On the (nonlinear) relationship between exchange rate uncertainty and trade - An investigation of US trade figures in the Group of Seven.

by

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Abstract

The issue to characterize the impact of exchange rate uncertainty on international trade has generated a huge body of both, theoretical and empirical literature. It has turned out that the relationship between exchange rate risk and import or export figures is at most weak and ambigous with respect to its sign. A particular gap not filled yet by the empirical literature is to investigate the potential of nonlinear relationships between exchange rate uncertainty and trade growth. Moreover, the state of the empirical literature has little to say about forecasting accuracy of competing modelling approaches. Analyzing US trade patterns within the Group of Seven this paper aims to contribute to both topics raised above. When estimating functions for growth of US imports and exports linear and nonlinear approaches are evaluated in terms of fitting and forecasting. Empirical results support the view that the relationship of interest might be nonlinear and, moreover, lacks of homogeneity across countries and imports vs exports. In particular, parametric nonlinear models are found to outperform linear regression models in terms of fitting. Nonparametric forecasting schemes deliver sequences of forecast errors with less dynamic structure than linear procedures.

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1 Introduction

Since the end of the Bretton Woods era a large body of theoretical and empirical literature has emerged that discusses the impact of exchange rate volatility on international trade flows. The seminal argument, put forth by Ethier (1973), is easily understood for a representative exporter invoicing in foreign currency. For this agent the cash flow to be received from some contract will often be uncertain. Then, under risk aversion the exporter might wish (if possible) to hedge exchange rate risk on future markets thereby facing additional costs which in turn reduce traded quantities. The policy implications are immediate: Perceived benefits of a flexible exchange rate system as e.g. the immunization of the domestic economy from foreign shocks have to be weighted against welfare losses provoked by hampering world wide specialization. In fact, one essential argument when building the European Monetary System or the European Monetary Union has been that both will reduce or overcome exchange rate risk and thus encourage trade (Commission of the European Communities 1990).

Summarizing the state of the theoretical literature, however, it is presently not clear if exchange rate uncertainty exerts the initially presumed adverse effect on trade (Artus 1983, Brodsky 1984, Demers 1991) or might even stimulate it (Franke 1991). De Grauwe (1988) formalizes a positive (negative) impact of exchange rate uncertainty on trade if the exporters revenues are convex (concave) in the exchange rate. Viane and De Vries (1992) provide a similar ambiguity of the relationship between volatility and trade by formally introducing price determination on forward markets.

Given the apparent ambiguity concerning the effects of exchange rate uncertainty on trade at the theoretical level it becomes an empirical issue to clarify if trade is hampered in periods of higher exchange rate volatility. Reviewing the empirical work as in McKenzie (1999) underscores, however, that there is also no concensus from an empirical point of view. The empirical literature offers conflicting conclusions: Among others De Grauwe and Bellefroid (1986), Bini-Smaghi (1991), and Quian and Varangis (1994) find significant adverse impacts of exchange rate uncertainty on trade. In sharp constrast, Asseery and Peel (1991), or Kumar and Dhawan (1991) give significant evidence for exchange rate volatility stimulating trade. Moreover, conflicting significant evidence (Bailey, Tavlas and Ulan 1987, or Koray and Lastrapes 1989) is available as well as other contributions that do not report any significant relation (Bailey, Tavlas and Ulan 1986, Medhora 1990).

Covering more than two decades the empirical debate gained a lot from major yardsticks in econometric technology. Firstly, in the light of the pioneering work of Engle and Granger (1987) on integration and cointegration early contributions formalizing regression models for nonstationary trade patterns to be explained by other nonstationary variables and some (mostly stationary) measure of exchange rate uncertainty might be criticized. Secondly, with the so-called autoregressive conditionally heteroskedastic time series processes (ARCH-processes), introduced by Engle (1982) and generalized (GARCH) by Bollerslev (1986), a framework of modeling exchange rate volatility is available that takes account of typical stylized properties of log exchange rate processes, as the martingale property, volatility clustering and unconditional leptokurtosis. In comparison to formerly used approximations as, for instance, historical variances the scope of the (G)ARCH framework is twofold. On the one hand this model class brings in a volatility measure which incorporates properties of the exchange rate generating process. On the other hand the so-called GARCH in mean model (Engle, Lilien and Robins 1987) allows to model trade growth and exchange rate uncertainty jointly (Kroner and Lastrapes 1993, Quian and Varangis 1994) instead of implementing some regression model with first step volatility estimates as explanatory variables.

Although the empirical literature has benefited a lot from recent econometric methods two promising directions of empirical work have not been followed yet: In the first place all available empirical studies concentrate a-priori on a linear relationship between the variables of interest. As Viane and De Vries (1992) conjecture, however, the underlying true impact of exchange rate uncertainty on trade might be nonlinear. Therefore, this empirical study provides a detailed comparison of linear vs. nonlinear model specifications for bilateral models of US import and export growth observed in the Group of Seven. Secondly, there appears to be no attempt in the empirical literature to employ the proposed (regression) models for ex-ante forecasting. One reason not to consider forecasting properties might be that most empirical models characterizing trade patterns fail to pass simple regression diagnostics (Arize 1996). For the vast majority of these models estimated error terms show significant autocorrelation, which is rarely accounted for and can be expected to deteriorate forecasting performance. In this paper competing models relating trade and exchange rate uncertainty are compared in terms of explanatory power, and also with respect to their accuracy in ex-ante forecasting.

The remainder of the paper is organized as follows: The next section provides a standard approach to quantifying the relationship of interest, namely the linear regression model. The latter is generalized in Section 3 where parametric and nonparametric extensions of the linear model are motivated and applied. 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 discussed in Sections 2 to 4. The paper ends with some conclusions and directions of future research.

2 On linear dynamics relating exchange rate uncertainty and trade

2.1 Methodology

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 the following bilateral specification is employed to test the marginal impacts of volatility on the growth of US trade observed towards the remaining Group of Seven economies, namely Canada (CA), Germany (GE), United Kingdom (UK), France (FR), Italy (IT) and Japan (JA):

$$\phi_i(B)\tilde{y}_{it} = \tilde{\mathcal{X}}_t \vartheta_i + \tilde{\varepsilon}_{it},\ i = 1, 2,\ t = 1, \ldots, T, \tag{1}$$

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

In (2) $\Delta = 1 - B$ is short for the first difference operator, e.g. $(1 - B)\tilde{y}_{it} = \tilde{y}_{it} - \tilde{y}_{it-1}$, $\tilde{y}_{1t} = \Delta m_t$, $\tilde{y}_{2t} = \Delta x_t$, and m_t and x_t are log US imports and log US exports measured in US Dollar, respectively. Moreover, ip_t (ip_t^*) and cp_t (cp_t^*) are the US (foreign) indices of industrial production and consumer prices (all variables in natural logarithms).

All series are sampled at the monthly frequency. Indices of industrial production are used here to measure economic activity within the involved economies. Note that a more direct approximation as, for instance, gross national product, is not available at the monthly frequency. For the same reason foreign and domestic consumer price indices are used to approximate prices of traded goods. Since production and trade processes show a marked seasonal pattern the series are adjusted by the X11 procedure implemented in Eviews 3.0. Although less seasonality is observed for price indices these series are also seasonally adjusted.

To complete the set of explanatory variables in (2) e_t is the log price of the US Dollar in terms of foreign currencies and $\tilde{v}_t^2$ is an estimated GARCH(1,1) variance series (Engle 1982, Bollerslev 1986) fitted to the corresponding log exchange rate changes (Δe_t):

$$\Delta e_t = \xi_t \tilde{v}_t,\ \xi_t \sim N(0, 1), \tag{3}$$

$$\tilde{v}_t^2 = \hat{\alpha}_0 + \hat{\alpha}_1(\Delta e_{t-1})^2 + \hat{\beta}_1 \tilde{v}_{t-1}^2. \tag{4}$$

As given in (3) and (4) the basic version of the GARCH(1,1)-process postulates a conditional normal distribution for Δe_t the variance of which is determined by means of information available in time $t - 1$ (Ω_{t-1}). To guarantee positivity of conditional variances $\tilde{v}_t^2$ it is sufficient to make sure that all parameter estimates governing $\tilde{v}_t$ in (4) are greater than zero ($\hat{\alpha}_0 > 0, \hat{\alpha}_1 > 0, \hat{\beta}_1 > 0$).

Since exchange rate uncertainty is unobservable one may in principle think of other measures than the GARCH approach, as for instance, absolute percentage changes (Bailey, Tavlas and Ulan 1986) or moving averages of historical exchange rate variations (Koray and Lastrapes 1989). From the empirical literature, however, it is known that the GARCH framework is suitable to capture stylized facts of foreign exchange rate processes such as volatility clustering and leptokurtosis. Moreover, 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).

With respect to the employed explanatory and dependent variables the proposed regression design is in complete analogy to McKenzie and Brooks (1997) analyzing monthly dynamics of 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 $\tilde{\varepsilon}_{it}$, finite order lag polynomials, $\phi_i(B) = 1 - \phi_{i1}B - \phi_{i2}B^2 - \ldots - \phi_{iq}B^q$, $i = 1, 2$, are introduced allowing for autoregressive dynamics of trade growth. It is worthwhile to note that poor diagnostic features of empirical trade models are mostly ignored in the literature (Arize 1996). When implementing (1) the polynomials $\phi_i(B)$ are selected such that the autocorrelation function of implied residuals $\hat{\varepsilon}_{it}$ does not show any significant estimate up to lag order 13. Preliminary estimates of $\hat{\phi}_{ij}, i = 1, 2,\ 1 \leq j \leq q$, which fail to be significant at the 5% level are eliminated from the empirical model. For most estimated specifications the final estimate of $\phi_i(B)$ characterizes an autoregressive subset model. 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 the growth rates of international trade positively. An exchange rate depreciation may lead to an increase in exports and a decrease in imports due to the relative price effect. Thus the estimated coefficient of e_t or e_{t-1} should be positive (negative) when modeling US imports ($i = 1$) (US exports, $i = 2$). Moreover, US imports are expected to be increasing (decreasing) in the domestic (foreign) price level. Modeling US exports the coefficient estimates of cp_t or cp_{t-1} (cp_t^* or cp_{t-1}^*) should be negative (positive). Exchange rate volatility could impact positively or negatively on trade flows. Apart from these a-priori considerations it is important to note that introducing autoregressive dynamics of the dependent variable $\tilde{y}_{it}$ via $\phi_i(B)$ might affect the coefficient estimates of the exogenous right hand side variables and their significance.

2.2 Empirical results

Data are sampled from two OECD databases, namely the "Monthly Statistics of International Trade" (exports, imports and exchange rates) and the "Main Economic Indicators" (indices of industrial production and consumer prices). As mentioned, the series are collected at the monthly frequency and (given necessary presample values) cover the period October, 1971 to March, 2000. Thus, 342 observations are available to estimate each of the 12 bilateral empirical models.

To estimate latent volatility of nominal log exchange rates measured towards the US Dollar a GARCH(1,1) model is considered. Estimation and diagnostic results for six exchange rate processes are provided in Table 1. For all empirical models at least one parameter estimate out of $\hat{\alpha}_1$ and $\hat{\beta}_1$ is significant at the 5% level, thus indicating the prevalence of volatility clustering in monthly exchange rates. When modelling volatility of the Canadian Dollar $\hat{\beta}_1$ fails to be significant. Therefore one might regard an ARCH(1) model to be more suitable. Similarly, the ARCH(1) specification might be favored whenever $\hat{\alpha}_1$ is not significantly estimated. The latter result is obtained when modelling volatility of the French Franc and the Japanese Yen. Note that in the GARCH(1,1) model it is essentially the parameter α_1 that generates time varying volatilities. In fact, employing an ARCH(1) model would yield significant $\hat{\alpha}_1$ estimates for all exchange rates considered. The GARCH(1,1) specification is here preferred firstly to allow a uniform treatment of all series. Secondly, and more importantly, one might conjecture that the implied volatility paths are somewhat smoother according to the GARCH(1,1) model since it is autoregressive in $\tilde{v}_t^2$. When modelling the impact of volatility on trade at the monthly frequency one may argue that current exchange rate uncertainty has only a minor impact on growth rates of trade due to lagged adjustment practiced by exporters and importers. However, given that the estimated volatility paths are sufficiently smooth it is sensible to regard current volatility as a reasonable approximation of exchange rate uncertainty entering the decisions of economic agents.

The estimated volatility models are suitable to remove any conditional heteroskedasticity from exchange rate data. According to the ARCH-LM(1)-test applied to the estimated GARCH(1,1) residuals $\hat{\xi}_t$ no evidence of remaining conditional heteroskedasticity is found. Applying the Jarque-Bera test the normality hypothesis for $\hat{\xi}_t$ is rejected when modeling volatility of the Italian Lira, the British Pound Sterling, and the Japanese Yen. The distribution of the innovations ξ_t is important for inference on significance of GARCH parameter estimates (Bollerslev and Wooldridge 1992, Hafner and Herwartz 2000). All $t-$ratios in Table 1 are obtained from (Quasi) Maximum Likelihood estimation whenever the normality assumption is maintained (rejected).

Ordinary least squares (OLS) estimation results for six US import and US export regression models are given in Table 2. To concentrate on the impact of (lagged) exogenous variables estimates of the intercept term and of model specific autoregressive parameters are not shown. With respect to the latter parameters, however, it is worthwhile to mention that they are significant at the 5% level throughout.

As it is often found for macroeconomic data adjusting US import and export growth rates for autoregressive dynamics leaves little room to detect further significant (exogenous) impacts on trade. The marginal impact of domestic and foreign industrial production is mostly positive. Domestic growth of industrial production exerts a positive impact on US imports which is for most trading partners significant at the 5% level. With respect to the influence of price variables (cp_t, cp_t^*, e_t) on trade numerous counterintuitive results are obtained. To pick out the worst case, US exports appear to be positively related to the domestic price level. Summing over cp_t and cp_{t-1} five out of twelve parameter estimates are positive at the 5% significance level. Similar results in the empirical literature (McKenzie and Brooks 1997) are sometimes explained as J-curve effects. Then, the results in Table 2 indicate that such effects might operate on even higher lags than one month.

The estimated linear impacts of exchange rate volatility on trade growth is insignificant of either sign in almost any equation. For the particular case of US imports from Canada, however, the estimated coefficient of $\tilde{v}_t$ shows a significantly positive effect of exchange rate volatility on trade.

Since numerous single equation estimates are insignificant Table 2 also provides regression results from models where the slope parameters in ϑ_i (see equation (1)) are assumed to be homogeneous over trading partners of the US. Counterintuitive effects of price variables on trade are still present on the level of pooled estimation. With respect to the impact of exchange rate volatility on trade the aggregate level delivers insignificant evidence of a positive (negative) relationship for US imports (US exports).

When estimating the empirical model (1) and (2) it is appealing to allow for contemporaneous correlation between the error terms of equations formalizing US import and export growth for a given trading partner. Therefore feasible generalized LS (GLS) estimation appears to be a natural competitor of OLS. Note, however, that the exogenous right hand side variables of import and export equations in (2) are identical, the representations of both differ only with respect to autoregressive dynamics. Thus, it should not be too surprising that feasible GLS yields almost the same results as OLS throughout. To underpin the latter argument Table 2 also contains feasible GLS results obtained on the level of pooled equations.

Table 3 shows a number of diagnostic results for the linear empirical models, namely the degree of explanation (R^2), the Durbin Watson statistic (DW), F-type tests on homoskedasticity and structural invariance (Het and Str, respectively), and the ARCH-LM statistic testing the homoskedastic model against an ARCH model of order 1 (ARCH1). The F-type statistics are computed from OLS regressions applied to two separate subsamples each containing approximately one half of the available observations. Note that the two types of heteroskedasticity, subjected to diagnostic testing, are of specific importance for the present investigation. On the one hand, one may conjecture that the error terms in (1) have different unconditional variances in the sequel of changing macroeconomic policies or the introduction of sophisticated financial innovations to hedge exchange rate risk. On the other hand, since the seminal article by Engle (1982) there is little doubt about the finding that variables measured on financial markets as e.g. exchange rates show patterns of conditional heteroskedasticity.

Since the applied regression models contain lagged dependent variables the Durbin Watson statistic cannot be used to infer against serial first order residual correlation but might indicate general model misspecification. To provide a test against (higher order) serial error correlation the last two columns of Table 3 display results for the LM-test (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.

As it is typical for the analysis of macroeconomic growth rates all empirical models offer some medium degree of explanation varying between 26.4% and 40.5%. Looking at the DW-test in the sense outlined before it appears that the employed regression models are not subjected to general misspecification. All entries for DW are between 1.817 and 2.112.

Except for two empirical models (US exports to Canada and Japan) all empirical models are characterized by a significant shift of the error term variance between the first and second half of the sample. Similarly, the hypothesis of homoskedasticity is rejected against an ARCH(1) alternative for most equations. Only when modeling US exports to Germany, Italy and Japan homoskedasticity is maintained when testing against conditional heteroskedasticity. For all empirical models the F-test on homogeneity of the dynamic structure does not provide any indication of misspecification, i.e. the employed empirical models are not subjected to structural shifts. This result is particularly important to justify the recursive analyses which will be of predominant interest when forecasting exercises are considered.

Some empirical models do not pass the diagnostic test on absence of serial error correlation. In particular when testing against higher order autocorrelation (LM(12)) in export equations the respective null hypothesis is rejected at the 5% level for US exports to 4 out of 6 economies in the sample. Modeling US imports less evidence of autocorrelation is obtained, 4 out of 6 import equations deliver uncorrelated error processes. The latter results may call for some respecification of the employed models. As mentioned, however, autoregressive dynamics of import and export equations ($\phi_i(B)$) were specified to delete any significant single lag autocorrelation up to order 13. Moreover, taking the results of diagnostic tests on homoskedasticity into account one should not give too much weight on LM-tests which are derived under the assumption that the underlying error processes are homoskedastic.

3 Modelling nonlinear impacts of exchange rate uncertainty on trade

Summarizing the results obtained from the regression model in (1) and (2) it is apparent that the linear effect of volatility on trade is (at most) weak and not unique across bilateral specifications of US trade. 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 used to fit US import and export growth. Since this approach will yield support for nonlinear dependence of trade growth on volatility a nonparametric model is applied as a second device.

3.1 Parametric extensions

3.1.1 Methodology

To concentrate on the relationship between volatility and trade growth partial regression (Ruud 2000) may be used as a means to respecify the regression model in (1) and (2). Let $\tilde{y}_i$ denote the vector of stacked observations on the dependent variables $\tilde{y}_{it}$. Moreover, $\widetilde{\mathcal{Y}}_i$ is a matrix containing regression specific autoregressive variables and $\widetilde{\mathcal{X}}$ contains all observations on exogeneous explanatory variables given in (2). Defining a vector $\underline{\phi}_i$ collecting the autoregressive parameters a compact representation of the model in (1) is:

$$\begin{aligned} \tilde{y}_i &= \widetilde{\mathcal{Y}}_i \underline{\phi}_i + \widetilde{\mathcal{X}} \vartheta_i + \tilde{\varepsilon}_i, & (5) \\ &= \widetilde{X}_i (\underline{\phi}_i', \vartheta_i')' + \tilde{\varepsilon}_i, \; i = 1, 2. & (6) \end{aligned}$$

In addition, let $X_i = \widetilde{X}_i \setminus \tilde{v}$ denote the set of all explanatory variables in (10) other than volatility and define

$$y_i = (I - X_i (X_i' X_i)^{-1} X_i') \tilde{y}_i \quad \text{and} \quad v = (I - X_i (X_i' X_i)^{-1} X_i') \tilde{v}, \tag{7}$$

where I is the $T \times T$ identity matrix. Then, the (partial) linear impact of volatility on trade is obtained from a bivariate regression model

$$y_{it} = c_i + v_t \theta_i + \varepsilon_{it}, \; c_i = 0, \; i = 1, 2. \tag{8}$$

Note that the model in (8) is an equivalent representation of the initial regression (1). When generalizing the relation between trade and exchange rate uncertainty, however, it might be more intuitive to consider the bivariate design in (8).

As mentioned, volatility clustering is a stylized feature of exchange rate changes. Taking this experience into account one may regard the relation between trade and volatility to differ across states of lower and higher volatility. Testing such a hypothesis is straightforward by means of a so-called dummy variable model (Judge, Hill, Griffiths, Lee and Lütkepohl 1988):

$$\text{M1:} \;\; y_{it} = c_i + v_t \theta_i + I_{(v_t > \text{med}[v_t])} c_{i1} + v_t I_{(v_t > \text{med}[v_t])} \theta_{i1} + \varepsilon_{it}. \tag{9}$$

In (9) $I_{(.)}$ denotes an indicator variable which is equal to 1 if the transformed volatility v_t exceeds its median. Note that the median of v_t may be regarded as a robust threshold to separate periods of higher and lower exchange rate uncertainty. To detect even further deviations from a homogeneous relationship between y_{it} and v_t the following models are also considered in this study:

$$\begin{aligned} \text{M2: } |y_{it}| &= c_i + v_t \theta_i + I_{(v_t > \text{med}[v_t])} c_{i2} + v_t I_{(v_t > \text{med}[v_t])} \theta_{i2} + \varepsilon_{it}, & (10) \\ \text{M3: } \;\; y_{it} &= c_i + |v_t| \theta_i + I_{(v_t > \text{med}[v_t])} c_{i3} + |v_t| I_{(v_t > \text{med}[v_t])} \theta_{i3} + \varepsilon_{it}, & (11) \\ \text{M4: } |y_{it}| &= c_i + |v_t| \theta_i + I_{(v_t > \text{med}[v_t])} c_{i4} + |v_t| I_{(v_t > \text{med}[v_t])} \theta_{i4} + \varepsilon_{it}. & (12) \end{aligned}$$

Since the equations (9) and (11) deliver a representation of y_{it} it is straightforward to employ these models for (ex-ante) forecasting of trade growth patterns. If the relationship between volatility and trade growth is stable across alternative states of volatility estimates of the parameters c_{ik} and θ_{ik}, $i = 1, 2$, $k = 1, \ldots, 4$, should be insignificant. Significant parameter estimates $\hat{c}_{ik}$ or $\hat{\theta}_{ik}$, however, question the adequacy of a homogeneous representation in general and of the linear model in (8) or (1) in particular. In this case it is worthwhile to investigate if the threshold models in (9) to (12) deliver unique results over the sets of bilateral models for US imports or exports. If such common features are not found the empirical interest might turn towards a nonparametric approach relating trade and volatility.

3.1.2 Empirical results

Estimates of the threshold parameters of the regression models (9) to (12) are given in Table 4 (US imports) and Table 5 (US exports). For completeness slope estimates obtained from the linear model, (8) say, are also provided. The bottom rows of both tables show some correlation estimates between the variables $y_{it}, |y_{it}|, y_{it}^2$ on the one hand and $v_t, |v_t|$ on the other.

In sharp contrast to the linear regression threshold models deliver parameter estimates which are significant at the 5% level for the majority of the considered bilateral specifications. Only when modeling US exports to Japan and US imports from Canada or Italy each estimate $\hat{c}_{ik}$, $\hat{\theta}_{ik}$, $k = 1, \ldots, 4$, is at most significant at the 10% level. Comparing the alternative dummy regression models, however, it appears that no particular model dominates in terms of fitting over all twelve trade functions that are considered.

Empirical correlation measures support the overall impression of deviations from the standard linear model. Whereas linear models exploit $\text{Cor}[y_{it}, v_t]$ threshold specifications are capable to take more complicated forms of data dependence into account. Consequently, the correlation between y_{it} and v_t is only significant when modelling US imports from Canada, the case where a significant linear slope estimate is obtained. Seven of the correlation estimates $\text{Cor}[|y_{it}|, |v_t|]$, $\text{Cor}[y_{it}^2, v_t]$, and $\text{Cor}[|y_{it}|, v_t]$ exceed $1.96/\sqrt{T} = 0.106$ in absolute value, thus providing additional support to consider nonlinear relationships between exchange rate uncertainty and trade growth.

Summarizing estimation results from more general parametric models it is striking that there is hardly any common feature over alternative trade functions relating y_{it} and v_t. For this reason it is sensible to follow a nonparametric approach where the conditional mean $E[y_{it}|v_t]$ is some unspecified function of volatility.

3.2 A nonparametric model

3.2.1 Methodology

As shown in Section 3.1.2 threshold models offer a promising strategy to improve the performance of linear regression designs when modeling the dependence of trade growth on exchange rate uncertainty. Modeling US trade growth the basic linear relationship is rejected by means of a variety of threshold specifications. Considering the performance of generalized regression models, however, it appears that nonlinear dynamics are mostly data specific. A framework which is able to nest a wide range of relations between y_{it} and v_t is the nonparametric regression model:

$$\begin{aligned} y_{it} &= E[y_{it}|v = v_t] + \epsilon_{it}, \\ &= a_i(v_t) + \epsilon_{it}, i = 1, 2,\ t = 1, 2, \ldots, T. \end{aligned} \tag{13}$$

By assumption the (heteroskedastic) error terms in (13) have a conditional mean of zero and finite variance, i.e.

$$E[\epsilon_{it}|v_t] = 0,\ E[\epsilon_{it}^2|v_t] = \zeta_i^2(v_t) < \infty. \tag{14}$$

The (unknown) conditional mean $a_i(v)$ and conditional variance function $\zeta_i^2(v)$ can be estimated by nonparametric kernel smoothers (Tjøstheim 1994), or locally linear estimators (Fan 1993, Masry 1996).

The locally linear estimator of $a_i(v)$ is the first component of $a_i = (a_{i0}, a_{i1})'$ solving the following minimization problem:

$$\min_{a_{i0},a_{i1}} Q(v) = \min_{a_{i0},a_{i1}} \sum_{t=1}^{T} K\left(\frac{v - v_t}{h}\right) [y_{it} - a_{i0} - a_{i1}(v - v_t)]^2, \tag{15}$$

$$\hat{a}_i(v) = \sum_{t=1}^{T} w(v, h, v_1, \ldots, v_T) y_{it}, \tag{16}$$

where $K(.)$ is a symmetric kernel–function and h denotes the so-called bandwidth parameter.

From (15) it is obvious that $\hat{a}_i(v)$ solves locally a common least squares optimization problem. The local linear estimator in (16) is a weighted average of the dependent variables y_{it} with weights depending on the distance between v_t and v, the bandwidth h and the employed kernel function. To illustrate the precision of nonparametric estimates pointwise confidence bands for $\hat{a}_i(v)$ are easily obtained from quantiles of the Gaussian distribution and some variance estimate $\hat{\zeta}_i^2(v)$. Opposite to pointwise inference the construction of confidence intervals where the nominal coverage probability holds asymptotically over some support of v, $b_u \leq v \leq b_o$, is more involved. As will become evident, however, such a framework allows to test particular parametric models against the nonparametric counterpart. For the present investigation such a procedure is sensible to test the linear model on the one hand and the assumption that trade and exchange rate uncertainty are unrelated on the other hand. Since such confidence intervals are rarely applied in econometrics a brief summary of the toolkit in Neumann and Kreiss (1998) is now given for completeness. Confidence bands with nominal coverage probability $(1-\alpha)$ over some support $b_u \leq v \leq b_o$ are generated in four steps:

- Firstly, estimate the variance of $\hat{a}_i(v)$ from estimated residuals, $\hat{\epsilon}_{it} = y_{it} - \hat{a}_i(v_t)$, and the applied weighting scheme in (16)

$$\hat{\zeta}^2_{a_i}(v) = \sum_{t=1}^{T} w^2(v, h, v_1, \ldots, v_T)\hat{\epsilon}^2_{it}.$$

- The stochastic properties of $\hat{a}_i(v)$ are governed by $\sum_{t=1}^{T} w(v, h, v_1, \ldots, v_T)\epsilon_{it}$. The distribution of this random variable can be approximated using a sufficiently large number of draws (R) from its bootstrap counterpart

$$\sum_{t=1}^{T} w(v, h, v_1, \ldots, v_T)\epsilon^*_{it}.$$

  In the heteroskedastic case, specified in (14), the random terms ϵ^*_{it} can be obtained from the so-called wild bootstrap (Wu 1986) as

$$\epsilon^*_{it} = \hat{\epsilon}_{it}\eta_t, \ \eta_t \sim N(0,1) \text{ and independent of } v_t.$$

- Next, for each bootstrap sample

$$D^*(v) = \frac{\sum_{t=1}^{T} w(v, h, v_1, \ldots, v_T)\epsilon^*_{it}}{\hat{\zeta}_{a_i}(v)}$$

  is computed.

- Finally, let t_α denote the $(1-\alpha)$–quantile of

$$\sup_{b_u \leq v \leq b_o} \{|D^*(v)|\}.$$

  Then, over $b_u \leq v \leq b_o$ a $(1-\alpha)$-confidence interval for the smoothed function $a_i(v)$ is

$$\hat{a}_i(v) \pm t_\alpha \hat{\zeta}_{a_i}(v).$$

The locally linear estimation is implemented by means of the Gaussian kernel (see e.g. Silverman 1986):

$$K(u) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}u^2\right). \tag{17}$$

A particular problem in nonparametric regression is to select the bandwidth parameter h (Härdle et al. 1988). Nonparametric estimates may be seen as local averages of the underlying true mean function, implying that $\hat{a}_i(v)$ essentially estimates a smoothed version of $a_i(v)$. The magnitude of the bias increases with the bandwidth h. Choosing too small a bandwidth, however, may result in a very wiggly pattern of $\hat{a}_i(v)$. Due to the large number of empirical models employed for estimation and recursive forecasting a data driven bandwidth selection is not feasible for this empirical study. Therefore a common rule of thumb bandwidth choice is preferred, i.e.

$$h = \sigma_v \left(\frac{3}{4T}\right)^{-0.2}, \tag{18}$$

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

3.2.2 Empirical results

To discuss particular nonparametric estimation results consider first modeling US imports from Canada. The upper panels of Figure 1 provide a scatterplot of v_t (x-axis) against y_{1t} jointly with the corresponding linear (upper left) and nonparametric (upper right) regression estimates. To have the graphical results on a reasonable scale a few observations with $v_t >$ 0.003 are not displayed. Both figures indicate only a weak dependence of growth rates of US imports from Canada on volatility. The degree of explanation is presumably low for the linear and the nonlinear estimator which both predict some positive overall relationship between volatility and trade. Applying the nonparametric model, however, it appears that this positive relationship is characterized by different slope coefficients depending on the volatility state. If volatility is low the slope of the estimated regression function is slightly negative whereas a positive relation is found for states of high exchange rate uncertainty. To give statistical support for the latter arguments consider the estimated regression function jointly with some measure of estimation uncertainty. The lower left panel of Figure 1 shows $\hat{a}_1(v)$ jointly with a 95% confidence interval which indicates that there is hardly any linear function relating volatility and trade that is not rejected at the 5% significance level. Formally the latter result can be deduced from the lower right panel of Figure 1 providing jointly the nonparametric estimator, the corresponding 95% confidence band, and the estimated linear regression function. The latter is not entirely captured by the confidence band, thus suggesting that the linear model might be too restrictive when modelling the relationship between US imports from Canada and exchange rate uncertainty. To further facilitate the graphical interpretation the lower right panel of Figure 1 also provides a horizontal line representing independence of trade and volatility. As can be seen this line is also not entirely captured by the nonparametric confidence bands, thus the hypothesis that there is no impact of exchange rate uncertainty on US imports from Canada is rejected for some states of high volatility.

In analogy to Figure 1 Figure 2 displays estimation results for US imports from Germany as function of exchange rate uncertainty. Here values of v_t are shown for the range $-0.008 \leq v_t \leq 0.008$. At a first glance a similar U-shaped pattern relating volatility and growth of US imports from Germany is obtained as in Figure 1 for US imports from Canada. From nonparametric point and interval estimates it appears that states of low volatility stimulate US imports from Germany. For periods of very small exchange rate variations the import growth estimate obtained from the linear regression is not covered by the nonparametric 95% confidence interval.

Figure 3 provides the intermediate conclusions obtained when modelling US imports from Canada and Germany jointly with analogous results for growth rates of US exports to these countries. Moreover the lower panels of Figure 3 show estimation results obtained after pooling $y_{it},\ i = 1, 2$, and v_t over all Group of Seven economies. Since all graphs show results for only some typical range of observations v_t the percentage of observations covered by these ranges is also reported. It turns out that depending on the particular analyzed data set the reported estimation results are representative for least 94% of available observations.

The lower left panel of Figure 3 reveals that the nonlinear relationship between volatility and US imports is maintained when aggregating US import data over the Group of Seven. On the level of pooled import equations both linear regression estimates and the hypothesis of no dependence between volatility and import growth are rejected. In fact within a small area of medium volatility states a significantly negative dependence of import growth on volatility is detected.

Regarding the estimated nonparametric 95% confidence bands in the right hand side panels of Figure 3 it appears that there is not any (significant) relationship between exchange rate uncertainty and growth of US exports, neither on the individual levels (represented by US exports to Canada and Germany) nor on the level of pooled observations. Note, however, that these confidence bands hold jointly for the entire support of v_t. Comparing linear and nonlinear estimates of export growth for particular states of volatility the convenient confidence intervals for $\hat{a}_2(v)$ are considerably smaller and thus may fail to contain the parametric estimates. In addition, it is worthwhile to note that conditional on the actual volatility state the nonparametric and the linear model provide ambiguous conclusions on the sign of expected export growth. The latter result might be of particular importance when it comes to the issue of forecasting trade patterns.

4 Evaluation of forecasting models

4.1 Methodology

As pointed out before empirical work on the relationship between trade and exchange rate volatility has ignored the performance of alternative models in forecasting. Moreover, this criterion is appealing in the sense that opposite to in sample fitting model evaluation according to ex-ante forecasting is less affected by factors as the number of model parameters or the flexibility of the assumed functional relation between dependent and explanatory variables. Since forecasting is an important area of applied econometrics this section will evaluate most of the models estimated before in terms of their forecasting accuracy.

Ex-ante forecasting exercises are performed for the linear specification (8), the threshold models (9) and (11) and the nonparametric model (13) estimated by means of the local linear estimator (15). Each of these models is employed recursively by increasing the actual sample size from $t^* = 120$ to $t^* = T-1$, $T = 342$, such that 222 forecasts are computed for each data set. Let $\hat{y}_{i,t^*+1}$ denote a one-step-ahead forecast for y_{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

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

The accuracy of a particular model in forecasting might be assessed firstly by means of the mean absolute forecast error (MAFE) which is here defined as:

$$\mathrm{MAFE} = \frac{1}{T-222}\sum_{t^*=120}^{T-1} |\hat{y}_{i,t^*+1} - y_{i,t^*+1}| = \frac{1}{T-222}\sum_{t^*=120}^{T-1} |z_{t^*+1}|.$$

In the second place, a forecasting scheme can be evaluated according to the randomness of recursive residuals. A 'good' forecasting model should deliver one-step-ahead forecast errors that are free of serial correlation. Finally, when quantifying forecasting accuracy both y_{i,t^*+1} and $\hat{y}_{i,t^*+1}$ can be regarded as a dichotomous random variable. From that a point of view a forecasting model is accurate if the distributional properties of $\hat{y}_{i,t^*+1}$ come close to the corresponding features of the target quantity y_{i,t^*+1}. For instance, it is often of specific importance to forecast the future change of trade patterns, i.e. to determine the sign of y_{i,t^*+1}. To illustrate this issue consider the following contingency tables which summarize the outcome of one-step-ahead growth rate forecasts of US imports from Canada obtained from the linear (8) and the nonparametric model (13), respectively:

	Nonparametric model (13)			Linear regression (8)		
	$\hat{y}_{1,t^*+1} \geq 0$	$\hat{y}_{1,t^*+1} < 0$	$\sum$	$\hat{y}_{1,t^*+1} \geq 0$	$\hat{y}_{1,t^*+1} < 0$	$\sum$
$y_{1,t^*+1} \geq 0$	0.127	0.396	0.523	0.217	0.306	0.523
$y_{1,t^*+1} < 0$	0.117	0.360	0.477	0.198	0.279	0.477
$\sum$	0.244	0.756	1	0.415	0.585	1

The frequency of hitting the sign of y_{1,t^*+1} (FS) is the sum over the diagonal elements of the upper contingency tables,

$$\mathrm{FS} = \mathrm{Prob}(\hat{y}_{i,t^*+1} \geq 0 \wedge y_{i,t^*+1} \geq 0) + \mathrm{Prob}(\hat{y}_{i,t^*+1} < 0 \wedge y_{i,t^*+1} < 0). \qquad (19)$$

If the employed forecasting procedure succeeds in approximating the distribution of the target variable FS should be greater than 0.5, the unconditional probability of a correct sign forecast. Confidence intervals for the empirical averages can be easily determined algebraically as

$$\mathrm{FS} \pm z_{1-\alpha/2}\sqrt{\mathrm{FS}(1-\mathrm{FS})/(T-222)},$$

where $z_{(.)}$ denotes a quantile of the Gaussian distribution.
The so-called Henrikkson Merton test (Henrikkson and Merton 1981) provides another look at contingency tables. Initially proposed to evaluate investment performance this statistic (HM) summarizes the conditional probabilities of forecasting positive or negative changes of the dependent variable, whenever this variable turns out to increase or decrease in t^*+1:

$$\begin{aligned} \mathrm{HM} \;=\; & \mathrm{Prob}(\hat{y}_{i,t^*+1} \geq 0 \wedge y_{i,t^*+1} \geq 0 | y_{i,t^*+1} \geq 0) \\ & + \mathrm{Prob}(\hat{y}_{i,t^*+1} < 0 \wedge y_{i,t^*+1} < 0 | y_{i,t^*+1} < 0) \end{aligned} \tag{20}$$

A successful forecasting scheme should deliver a HM statistic greater than unity. Opposite to the FS statistic critical values for the Henrikkson Merton test are here determined by simulation where under the null hypothesis of trivial forecasting accuracy (HM=1) target variables y_{i,t^*+1} are identically and independently drawn from a Gaussian distribution.

4.2 Forecasting results

The left hand side panel of Table 6 provides mean absolute forecast errors obtained from four competing forecasting schemes, namely the parametric models (8), (9), (11) and the nonparametric approach (13). Apart from single equation results empirical averages for the sets of import and export equations are also shown.

Providing the most flexible functional form to fit trade patterns the nonparametric model is clearly outperformed in terms of the MAFE criterion by the parametric specifications in general and the linear model in particular. It turns out, however, that for the vast majority of forecasting models the MAFE estimate is dominated by a few outlying observations. Taking into account that the nonparametric estimate could become quite wiggly at the boundaries of v_t one should not overvalue the MAFE criterion. As an appealing alternative to average performance one might consider the relative frequency of each model providing the smallest absolute forecast error over the set of 222 available predictions. The latter empirical frequencies are shown in the right hand side panel of Table 6. Over all considered regression models the empirical probability of providing the best forecast varies for the linear specification between 23% (US exports to Canada) and 46.4% (US exports to Germany). On average the latter probability is 37.1%. For four of twelve empirical models (US imports from Italy, US exports to Canada, Italy and Japan) the nonparametric approach is characterized by the highest probability to deliver best predictions. Additional evidence in favor of nonlinear dynamics is found when considering the average performance of the parametric nonlinear models. Over all import and export equations M1 and M3 provide minimum absolute errors for 17.0% and 15.9% of all forecasts, respectively.

As mentioned the suitability of a particular forecasting scheme is often deduced from the stochastic properties of recursive residuals (z_{t^*+1}). Following these lines Table 7 displays LM-test statistics on serial correlation (LM(1) and LM(12)) of z_{t^*+1} obtained from the alternative forecasting procedures. It is a striking result that recursive residuals exhibit serial correlation for most empirical models explaining US imports whereas specifications of US export patterns pass these diagnostic tests satisfactorily. It is worthwhile to note that the autocorrelation properties of recursive residuals and error terms obtained from in sample fitting are contradictory. Recalling LM-test results for the latter (see Table 3) serial correlation is diagnosed (not found) for residual estimates obtained from the majority of export (import) equations.

With respect to model comparison LM-tests for recursive residuals provide some additional support for the nonparametric approach to modelling US trade growth. Almost all LM-statistics obtained from the nonparametric forecasting scheme are smaller than the corresponding statistics computed from the linear model. When modeling US imports from Canada and France the LM(12) statistic is significant at the 5% level for recursive OLS residuals whereas the nonparametric forecast errors yield an insignificant LM(12) statistic.

To complete the comparison of alternative forecasting schemes Table 8 displays the empirical probabilities of forecasting the correct sign of US trade growth (FS) and the Hendrikkson Merton statistics (HM). For most empirical models the FS and HM statistics are close to 0.5 and 1.0, respectively, and thus not significant. When modelling US exports to Italy and Japan the nonparametric forecasting procedure delivers HM statistics that exceed unity with 5% significance. Moreover, the nonparametric forecasting schemes yield on the level of pooled export equations a HM statistic which is also significant. On average the linear approach to forecasting trade growth is in most cases (FS statistics for US imports and exports, HM statistic for US imports) slightly inferior to the nonlinear models. For particular equations, however, the linear model is clearly outperformed by competing models. Employing a linear scheme to forecast, for instance, US imports from Italy or US exports to the UK and France the involved FS statistics vary between 41.4% and 46.8%. Regarding the corresponding statistics under the nonparametric schemes neither of these numbers is below 50%.

5 Conclusions and Outlook

Modeling US trade figures observed within the Group of Seven this study focusses on two important econometric issues, namely detecting nonlinear dynamics and forecasting. Parametric threshold models give a first indication of a nonlinear relationship governing trade dynamics in response to a change in exchange rate uncertainty. In general the partial degree of explanation offered by linear and nonlinear models relating trade growth and exchange rate volatility is weak. The latter result confirms in some way the state of the empirical literature on the topic which delivers little evidence for some significant linear relationship. The results from threshold models are mostly specific on the investigated trade function thereby motivating to employ general nonparametric functions relating growth of US trade and exchange rate volatility. Tests of the linear model derived under locally linear estimation give significant evidence against the linear regression mostly employed in the empirical literature. Summarizing the results from threshold regression and nonparametric models the dependence of US trade growth on volatility is state specific, i.e. different causal relations are found for periods of high and low volatility. Apart from regression results the paper also delivers some evaluation of competing econometric models in terms of forecasting accuracy. Nonparametric ex-ante forecasting schemes deliver forecast error with less dynamic structure compared to the linear regression.

The evidence in favor of nonlinear dependence of US trade figures on exchange rate uncertainty motivates to consider two related empirical issues. Firstly, the vast majority of empirical literature on the topic concentrates on aggregated trade data thereby assuming that the marginal impact of exchange rate variation on import or export growth is homogeneous across different sectors of the economy. Klein (1990) and McKenzie (1998) follow a sector specific approach and it appears that on the disaggregated level trade figures show more pronounced dependence on exchange rate dynamics. Then it is of interest to investigate if the relative superiority of nonlinear models over the linear regression still prevails for particular sectors of the economy. Secondly, since nonlinear models provide some significant relation between volatility and trade it is sensible to follow such an approach to quantify trade dynamics in systems of close monetary cooperation as, for instance, the EMS. In this respect diagnosing trade growth dynamics to depend on the volatility state could provide some powerful argument in favor of such systems.

References

Arize, A.C., 1996, Real Exchange Rate Volatility and Trade Flows: The Experience of Eight European Economies. *International Review of Economics and Finance* **5**, 187-205.

Artus, J.R., 1983, Toward a More Orderly Exchange Rate System. *Finance and Development* **20**, 10–13.

Asseery, A., D.A. Peel, 1991, The Effects of Exchange Rate Volatility on Exports. *Economics Letters* **37**, 173–177.

Bailey, M.J., Tavlas, G.S., M. Ulan, 1986, Exchange Rate Variability and Trade Performance: Evidence for the Big Seven Industrial Countries. *Weltwirtschaftliches Archiv* **122**, 466–477.

Bailey, M.J., Tavlas, G.S., M. Ulan, 1987, The Impact of Exchange Rate Volatility on Export Growth: Some Theoretical Considerations and Empirical Results. *Journal of Policy Modeling* **9**, 225–243.

Bini-Smaghi, L., 1991, Exchange Rate Variability and Trade: Why is it so Difficult to Find any Relationship. *Applied Economics* **23**, 927–936.

Bollerslev, T., 1986, Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics* **31**, 307–327.

Bollerslev, T. and J.M. Wooldridge, 1992, Quasi Maximum Likelihood Estimation and Inference in Dynamic Models With Time Varying Covariances, *Econometric Reviews* **11**, 143-172.

Breusch, T.S., 1978, Testing for Autocorrelation in Dynamic Linear Models *Australian Economic Papers* **17**, 334-355.

Brodsky, D.A., 1984, Fixed Versus Flexible Exchange Rates and the Measurement of Exchange Rate Instability. *Journal of International Economics* **16**, 295–306.

Commission of the European Communities, 1990, One Market, One Money. *European Economy* **44**.

De Grauwe, P., 1988, Exchange Rate Variability and the Slowdown in the Growth of International Trade, *IMF Staff Papers* No.35, 63–84.

De Grauwe, P., D. Bellefroid, 1986, Long Run Exchange Rate Variability and International Trade. Ch. 8. In: Arndt, S. and Richardson, J.D. (eds), Real Financial Linkages Among Open Economies. England, The MIT Press.

Demers, M., 1991, Investment Under Uncertainty, Irreversibility and the Arrival of Information Over Time. *Review of Economic Studies* **58**, 333–350.

Engle, R.F., 1982, Autoregressive Conditional Heteroskedasticity With Estimates of the Variance of U.K. Inflation. *Econometrica* **50**, 987–1008.

Engle, R.F., C.W.J. Granger (1987), Co-Integration and Error Correction: Representation, Estimation and Testing. *Econometrica* **55**, 251–276

Engle, R.F., D.M. Lilien, R.P. Robins, 1987, Estimating Time Varying Risk Premia in the Term Structure: The ARCH-M Model, *Econometrica* **55**, 391-407.

Ethier, W., 1973, International Trade and the Forward Exchange Market. *American Economic Review* **63**, 494–503.

Fan, J., 1993, Local Linear Regression Smoothers and their Minimax Efficiency. *The Annals of Statistics* **21**, 196–216.

Franke, G., 1991, Exchange Rate Volatility and International Trading Strategy. *Journal of International Money and Finance* **10**, 292–307.

Godfrey, L.G., 1978, Testing for Multiplicative Heteroskedasticity, *Journal of Econometrics* **8**, 227-236.

Hafner, C.M., Herwartz, H., 2000, Testing for Linear Autoregressive Dynamics under Heteroskedasticity. *The Econometrics Journal* **3**, 177-197.

Henriksson, R.D., Merton, R.C., 1981. On Market Timing and Investment Performance, II: Statistical Procedures for Evaluating Forecast Skills. *Journal of Business* **54**, 513–533.

Judge, G.G., R.C. Hill, W.E. Griffiths, H. Lütkepohl, T.C. Lee (1988). *Introduction to the Theory and Practice of Econometrics.* Wiley, New York.

Klein, M.W., 1990, Sectoral Effects of Exchange Rate Volatility on United States Exports. *Journal of International Money and Finance* **9**, 299–308

Koray, F. and Lastrapes W.D., 1989, Real Exchange Rate Volatility and U.S. Bilateral Trade: A VAR Approach. *The Review of Economics and Statistics* **71**, 708–712.

Kroner, K.F., W.D. Lastrapes, 1993, The Impact of Exchange Rate Volatility on International Trade: Reduced Form Estimates Using the GARCH-in-Mean Model. *Journal of International Money and Finance*, **12**, 298-318.

Kumar, R. and Dhawan, R., 1991, Exchange Rate Volatility and Pakistans Exports to the Developed World, 1974-1985. *World Development* **19**, 1225–1240.

E. Masry, 'Multivariate Local Polynomial Regression for Time Series: Uniform Strong Consistency and Rates', *Journal of Time Series Analysis*, **17**, 571–599, (1996).

McKenzie, M.D., 1998, The Impact of Exchange Rate Volatility on Australian Trade Flows, *Journal of International Financial Markets, Institutions and Money*, **8**, 21–38.

McKenzie, M., 1999, The Impact of Exchange Rate Volatility on International Trade Flows. *Journal of Economic Surveys* **13**, 71-106.

McKenzie, M., R. Brooks, 1997, The Impact of Exchange Rate Volatility on German-U.S. Trade Flows. *Journal of International Financial Markets, Institutions and Money* **7**, 73–87.

Medhora, R., 1990, The Effect of Exchange Rate Variability on Trade: The Case of the West African Monetary Union's imports. *World Development* **18**, 313–324.

Neumann, M.H. and Kreiss, J.P., 1998, Regression Type Inference in Nonparametric Autoregression. *The Annals of Statistics* **26**, 1570-1613.

Pagan, A.R., 1984, Econometric Issues in the Analysis of Regressions with Generated Regressors. *International Economic Review* **25**, 221-247.

Qian, Y. and Varangis, P., 1994, Does Exchange Rate Volatility Hinder Export Growth: Additional Evidence. *Empirical Economics* **19**, 371–396.

Ruud, P.A., 2000, Classical Econometric Theory, Oxford University Press, Oxford.

B.W. Silverman, 1986, Density Estimation for Statistics and Data Analysis, Chapman and Hall, London.

D. Tjøstheim, 'Nonlinear Time Series: A Selective Review', *Scandinavian Journal of Statistics* **21**, 97–130, (1994).

Viaene, J.M., C. de Vries, 1992, International Trade and Exchange Rate Volatility. *European Economic Review* **36**, 1311–1321.

Wu, C.F.J., 1986, Jackknife, Bootstrap, and Other Resampling Methods in Regression Analysis (with discussion). *Annals of Statistics* **14**, 1261–1295.

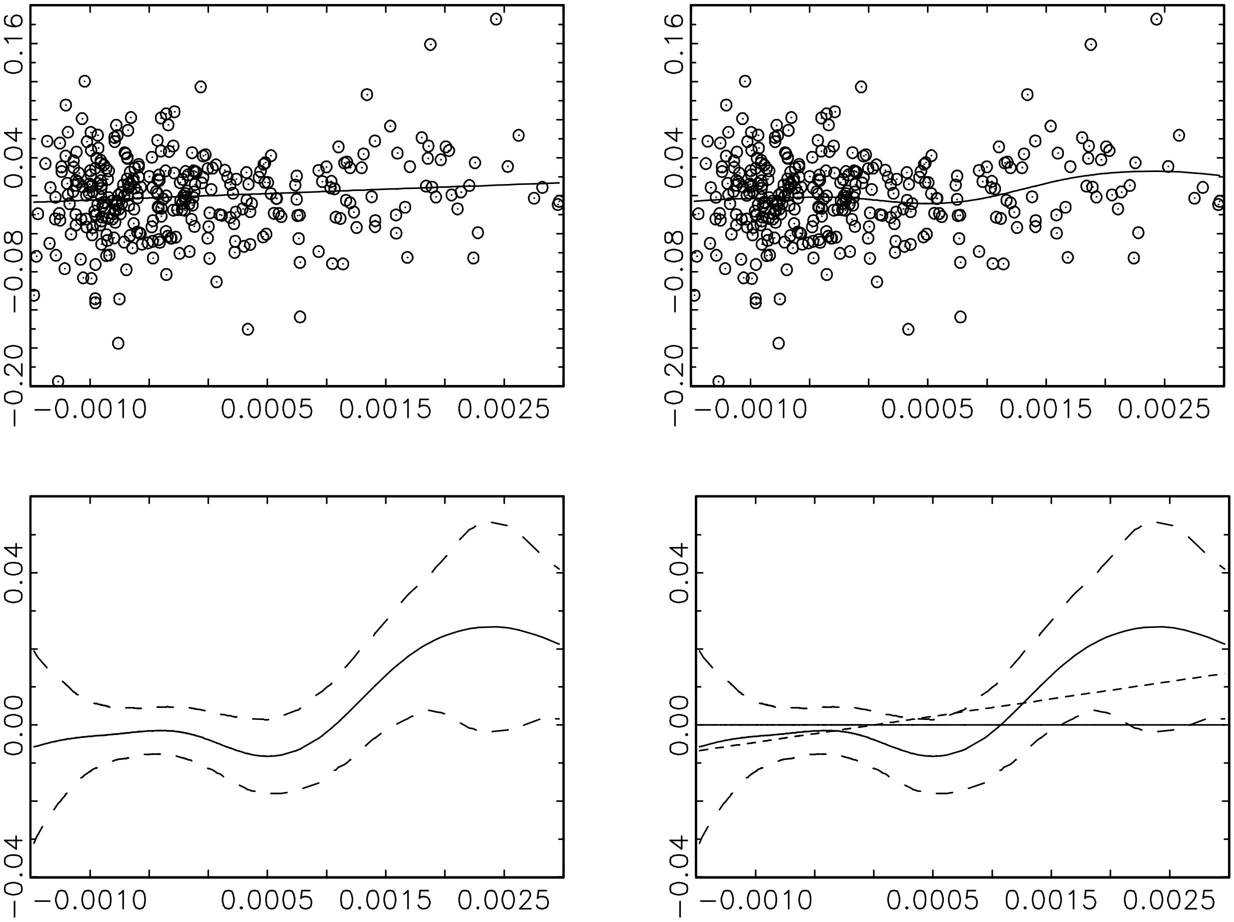

Figure 1. Linear vs. nonparametric modeling of US imports from Canada. Upper panels: Scatterplots of v_t vs. y_{1t} jointly with OLS-estimate (upper left) and locally linear estimate $\hat{a}_1(v)$ (upper right). Lower panels: $\hat{a}_1(v)$ jointly with 95% confidence band (lower left), linear estimate and horizontal line $y_{1t} = 0$ (lower right).

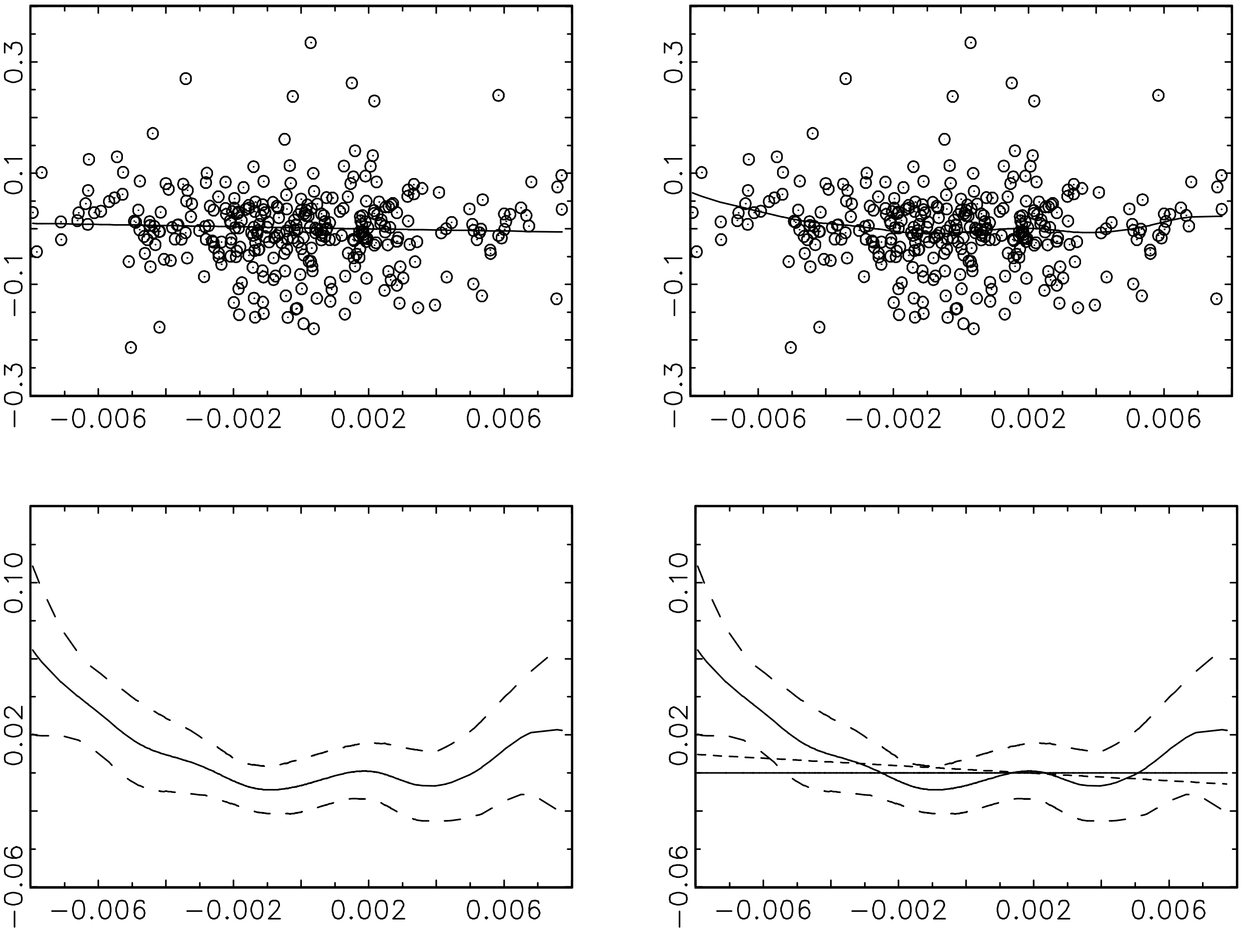

Figure 2. Linear vs. nonparametric modeling of US imports from Germany. Upper panels: Scatterplots of v_t vs. y_{1t} jointly with OLS-estimate (upper left) and locally linear estimate $\hat{a}_1(v)$ (upper right). Lower panels: $\hat{a}_1(v)$ jointly with 95% confidence band (lower left), linear estimate and horizontal line $y_{1t} = 0$ (lower right).

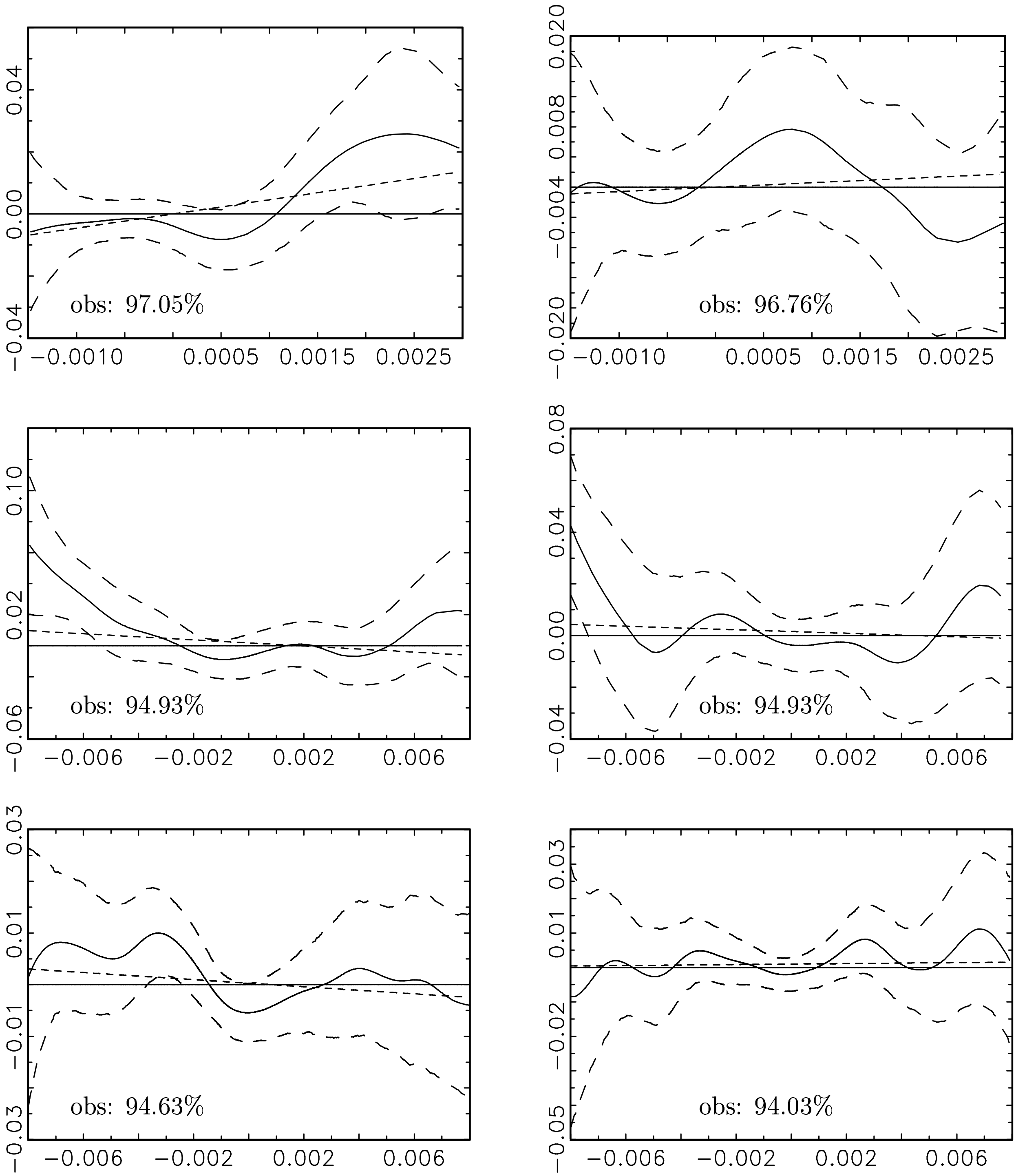

Figure 3. Linear vs. nonparametric modeling of US imports (left hand side panels) and exports (right hand side panels). Each panel displays $\hat{a}_i(v)$ jointly with 95% confidence band (lower left), linear estimate and horizontal line $y_{1t} = 0$. Results are shown for US trade with Canada (upper panels), Germany (medium panels) and aggregated over all Group of Seven economies (lower panels).

Country	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\beta}_1$	JB	ARCH1
CA	5.34E-05	0.190^b	0.295	4.933	0.046
	(1.77)	(2.00)	(0.87)	(0.09)	(0.83)
GE	6.63E-05^b	0.078^c	0.837^c	5.756^b	1.641
	(2.27)	(2.80)	(15.1)	(0.06)	(0.20)
UK	9.12E-05^b	0.247^c	0.628^c	7.78^b	0.00
	(2.13)	(3.09)	(5.82)	(0.020)	(0.953)
FR	3.32E-05	0.0345	0.918^c	3.41	2.4E-04
	(0.78)	(1.49)	(12.4)	(0.18)	(0.99)
IT	1.12E-04^c	0.306^c	0.553^c	21.0^c	9.33E-07
	(2.66)	(3.40)	(5.53)	(0.00)	(1.00)
JA	1.99E-04	0.107	0.661^c	40.6^c	2.185
	(1.12)	(1.47)	(2.62)	(0.00)	(0.14)

Table 1: Parameter estimates and diagnostic tests for GARCH(1,1) models fitted to changes of log exchange rates, i.e. log foreign prices of the US Dollar. Diagnostic test are the Jarque Bera test on unconditional normality and an ARCH LM test against remaining conditional heteroskedasticity of order 1. Underneath the parameter estimates (diagnostic statistics) $t-$ratios (p-values) are given. ^{a}, ^{b}, ^{c} indicate significance at the 10%, 5% and 1% level, respectively.

	CA	GE	UK	FR	IT	JA	all_O	all_G
Imports								
Δip^*	0.538	0.413	0.268	0.799^a	-0.656^c	0.195	0.028	0.029
	(2.17)	(1.60)	(0.89)	(1.94)	(−3.65)	(0.71)	(0.27)	(0.28)
Δip	1.857^c	1.078^a	1.225^b	1.857^c	2.157^c	1.139^c	1.628^c	1.625^c
	(5.16)	(1.86)	(1.99)	(2.71)	(3.70)	(2.37)	(7.25)	(7.22)
Δcp^*	1.674^a	−1.107	−0.474	−0.702	−1.813	−0.052	−0.037	−0.042
	(1.93)	(−0.58)	(−0.39)	(−0.27)	(−1.39)	(−0.07)	(−0.07)	(−0.08)
Δcp^*_{-1}	-1.886^b	-4.714^b	−1.656	0.450	0.921	0.217	-0.913^a	-0.914^a
	(−2.09)	(−2.45)	(−1.37)	(0.18)	(0.70)	(0.27)	(−1.80)	(−1.80)
Δcp	0.292	0.069	4.607^b	1.532	2.042	−0.206	1.236^a	1.261^a
	(0.28)	(0.04)	(2.50)	(0.68)	(1.14)	(−0.15)	(1.84)	(1.87)
Δcp_{-1}	0.998	3.416^b	1.701	1.984	1.103	2.210	1.803^c	1.797^c
	(0.93)	(2.02)	(0.90)	(0.90)	(0.62)	(1.59)	(2.67)	(2.65)
Δe	0.019	−0.193	−0.195	−0.032	−0.324	0.040	-0.135^a	-0.137^a
	(0.07)	(−1.14)	(−0.96)	(−0.15)	(−1.70)	(0.30)	(−1.83)	(−1.85)
Δe_{-1}	−0.205	-0.372^b	−0.088	−0.330	−0.008	-0.283^b	-0.229^c	-0.226^c
	(−0.80)	(−2.20)	(−0.43)	(−1.57)	(−0.04)	(−2.06)	(−3.11)	(−3.07)
$\tilde{v}$	4.567^b	−0.589	0.061	0.692	0.331	−1.251	0.211	0.207
	(2.31)	(0.54)	(0.09)	(0.27)	(0.54)	(−1.20)	(0.60)	(0.59)
Exports								
Δip^*	0.804^c	0.429	0.283	0.179	0.252	0.800^b	0.388^c	0.389^c
	(3.46)	(1.74)	(0.79)	(0.51)	(1.18)	(2.53)	(3.51)	(3.52)
Δip	1.015^c	0.423	1.295^a	0.399	−0.229	0.459	0.557^b	0.562^b
	(3.03)	(0.76)	(1.83)	(0.69)	(−0.34)	(0.83)	(2.38)	(2.40)
Δcp^*	−0.197	−2.871	−1.950	−1.704	−0.563	0.777	−0.696	−0.714
	(−0.24)	(−1.55)	(−1.40)	(−0.78)	(−0.37)	(0.86)	(−1.33)	(−1.36)
Δcp^*_{-1}	−0.329	−2.804	0.398	−3.106	−1.925	0.053	−0.769	−0.772
	(−0.39)	(−1.50)	(0.29)	(−1.43)	(−1.23)	(0.06)	(−1.45)	(−1.46)
Δcp	1.235	1.920	4.937^b	4.465^b	8.227^c	4.248^c	3.846^c	3.859^c
	(1.28)	(1.16)	(2.33)	(2.33)	(3.84)	(2.62)	(5.45)	(5.46)
Δcp_{-1}	0.283	2.895^a	1.121	4.738^b	0.755	−0.229	1.331^a	1.348^a
	(0.28)	(1.76)	(0.52)	(2.50)	(0.35)	(−0.14)	(1.86)	(1.88)
Δe	−0.368	−0.247	0.134	0.019	−0.149	−0.173	−0.109	−0.110
	(−1.52)	(−1.51)	(0.58)	(0.11)	(−0.66)	(−1.11)	(−1.41)	(−1.42)
Δe_{-1}	0.286	0.119	0.187	-0.342^a	-0.500^b	−0.236	-0.149^a	-0.153^b
	(1.19)	(0.73)	(0.80)	(−1.92)	(−2.13)	(−1.47)	(−1.93)	(−1.97)
$\tilde{v}$	0.584	1.061	−0.379	−0.352	0.032	1.031	−0.151	−0.155
	(0.31)	(1.00)	(−0.47)	(−0.16)	(0.04)	(0.85)	(−0.41)	(−0.42)

Table 2: Estimates for the basic linear regression in (1) and (2) modeling bilateral US imports and exports in the Group of Seven. $t-$ratios in parentheses. The two last columns provide pooled OLS and GLS estimates (all_O and all_G) with slope coefficients restricted to be equal across equations. ^{a},^{b},^{c} indicate significance at the 10%, 5% and 1% level, respectively.

	R^2	DW	Het	Str	ARCH1	LM(1)	LM(12)
	Imports						
CA	0.465	2.139	1.476^c	0.437	22.26^c	7.923^c	22.92^b
GE	0.358	1.931	3.260^c	0.257	18.14^c	0.324	15.40
UK	0.414	2.008	2.567^c	0.636	3.482^a	1.550	18.72^a
FR	0.420	1.930	2.536^c	1.105	12.22^c	0.359	15.06
IT	0.315	2.016	3.287^c	0.777	4.024^b	0.665	5.650
JA	0.416	2.070	2.519^c	0.838	6.883^c	2.150	7.230
	Exports						
CA	0.405	2.133	1.169	0.731	6.529^b	8.468^c	26.43^c
GE	0.326	1.813	2.042^c	0.944	0.104	8.204^c	28.43^c
UK	0.345	1.899	1.724^c	0.414	10.15^c	1.052	32.93^c
FR	0.353	1.888	2.105^c	0.401	23.20^c	0.040	17.64
IT	0.390	1.945	2.401^c	0.502	0.032	0.002	25.32^b
JA	0.310	2.023	1.066	0.555	0.479	1.203	12.59

Table 3: Diagnostic results for the basic linear regression in (1) and (2) modeling bilateral US imports and exports in the Group of Seven. In particular the following statistics are displayed: The degree of explanation (R^2), the Durbin-Watson statistic (DW) F-type tests against unconditional heteroskedasticity and structural change (Het, Str), an ARCH-LM test against conditional heteroskedasticity of order 1 (ARCH1) and LM-type tests against first and twelfth order autocorrelation (LM(1), LM(12)).
The statistics Het and Str are obtained from OLS regression applied to two subsamples each containing half of the initial sample. ^{a},^{b} ,^{c} indicate significance at the 10%, 5% and 1% level, respectively.

	CA	GE	UK	FR	IT	JA
	Linear regression					
$\hat{\theta}_1$	4.567^b	0.589	0.061	0.692	0.331	−1.251
	(2.35)	(0.55)	(0.09)	(0.27)	(0.55)	(−1.23)
	M1: Dummy regression y_1 on v					
$\hat{c}_{11}$	−0.003	−0.004	-0.046^b	0.018	−0.015	-0.031^b
	(−0.24)	(−0.28)	(−2.47)	(1.06)	(−0.95)	(−2.12)
$\hat{\theta}_{11}$	2.299	2.029	−5.496	22.50^b	−2.751	−5.637
	(0.18)	(0.63)	(−1.55)	(2.51)	(−1.04)	(−1.11)
	M2: $\|y_1\|$ on v					
$\hat{c}_{12}$	0.009	0.018^b	−0.023	−0.003	0.019^a	−0.009
	(1.05)	(2.03)	(−1.85)	(−0.26)	(1.68)	(−0.89)
$\hat{\theta}_{12}$	16.23^a	6.341^c	-4.613^a	−6.822	1.556	−2.273
	(1.90)	(2.79)	(−1.94)	(−1.09)	(0.83)	(−0.63)
	M3: y_1 on $\|v\|$					
$\hat{c}_{13}$	−0.005	−0.004	-0.047^b	0.018	−0.018	-0.030^b
	(−0.38)	(−0.28)	(−2.47)	(1.06)	(−1.10)	(−2.07)
$\hat{\theta}_{13}$	10.66	1.689	7.431^b	−8.630	3.665	6.018
	(0.83)	(0.52)	(2.09)	(−0.96)	(1.37)	(1.18)
	M4: $\|y_1\|$ on $\|v\|$					
$\hat{c}_{14}$	0.008	0.018^b	-0.023^a	−0.003	0.020^a	−0.009
	(0.98)	(2.03)	(−1.83)	(−0.26)	(1.70)	(−0.89)
$\hat{\theta}_{14}$	−11.80	-7.196^c	3.238	2.416	−2.420	3.081
	(−1.37)	(−3.17)	(1.36)	(0.39)	(−1.29)	(0.85)
	Correlations					
$\mathrm{Cor}[y_{1t}, v_t]$	0.127^b	0.030	0.005	0.015	0.030	-0.066
$\mathrm{Cor}[\|y_{1t}\|, \|v_t\|]$	0.079	0.122^b	-0.080	-0.055	-0.007	0.004
$\mathrm{Cor}[y_{1t}^2, v_t]$	0.018	-0.162^c	-0.108^b	0.004	0.007	-0.011
$\mathrm{Cor}[\|y_{1t}\|, v_t]$	0.005	-0.117^b	-0.071	0.005	0.012	0.009

Table 4: Estimates for threshold parameters of regressions (9) to (12) modeling bilateral US imports in the Group of Seven ($t-$ratios in parentheses). For comparison the second line provides the slope estimate obtained from the linear model (8). Empirical cross correlations between import growth and volatility after regressing out impacts of remaining variables ($X_1 = \widetilde{X}_1 \setminus \tilde{v}$) are shown in the lower block. ^{a},^{b},^{c} indicate significance at the 10%, 5% and 1% level, respectively.

	CA	GE	UK	FR	IT	JA
	Linear regression					
$\hat{\theta}_2$	0.584	1.061	−0.379	−0.352	0.032	1.031
	(0.32)	(1.01)	(−0.48)	(−0.16)	(0.05)	(0.86)
	M1: Dummy regression y_2 on v					
$\hat{c}_{21}$	0.010	−0.018	−0.008	0.001	−0.013	0.012
	(0.79)	(−1.44)	(−0.36)	(0.08)	(−0.66)	(0.72)
$\hat{\theta}_{21}$	6.520	0.184	-7.502^a	15.44	−4.908	0.914
	(0.50)	(0.06)	(−1.86)	(2.03^b)	(−1.61)	(0.16)
	M2: $\|y_2\|$ on v					
$\hat{c}_{22}$	-0.022^c	0.016^a	0.012	0.000	0.020	0.000
	(−2.78)	(1.95)	(0.79)	(0.01)	(1.57)	(0.02)
$\hat{\theta}_{22}$	-19.31^b	9.700^c	6.444^b	4.386	5.410^c	0.078
	(−2.24)	(4.63)	(2.28)	(0.83)	(2.68)	(0.02)
	M3: y_2 on $\|v\|$					
$\hat{c}_{23}$	0.011	−0.018	−0.007	0.001	−0.012	0.012
	(0.85)	(−1.44)	(−0.32)	(0.08)	(−0.61)	(0.71)
$\hat{\theta}_{23}$	−8.070	5.466	3.177	−2.951	2.828	−0.869
	(−0.61)	(1.74)	(0.79)	(−0.39)	(0.92)	(−0.15)
	M4: $\|y_2\|$ on $\|v\|$					
$\hat{c}_{24}$	-0.022^c	0.016^a	0.011	0.000	0.020	0.000
	(−2.71)	(1.95)	(0.75)	(0.01)	(1.61)	(−0.01)
$\hat{\theta}_{24}$	17.01^b	-5.397^c	−4.587	−2.576	-5.851^c	0.995
	(1.97)	(−2.58)	(−1.62)	(−0.49)	(−2.88)	(0.23)
	Correlations					
$\mathrm{Cor}[y_{2t}, v_t]$	0.017	0.055	-0.026	-0.009	0.002	0.047
$\mathrm{Cor}[\|y_{2t}\|, \|v_t\|]$	-0.070	0.227^c	0.088	0.039	0.042	0.020
$\mathrm{Cor}[y_{2t}^2, v_t]$	-0.101^a	-0.160^c	-0.070	-0.043	-0.118^b	0.031
$\mathrm{Cor}[\|y_{2t}\|, v_t]$	-0.100^a	-0.068	-0.033	-0.037	-0.111^b	0.030

Table 5: Estimates for threshold parameters of regressions (9) to (12) modeling bilateral US emports in the Group of Seven ($t-$ratios in parentheses). For comparison the second line provides the slope estimate obtained from the linear model (8). Empirical cross correlations between import growth and volatility after regressing out impacts of remaining variables ($X_1 = \widetilde{X}_1 \setminus \tilde{v}$) are shown in the lower block. ^{a},^{b},^{c} indicate significance at the 10%, 5% and 1% level, respectively.

Country	MAFE*100				best			
	lin	M1	M3	np	lin	M1	M3	np
	US imports							
CA	3.380	3.410	3.410	3.460	0.441	0.149	0.149	0.261
GE	5.070	5.130	5.130	5.150	0.369	0.176	0.117	0.338
UK	6.000	6.090	6.100	6.490	0.441	0.131	0.149	0.279
FR	6.670	6.750	6.760	6.830	0.419	0.131	0.185	0.266
IT	5.240	5.240	5.230	5.330	0.288	0.203	0.149	0.360
JA	4.410	4.430	4.420	4.710	0.392	0.189	0.212	0.207
all	5.128	5.175	5.175	5.328	0.392	0.163	0.160	0.285
	US exports							
CA	3.350	3.380	3.390	3.350	0.230	0.252	0.140	0.378
GE	5.060	5.150	5.150	5.100	0.464	0.122	0.180	0.234
UK	6.350	6.500	6.500	7.460	0.423	0.162	0.149	0.266
FR	5.400	5.380	5.380	5.500	0.392	0.099	0.189	0.320
IT	6.350	6.370	6.360	6.650	0.320	0.176	0.153	0.351
JA	4.820	4.820	4.820	5.030	0.270	0.248	0.131	0.351
all	5.222	5.267	5.267	5.515	0.350	0.176	0.157	0.317

Table 6: Ex ante forecasting performance of competing empirical models (I). MAFE is the mean absolute forecast error and 'best' gives the model specific empirical probability of obtaining the smallest absolute error for the set of 222 considered one-step-ahead predictions.

	CA	GE	UK	FR	IT	JA	CA	GE	UK	FR	IT	JA
	US imports						US exports					
	Linear regression											
LM(1)	11.6^c	9.87^c	11.6^c	3.56^a	6.36^b	6.03^b	0.13	0.35	0.19	0.41	4.06	0.14
LM(12)	23.3^b	19.2^a	26.8^c	21.8^b	14.0	23.2^b	23.9^b	17.7	11.1	14.5	16.6	15.5
	Dummy regression M1											
LM(1)	9.60^c	8.88^c	10.2^c	1.82	6.30^b	5.25^b	0.19	0.30	0.99	0.93	3.43	0.16
LM(12)	21.7^b	17.3	25.6^b	18.5	13.3	22.8^b	23.9^b	17.3	17.0	17.7	16.5	15.7
	Dummy regression M3											
LM(1)	9.03^c	8.86^c	10.0^c	1.82	6.01^b	5.33^b	0.22	0.30	0.93	0.99	3.37	0.16
LM(12)	21.4^b	17.4	25.5^b	18.6^a	13.0	23.0^b	24.1^b	17.3	17.0	17.8	16.4	15.8
	Nonparametric regression											
LM(1)	5.90^b	8.78^c	7.41^c	1.62	4.66^a	7.73^c	0.16	0.20	0.38	0.62	0.18	0.62
LM(12)	17.6	16.4	21.9^b	17.2	9.70	22.5^b	23.8^b	16.1	8.19	15.1	7.05	12.7

Table 7: Ex ante forecasting performance of competing empirical models (II). Lagrange Multiplier tests (Breusch 1978, Godfrey 1978) against first and twelfth order autocorrelation in series of one-step-ahead forecast errors $z_{t^*+1} = \hat{y}_{i,t^*+1} - y_{i,t^*+1}$. Test results for the linear model, two parametric nonlinear models and the nonparametric specification are distinguished. ^{a},^{b},^{c} indicate significance at the 10%, 5% and 1% level, respectively.

Country	FS				HM			
	lin	M1	M3	np	lin	M1	M3	np
	US imports							
CA	0.495	0.486	0.505	0.486	0.999	0.979	1.017	0.996
GE	0.495	0.500	0.495	0.491	0.989	0.999	0.990	0.991
UK	0.477	0.468	0.468	0.464	0.964	0.936	0.936	0.934
FR	0.495	0.527	0.527	0.505	1.001	1.062	1.062	1.025
IT	0.468	0.491	0.491	0.509	0.940	1.016	1.008	1.043
JA	0.527	0.554^a	0.541^a	0.518	1.059	1.099	1.074	1.043
pool	0.493	0.505	0.505	0.495	0.992	1.015	1.015	1.005
	US exports							
CA	0.477	0.486	0.437	0.491	0.961	0.970	0.871	0.978
GE	0.523	0.468	0.473	0.477	1.039	0.931	0.939	0.963
UK	0.468	0.536	0.536	0.527	0.938	1.071	1.071	1.056
FR	0.414	0.527	0.527	0.500	0.836	1.057	1.057	0.970
IT	0.527	0.505	0.505	0.559^a	1.054	1.009	1.009	1.117^b
JA	0.536	0.527	0.536	0.545^a	1.081	1.033	1.049	1.129^b
pool	0.491	0.508	0.502	0.517	0.985	1.012	0.999	1.036^a

Table 8: Ex ante forecasting performance of competing empirical models (III). FS is the empirical probability of forecasting the sign of trade growth correctly. HM is the Hendrikkson Merton statistic. ^{a},^{b} indicate significance at the 10%, and 5% level, respectively.