13
	TM2	1.049	1.012	1.097	1.027	1.052	1.039	1.032	1.113	1.129	1.054	0.963	0.988	1.256	1.062	3.022	11	0.01

Table 3: Country and sector specific Henrikkson–Merton statistics (hm) for models explaining import growth rates. $\overline{\text{hm}}$ and t_{hm} are rowwise average hm-statistics and the corresponding t-ratios when testing $H_0 : \text{hm} = 1$. #hm is the number of hm-statistics exceeding unity and Bin is the value of the cumulative binomial distribution of #hm−1 modelling 13 independent draws from a bernoulli distribution with success probability $p = .5$. Alternative ex-ante forecasting schemes are the linear model (LIN), the semiparametric model (SPA) and threshold models (TM1,TM2).

Sec		AT	CA	GE	FI	FR	UK	IT	JP	NL	NO	SW	GR	PR	$\overline{\text{hm}}$	t_{hm}	#hm	Bin
1	LIN	0.984	0.960	1.021	1.034	1.081	1.032	1.063	0.998	1.067	1.007	1.018	0.901	0.939	1.008	0.552	8	0.29
	SPA	1.025	1.012	1.030	0.911	0.969	1.000	1.063	0.880	0.889	0.948	1.009	0.961	0.946	0.972	−1.745	6	0.71
	TM1	1.055	0.953	1.026	1.030	0.960	0.951	1.036	0.916	1.027	1.040	1.027	0.952	0.842	0.986	−0.814	7	0.50
	TM2	1.047	0.971	1.026	1.039	0.952	0.969	1.036	0.917	1.027	1.040	1.036	0.952	0.813	0.987	−0.713	7	0.50
2	LIN	1.142	1.004	1.043	1.100	0.991	0.968	1.088	0.892	1.051	0.855	1.012	0.942	0.753	0.988	−0.407	7	0.50
	SPA	1.023	0.971	0.996	0.994	0.833	0.971	1.015	1.004	1.072	0.826	0.868	0.981	1.142	0.977	−0.943	5	0.87
	TM1	1.023	0.989	0.902	1.064	0.855	0.933	1.007	0.891	1.094	0.927	1.005	1.075	1.260	1.002	0.064	7	0.50
	TM2	1.022	0.977	0.911	1.064	0.864	0.924	1.034	0.925	1.094	0.936	0.994	1.075	1.260	1.006	0.212	6	0.71
3	LIN	0.944	0.903	0.916	0.839	1.011	0.978	0.899	0.979	0.909	0.929	0.968	1.014	0.878	0.936	−4.43	2	1.00
	SPA	1.002	0.962	1.091	1.008	1.008	1.078	1.014	0.912	1.038	0.929	0.989	1.026	0.974	1.002	0.165	8	0.29
	TM1	1.117	1.017	1.022	0.991	0.922	1.049	0.946	0.958	1.026	1.074	1.053	0.935	0.787	0.992	−0.341	7	0.50
	TM2	1.117	0.999	1.040	0.991	0.922	1.049	0.955	1.034	1.026	1.099	1.053	0.955	0.823	1.005	0.223	7	0.50
4	LIN	0.993	0.975	0.966	1.027	0.909	1.031	1.066	0.994	0.983	0.982	0.992	1.070	1.124	1.009	0.566	5	0.87
	SPA	1.047	1.022	0.971	1.008	0.973	0.949	1.033	1.002	1.031	0.924	1.037	0.941	1.166	1.008	0.465	8	0.29
	TM1	1.050	1.003	1.025	1.032	0.938	0.979	1.012	0.978	1.085	0.928	1.038	1.031	0.946	1.004	0.273	8	0.29
	TM2	1.007	0.984	1.016	1.051	0.938	0.945	1.001	0.989	1.085	0.937	1.068	1.019	0.905	0.996	−0.280	7	0.50
5	LIN	0.903	1.026	0.954	1.106	0.873	0.972	0.907	1.069	1.044	0.966	0.900	0.960	0.940	0.970	−1.521	4	0.95
	SPA	0.912	1.082	0.964	1.121	0.979	1.005	0.959	1.010	1.037	1.033	0.950	0.918	0.999	0.998	−0.116	6	0.71
	TM1	0.976	1.051	1.014	1.072	0.879	1.071	0.993	0.972	1.062	0.951	0.899	0.901	1.052	0.992	−0.427	6	0.71
	TM2	1.013	1.070	1.014	1.083	0.879	1.071	1.025	1.005	1.053	0.951	0.913	0.890	1.052	1.001	0.0699	9	0.13

Table 4: Country and sector specific Henrikkson-Merton statistics (hm) for models explaining export growth rates. $\overline{\text{hm}}$ and t_{hm} are rowwise average hm-statistics and the corresponding t-ratios when testing $H_0 : \text{hm} = 1$. #hm is the number of hm-statistics exceeding unity and Bin is the value of the cumulative binomial distribution of #hm−1 modelling 13 independent draws from a Bernoulli distribution with success probability $p = .5$. Alternative ex-ante forecasting schemes are the linear model (LIN), the semiparametric model (SPA) and threshold models (TM1,TM2).

	#hm	Bin	$\overline{\text{hm}}$	t_{hm}	#hm	Bin	$\overline{\text{hm}}$	t_{hm}
	Imports				Exports			
LIN	29	0.839	0.996	−0.463	26	0.959	0.982	−2.026
SPA	35	0.310	1.006	0.735	33	0.500	0.991	−1.078
TM1	41	0.023	1.019	2.035	35	0.310	0.995	−0.491
TM2	44	0.002	1.020	2.184	36	0.228	0.999	−0.111

Table 5: Summary statistics for Tables 3 and 4. Bin is 1 minus the cumulative binomial distribution function modelling 65 independent draws from a bernoulli distribution with success probability $p = .5$ evaluated at #hm−1. $\overline{\text{hm}}$ and t_{hm} are average hm-statistics and the corresponding t-ratios when testing H_0 : hm = 1, respectively.

	Imports		Exports		Aggregate	
LOGIT	est.	$t-$ratio	est.	$t-$ratio	est	$t-$ratio
	Unrestricted logit model					
α	−0.008	−0.409	−0.024	−1.146	−0.019	−1.308
δ_{spa}	0.025	1.038	0.009	0.360	0.018	1.028
δ_{tm1}	0.050	2.072	0.027	1.109	0.040	2.296
δ_{tm2}	0.055	2.239	0.036	1.466	0.046	2.668
v_t^k	−2.400	−1.048	−2.322	−1.014	−2.372	−1.465
$I_{(v_t^k > med[v_t^k])}$	0.012	0.544	0.023	1.033	0.018	1.156
LR	8.440 (0.133)		4.602 (0.466)		12.281 (0.031)	
	Restricted logit model					
α	−0.006	−0.328	−0.015	−0.852	−0.010	−0.834
δ_{spa}	0.026	1.069	0.009	0.387	0.018	1.029
δ_{tm1}	0.051	2.109	0.028	1.140	0.040	2.298
δ_{tm2}	0.055	2.277	0.037	1.499	0.046	2.670
LR$_{restr}$	7.544 (0.056)		3.395 (0.334)		9.536 (0.0229)	

Table 6: Parameter estimates (est.) and t-ratios obtained from logit models characterizing the empirical probabilities of hitting the correct sign of trade growth. Aggregates over all import growth models, export growth models and over both are considered. Parameters $\delta_.$ measure the relative performance of semiparametric (SPA) and threshold models (TM1,TM2) relative to the linear forecasting scheme. The coefficients of v_t^k and the indicator variable allow for additional state specific forecasting success. LR is the LR-test on joint significance of explanatory variables in the logit model (p-values underneath in parentheses).

Sec	Imports				Exports			
	LR	p	LR_{restr}	p	LR	p	LR_{restr}	p
1	10.58	0.060	4.798	0.187	3.734	0.588	1.431	0.698
2	1.196	0.945	0.227	0.973	3.086	0.686	1.877	0.598
3	0.719	0.981	0.571	0.903	29.78	0.000	10.58	0.014
4	12.58	0.027	5.989	0.112	11.06	0.050	0.174	0.981
5	3.175	0.673	0.657	0.883	6.722	0.242	2.007	0.570

Table 7: Sector specific LR-statistics with p-values obtained from logit models characterizing the empirical probabilities of hitting the correct sign of trade growth (see also Table 6).

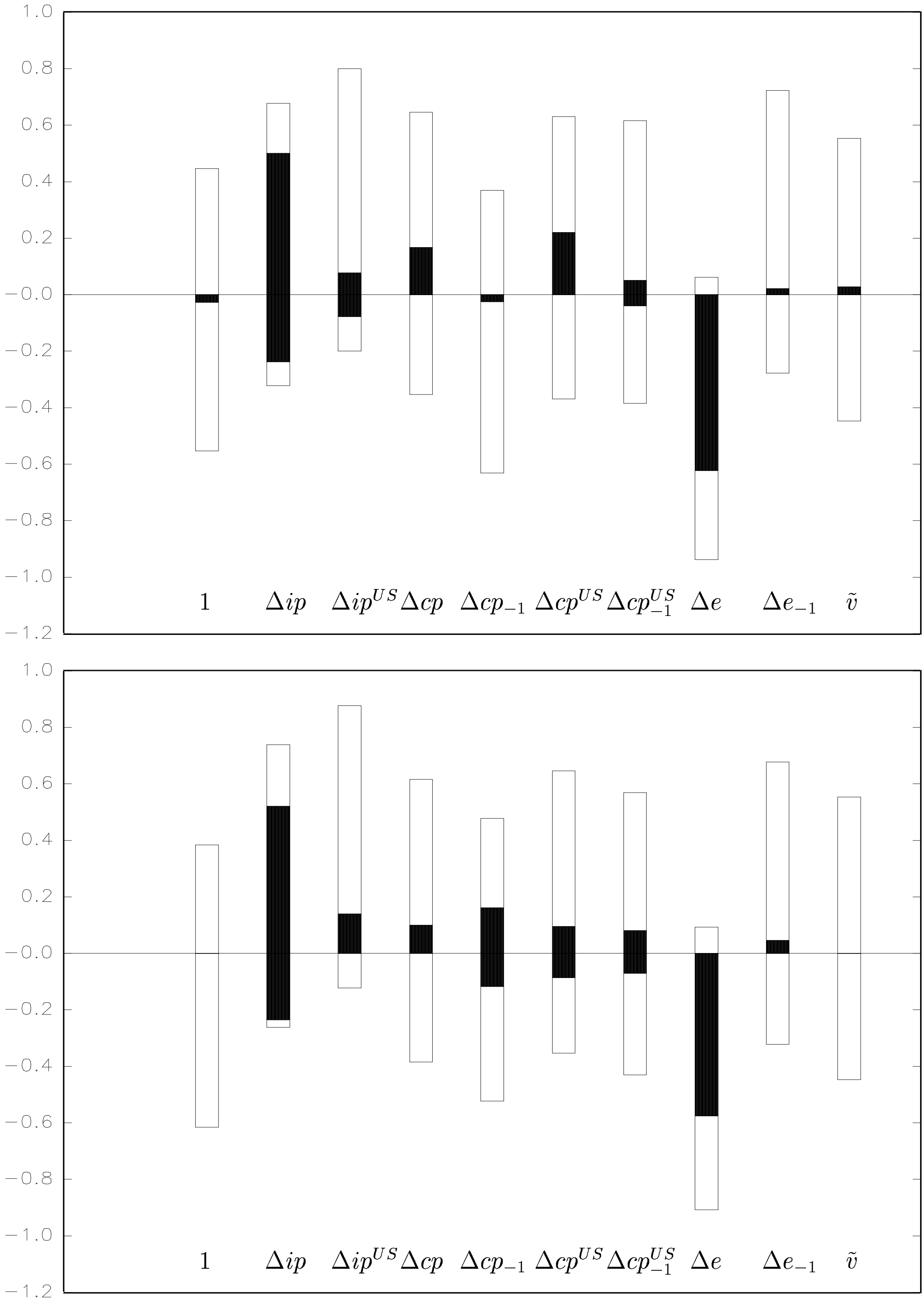

Figure 1: Relative frequencies of signs of coefficient estimates from the initial linear regression excluding lagged dependent variables ($\phi_i^{jk}(B) = 1$). Models for import growth (upper panel) and export growth (lower panel) are distinguished. The relative frequencies of coefficients estimates which are significant at the 5% level are displayed as dark fractions.

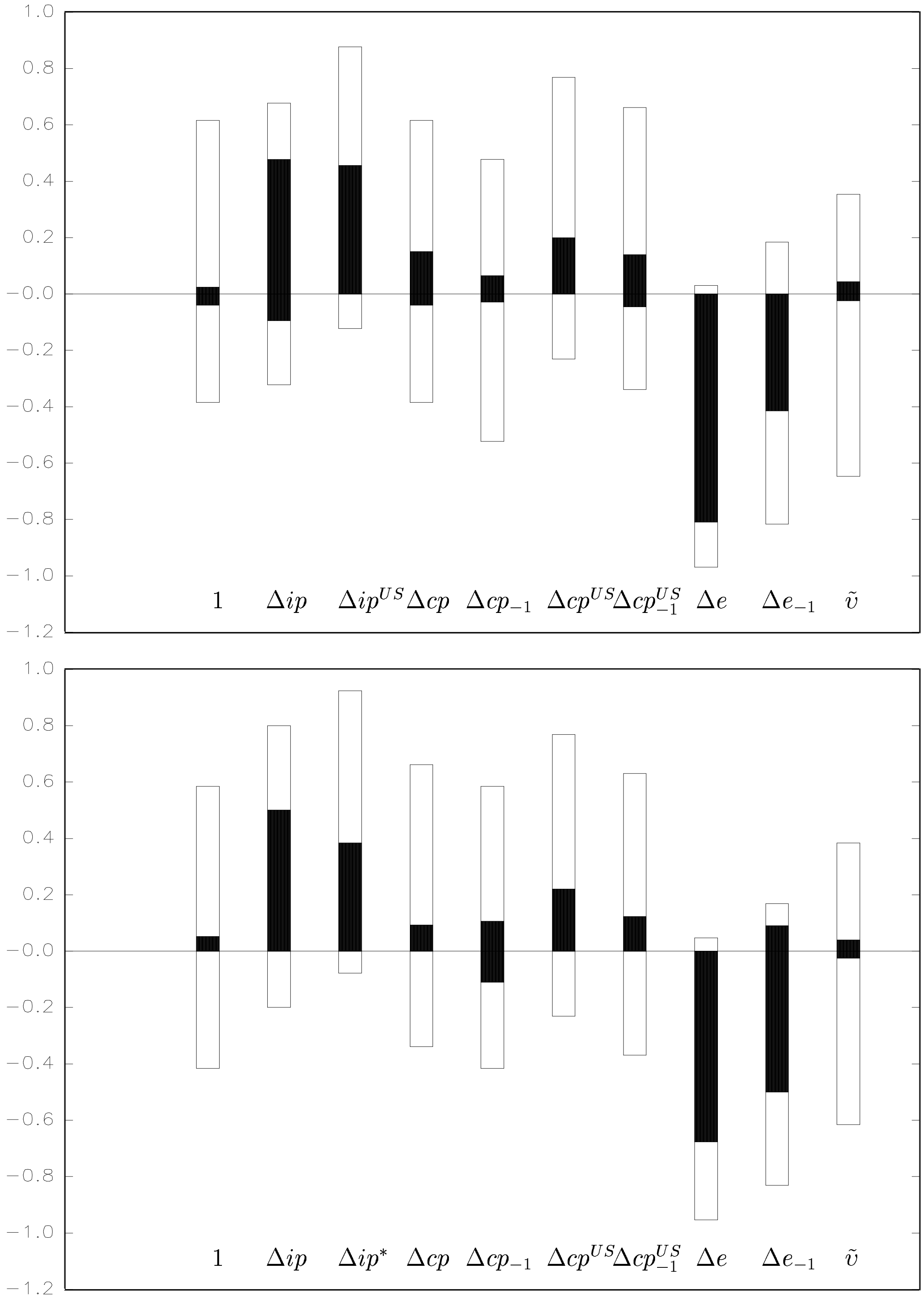

Figure 2: Relative frequencies of signs of coefficient estimates from the initial linear regression excluding lagged dependent variables ($\phi_i^{jk}(B) \neq 1$). Models for import growth (upper panel) and export growth (lower panel) are distinguished. The relative frequencies of coefficients estimates which are significant at the 5% level are displayed as dark fractions.

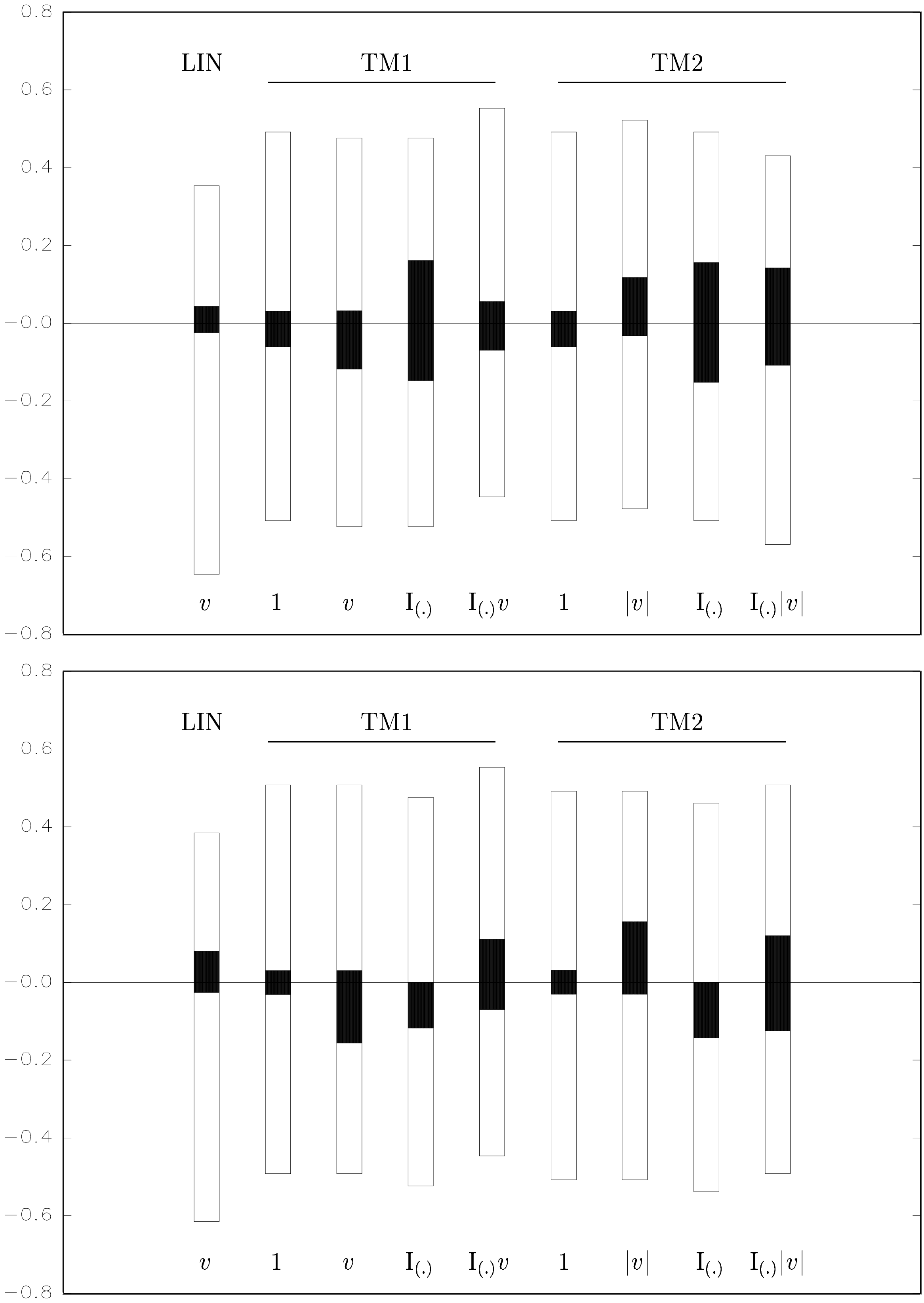

Figure 3: Relative frequencies of signs of coefficient estimates from threshold regressions (TM1, TM2). The first bar shows the corresponding result for the marginal impact of volatility estimated from linear models (transferred from Figure 2). Models for import growth (upper panel) and export growth (lower panel) are distinguished. The relative frequencies of coefficients estimates which are significant at the 5% level are displayed as dark fractions.

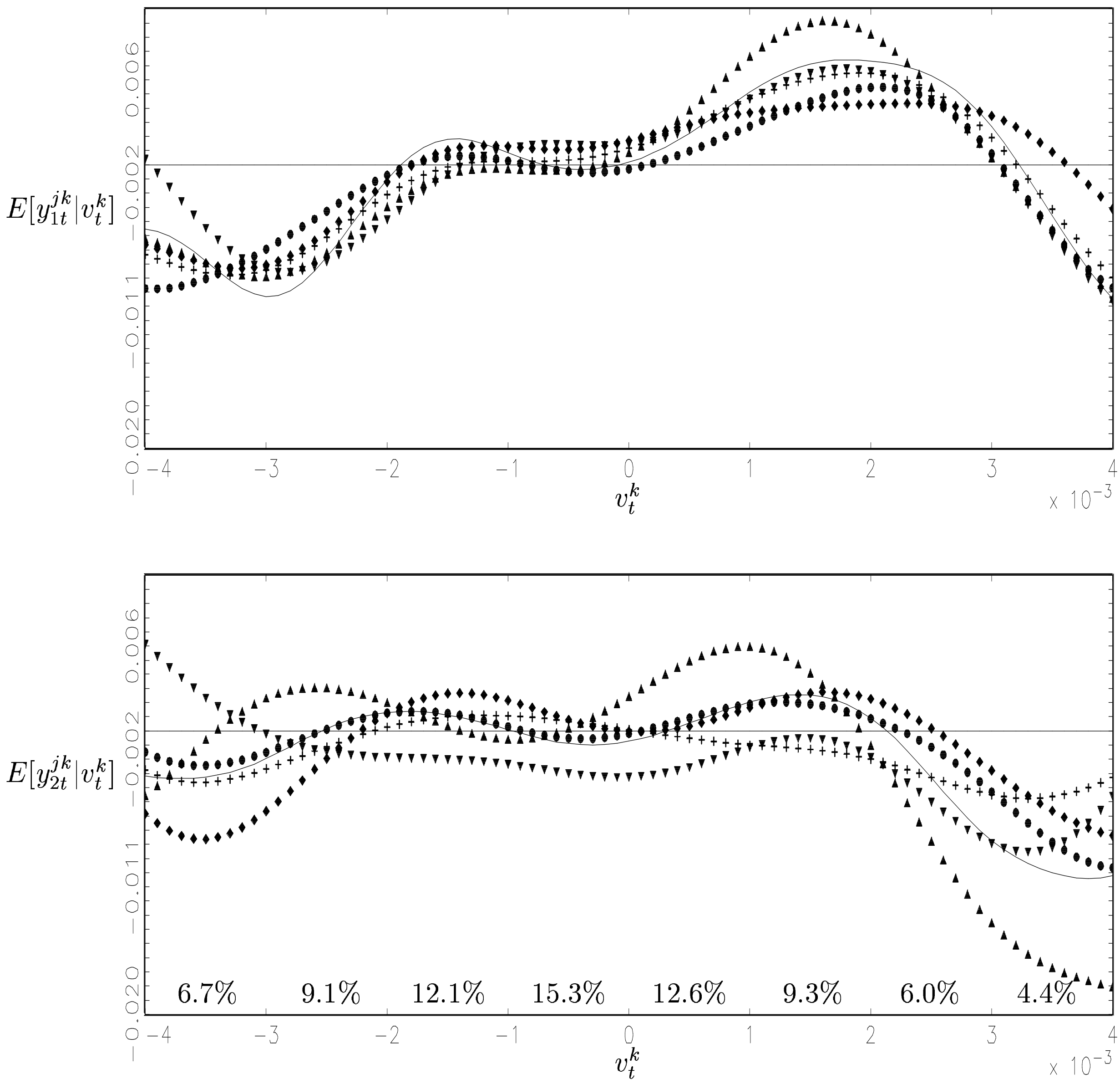

Figure 4: Estimation results for the semiparametric model. Growth functions for imports (upper panel) and exports (lower panel) are distinguished. Dotted lines represent sector specific results obtained when aggregating all available data over 13 economies. The solid line is the semiparametric estimates obtained when aggregated over economic sectors and economies. Percentage entries in the lower panel characterize the distribution of the explanatory variable (aggregated over 13 economies) by means of relative frequencies measured for 8 intervals over its empirical support. (sector 1 •, sector 2 ⧫, sector 3 ▲, sector 4 +, sector 5 ▼)