Institute of Economic Studies, Faculty of Social Sciences
Charles University in Prague

The impact of exchange rate volatility on trade: Evidence for the Czech Republic

Oxana Babecká Kucharčuková

IES Working Paper: 03/2014

Institute of Economic Studies,
Faculty of Social Sciences,
Charles University in Prague

[UK FSV – IES]

Opletalova 26
CZ-110 00, Prague
E-mail : ies@fsv.cuni.cz
http://ies.fsv.cuni.cz

Institut ekonomických studií
Fakulta sociálních věd
Univerzita Karlova v Praze

Opletalova 26
110 00 Praha 1

E-mail : ies@fsv.cuni.cz
http://ies.fsv.cuni.cz

Bibliographic information:
Babecká Kucharčuková, O. (2014). "The impact of exchange rate volatility on trade: Evidence for the Czech Republic" IES Working Paper 03/2014. IES FSV. Charles University.

This paper can be downloaded at: http://ies.fsv.cuni.cz

The impact of exchange rate volatility on trade: Evidence for the Czech Republic

Oxana Babecká Kucharčuková [a]

[a] IES, Charles University Prague and Czech National Bank
E-mail: Oxana.Babecka-Kucharcukova@cnb.cz

January 2014

Abstract:
This paper aims to quantify the impact of nominal exchange rate volatility on nominal trade flows with a particular focus on the Czech Republic. The paper shows that the magnitude of the impact differs when a dynamic model is used instead of static model.

Keywords: Gravity model of trade, Exchange rate volatility, Poisson estimator

JEL: F14, F31, F4

Acknowledgements:
The opinions expressed in this article are those of the author and do not reflect the official position of the Czech National Bank. The author is grateful to Jan Babecký and Tomáš Harvánek for valuable comments. Financial support from the Grant Agency of the Czech Republic no. P402/12/0982 is gratefully acknowledged.

1. Introduction

According to theory a negative relation is expected between exchange rate volatility and trade. However, numerous empirical results[1], are ambiguous, jumping from negative to positive or even zero impact on trade. One explanation refers to other factors, such as hedging strategies, which could mask the true impact of exchange rate volatility on trade. An alternative justification to the observed diversity in results is a difference in applied econometric procedures. The paper contributes to this stream of the empirical literature with a particular focus on the Czech Republic. While the existing literature extensively discusses the sign of the impact in question, its magnitude remains out of focus in almost all studies. This paper aims to quantify the impact of nominal exchange rate volatility on trade, using the gravity approach. In addition the paper shows how sensitive the size of the impact is to different econometric procedures, particularly, broadly used static models vs. dynamic models, which are less explored in gravity models. Furthermore, in contrast to the majority of gravity equation estimates using annual data, the results in this paper are based on a quarterly sample which allows addressing stationarity issues when the time period is relatively short.

The paper is structures as follows. The next section describes the measures of exchange rate volatility. Section three discusses the empirical model and shows the data properties. Sections four explains the econometric approach and briefly discusses potential biases, as well as advantages, of the proposed econometric procedures. Section five explains computation formulas. Results are presented in section six. Finally, section seven concludes.

2. Measures of exchange rate volatility

There is no conventional measure of exchange rate volatility. Depending on the purpose of a study, the estimation method is based on standard deviation, variance, extreme values or ARCH-type models. In this paper exchange rate volatility (V_{ijt}) is computed as the standard deviation (σ) of the log difference of nominal bilateral exchange rate (s_{ijt}). This formula is one of the most commonly used in studies focused on the gravity model. It implies zero volatility, when the exchange rate is fixed vis-à-vis another currency. In order to lower autocorrelation, as well as to adjust volatility measures to a quarterly sample, V_{ijt} is estimated

[1] For a comprehensive survey see Côté, 1994, McKenzie 1999, Clark et al. 2004.

on weekly non-overlapping data, i.e., separately for each quarter (2.1).[2] Higher frequency data is not considered for two reasons. First, it is not available for all countries. Second, daily fluctuations of exchange rates contain a lot of noise unrelated to the decision to trade.

$$V_{ijt} = \sigma\left(\sum_{k=1}^{m} \Delta \ln\left(s_{ijk}^{t}\right)\right), \tag{2.1}$$

where t is time index at quarterly frequency, m is a number of weeks in a given quarter, and s refers to exchange rate.

An alternative measure of exchange rate volatility is moving window standard deviation measuring variation in time in the absolute magnitude of changes in natural logarithm of exchange rate (Arize, 1996). In contrast to (2.1), this volatility estimated according to this formula better reflects persistence in exchange rate movements accounting for periods of high and low uncertainty (2.2.).

$$V_{ij,t+l} = \sqrt{\frac{1}{L}\sum_{l=1}^{L}\left(\ln s_{ij,t+l-1} - \ln s_{ij,t+l-2}\right)}, \tag{2.2}$$

where l is the order of moving average.

The formula used by Esquivel and Larraín (2002) is based on variance and by construction accounts for deviation from a certain level observed in a given period (2.3).

$$V_{ij,t+l} = \frac{\sqrt{\frac{1}{L}\sum_{l=1}^{L}\left(s_{ij,t+l-1} - s_{ij,mean}\right)^{2}}}{s_{ij,mean}}, \tag{2.3}$$

Scrimgeour (2002) uses two-step procedure. First, volatility is measured as a simple variance of the quarter-on-quarter percentage change in the exchange rate. Then, the author distinguishes between short run volatility and cyclical volatility extracted using the band-pass filter. Fontagné (1999) computes exchange rate volatility, using the ratio of minimum and maximum values.

[2] Previous studies often compute volatility on overlapping periods, e.g. volatility at annual frequency is retrieved from quarterly or monthly data over the last five years. While it helps to collect more observations, the quantification of the impact on trade it is not trivial in this case.

Another way to model exchange rate volatility is to predict volatility by using past values in the ARCH/GARCH framework, where past variances in exchange rates generate future variances in exchange rates. McKenzie and Brook (1997) apply the ARCH model. Baum and Caglayan (2010) directly obtain exchange rate volatility from the bi-variate GARCH model of exchange rate volatility and trade. Since it is hard to predict exchange rates, the observed volatility measure is used in this study. Furthermore, the GARCH model may not function properly in a finite sample models.

3. Selected empirical model and data properties

The impact of exchange rate volatility on trade is based on estimates of the gravity equation, which is a reduced form trade model derived from partial equilibrium under CES assumptions. The idea of gravity the equation is similar to Newton's law of universal gravitation. Export, import or total trade (Z_{ijt}) between country *i* and *j* is proportional to the "mass" of trade partners measured by their GDP (Y_{it} and Y_{jt}) and inversely proportional to distance between countries or trade costs Ψ. An empirical specification of the gravity equation varies substantially across studies. The augmented version of gravity equation often considers factors that decrease trade costs, and consequently favor trade, e.g. currency union or common history. Coefficients on these variables are expected to have a positive sign. The empirical specification contains an error term η_{ijt} (3.1).

$$Z_{ijt} = Y_{it}^{\beta_1} * Y_{jt}^{\beta_2} * \prod_{\mu=1}^{M} \Psi_{\mu} * \eta_{ijt} \, , \tag{3.1}$$

Trade costs are commonly approximated by at least bilateral geographical distance. Usually geographical distance has a strong negative impact on trade, while one can argue that its impact is decreasing over time possibly due to globalization and an increasing importance of information costs. Despite a wide application, distance variable is not used in this paper. Given a relatively long time period, distance would have a significant number of repeated values. At the same time geographical proximity appears less crucial for European countries which dominate in the selected sample. Furthermore, time invariant variable is automatically dropped when differentiation is applied. In order to preserve comparability of results based on various econometric procedures, geographical distance is excluded from the model.[3] It is assumed that its impact on trade captured through fixed effects and residuals. Trade costs are therefore approximated by exchange rate volatility (V_{ijt}) only. Anderson and van Wincoop (2003) propose a theoretical foundation of gravity equation, suggesting augmenting the model by country-pair fixed effects which are an approximation of theoretically grounded multilateral resistance term. Bilateral country-pair effects may correlate with bilateral exchange rate volatility artificially decreasing its impact on trade or reversing the sign. For this reason bilateral fixed effects, when they are applicable, are replaced by fixed effects specific to reporter country (FE_i). In addition gravity equation contains fixed time effects (D_t) capturing changes specific to a particular period. Therefore, gravity equation obtains the following multiplicative form (3.2).

$$Z_{ijt} = Y_{it}^{\beta_1} * Y_{jt}^{\beta_2} * e^{\beta_3 V_{ijt} + \sum_{i=1}^{N} \gamma_i FE_i + \sum_{t=1}^{T} \gamma_t D_t} * \eta_{ijt}, \qquad (3.2)$$

The Gravity model is estimated on quarterly data starting in 1999:1 and ending in 2008:2.[4]

As long as estimated coefficients depend on the sample mean, there is a trade-off between a number of selected countries and representativeness of the sample. When the sample size is relatively small, or there is insufficient variation in the data, the gravity equation may fail to capture the expected effect, and the regression coefficients turn to be insignificant. On the other extreme, there is a large data sample tending to cover all countries once the data exist. Constructed in this way the gravity equation has the values of estimated parameters closest to the true mean from a global perspective. However, it has two important drawbacks. First, the share of missing data rises with a sample size. Second, quality and reliability of the data differ across countries. The average quality may even decrease in a large sample compared to its subsample. Both missing and misreported data negatively affect the quality of econometric estimates resulting sometime in the biased estimations. Last but not least, inappropriate sample selection is misleading. Rose (2000) finds extremely large effect of currency union on trade but his estimates was done on a sample containing currency unions of small countries.

[3] Fidrmuc (2009) focuses on time-series properties of the data and uses specification without distance.

[4] In order to make results based on static version of the model more comparable with the results based on a dynamic version the sample was stopped before the intensification of the crisis and amplification its adverse impact on trade. It is hard to account for potential non-linearities in the most recent period (after 2008q2) with a selected panel structure of the data due to a small number of observations. These non-linearities could however impact differently dynamic and static versions of the model.

Rose effect evoked an avalanche of criticism, as well as new estimates focused specifically on the euro area or proposing alternative econometric procedures. Havránek (2010) by applying meta-analysis of the effect of currency union on trade points the striking difference in results between euro and non-euro studies.

This paper is based on a sample that includes principal trade partners of the Czech Republic and other transition economies. The full sample (Panel-38) contains 38 countries at which 12 are transition economies, preserving a certain degree of flexibility in exchange rate regime vis-à-vis euro during all estimated period or its major part (TE-12). The other 26 countries are 11 core euro area countries, 6 non-euro area EU countries, and 9 other industrial countries or emerging economies (see Table A1 in the annex for details). The selected sample covers on average 90% of total TE-12 trade in 2008 and has up to 37x38=1406 trade flows observed during 9,5 years. In order to test the sensitivity of results to sample selection, the results based on a full sample are compared with its truncated versions. The shorter sample (Panel-12) covers trade of 12 transition economies (*i* – dimension) with 38 selected countries (*j* – dimension). Two other samples refer explicitly to the Czech Republic. Panel-CZ represents Czech trade (*i* – dimension) with 37 selected countries (*j* – dimension). The last sample (CZ-AGR) is obtained by aggregating Panel-CZ sample across trade partners. Interpretation of results based on this sample should be done with caution amid to potential aggregation bias and small sample size (38 observations).

The IMF-DOTS database is the main source for nominal trade flows in USD. A substantial part of missing values was filled using mirror trade flows from the same source and then adjusted for C.I.F/F.O.B. ratio or from the COMEXT. In this case the data was converted into US dollars. Nominal GDP is taken from the IFS, the EIU (Economist Intelligence Unit), and Eurostat. Data from Eurostat are converted into US dollars as well. Nominal spot exchange rate in units of national currency per USD is taken from the Datastream.

The choice of estimation method depends on statistical properties of the data. ARMA diagnostic indicates the presence of partial autocorrelation in $\log(GDP_i)$ in the first lag, in $\log(Z_{ijt})$ up to second lag and in V_{ijt} up to three lags (Table A2 in the annex). At the same time autocorrelation fades out very slowly, suggesting MA(∞) or AR(1) specification. The Granger (1969) causality test indicates that past exchange rate volatility explains current trade but not vice versa (Table A3 in the annex).

The following panel unit roots tests were applied to test for stationarity. The first one is Levin, Lin and Chu (2002) testing H0 of common unit root process. Other tests (Im, Pesaran and Shin, 2003, Fisher-type ADF and Phillips-Perron) assume individual unit root process. ADF test is used for time series. Panel and individual unit root tests based on the specification with the constant term indicate that trade and both GDP taken in logarithms follow I(1) process. These variables became stationary when the tested specification is augmented by trend individual to each country-pair. Trade and GDP taken in log difference and volatility in levels are I(0).

4. Estimation methods

As it was repeatedly mentioned in the literature, empirical estimates of gravity equation suffers or likely to suffer of various biases. In the absence of parsimonious econometric approach several econometric procedures are proposed. Their advantages and shortcomings are discussed in this section.

4.1. Static approach and time varying coefficients estimates

Conventional practice suggests estimating gravity equation by fixed effect OLS estimator in static log-linear form. Following the common approach (3.2) is log-linearized and estimated by OLS (4.1):

$$\ln Z_{ijt} = \beta_1 \ln Y_{it} + \beta_2 \ln Y_{jt} + \beta_3 V_{ijt} + \sum_{i=1}^{N} \gamma_i FE_i + \sum_{t=1}^{T} \gamma_t D_t + \varepsilon_{ijt},\ \varepsilon_{ijt} = \ln \eta_{ijt} \qquad (4.1)$$

Specification (4.1) constrains the impact of volatility on trade to be the same across all countries in the sample. This assumption is relaxed latter assuming that the impact of volatility on trade differs across reporter-countries (4.2). Due to possible correlation between country-specific volatilities and country fixed effects the constant term β_0 in (4.2) substitutes $\sum_{i=1}^{N} \gamma_i FE_i$.

$$\ln Z_{ijt} = \beta_0 + \beta_1 \ln Y_{it} + \beta_2 \ln Y_{jt} + \sum_{i=1}^{N} \beta_3^i V_{ijt}^i + \sum_{p=1}^{P} \gamma_p D_t + \varepsilon_{ijt}\ ,\ \varepsilon_{ijt} = \ln \eta_{ijt} \qquad (4.2)$$

In order to account explicitly the direction of causality between volatility and trade (4.1) and (4.2) are re-estimated with one-period lagged exchange rate volatility instead of contemporaneous exchange rate volatility.

Santos Silva and Tenreyro (2006) point out various biases when log-liner gravity equation is estimated by OLS. First, in log-linear form trade is assumed being strictly positive, while in reality it can be zero. In practice missing and zero values are sometimes replaced by a very small positive number to keep zero-trade country-pairs. If such a case, small number is attributed to a trade flows which is literarily zero, and the measurement error is marginal. At the same time, once a small number mistakenly replaces an important value (or volume) of trade missing for statistical reasons, it leads to a considerable measurement error which becomes even more important after log-linearization. Accounting for zero-trade flows is therefore necessarily for proper estimation of gravity models.

Second source of bias is generated by the combination of heteroscedasticity and Jensen's inequality implying that the expected value of the logarithm of a random variable is not equal to the logarithm of its expected value: $\mathrm{E}(\ln Z) \neq \ln \mathrm{E}(Z)$. Santos Silva and Tenreyro (2006) show that in presence of heteroscedastisity Jensen's inequality leads to inconsistent OLS estimates in all types of constant elasticity models, including gravity equation, because it is no longer possible to consider estimated parameters of log-linearized model as elasticities, so the estimation of true elasticities is biased. For illustration consider a simple stochastic version of gravity equation (4.3).

$$Z_{ij} = \alpha * Y_i^{\beta_1} * Y_j^{\beta_2} * e^{\beta_3 V_{ij}} * \eta_{ij}, \tag{4.3}$$

where trade is non-negative ($Z_{ij} \geq 0$) and the error term is statistically independent from regressors $\mathrm{E}(\eta_{ij} | Y_{i,}, Y_j, V_{ij}) = 1$. Assume that the variance of error term depends on regressors $\sigma_{ij}^2 = f(Y_{i,}, Y_j, V_{ij})$. General practice suggests estimate (4.3) in log-linear additive form (4.4).

$$\ln Z_{ij} = \ln \alpha + \beta_1 \ln Y_i + \beta_2 \ln Y_j + \beta_3 V_{ij} + \ln \eta_{ij}. \tag{4.4}$$

Log-linearization in error term implies its dependency of its mean and higher-order moments of distribution. If variance of η_{ijt} depends on GDP and exchange rate volatility, the expected value of $\ln \eta_{ijt}$ will also depend on GDP and exchange rate volatility leading to inconsistency of OLS. For instance, assuming that η_{ijt} follows log-normal distribution, then log-linearized error term will follow normal distribution with $\mathrm{E}(\ln \eta_{ij} | Y_{i,}, Y_j, V_{ij}) = -\frac{1}{2}\ln(1 + \sigma_{ij}^2)$, which is also a function of GDP and exchange rate volatility.

While, there is no information about the second moment of the error term, the error term in gravity equation is likely being heteroscedastic owing the properties of trade data. Conditional expectation of trade given regressors approaches to zero for small values of trade flows ($\mathrm{E}(Z_{ij} | Y_{i,}, Y_j, \ldots) \to 0$) and is expected being very large when trade flows are important. At the same time, because trade is non-negative, when the probability of positive value of trade approaches to zero, conditional variance passes to zero as well ($V\left(Z_{ij} \middle| Y_{i,}, Y_j, ...\right) \to 0$) and vice versa implying possible heteroscedasticity in the error term.

As far as the gravity model is based on constant elasticity model, it can be estimated in exponential form instead of log-linear form. Santos Silva and Tenreyro (2006) suggest for this purpose to use Poisson pseudo maximum likelihood estimator (PPML). The absence of log transformation helps to avoid Jensen's inequality problem and allows for consistent parameters estimates. At the same time PPML estimator properly accounts for zero-trade flows.[5] In addition, as Santos Silva and Tenreyro show, trade is not required being integer. Tenreyro (2007) applies this estimation method for studying the impact of exchange rate volatility on trade in a gravity framework. Siliverstovs and Schumacher (2009) test Poisson maximum likelihood estimator against traditional OLS in the gravity framework and prove Santos Silva and Tenreyro findings. As far as the size of the bias evoked by heteroscedastisity is unknown, traditional OLS estimates are complemented by estimates using PPML. Gravity equation is re-estimated in following exponential forms (4.5) and (4.6):

$$Z_{ijt} = \exp\left(\beta_1 \ln Y_{it} + \beta_2 \ln Y_{jt} + \beta_3 V_{ijt} + \sum_{i=1}^{N} \gamma_i FE_i + \sum_{t=1}^{T} \gamma_t D_t \right) + \varepsilon_{ijt} \tag{4.5}$$

and

$$Z_{ijt} = \exp\left(\beta_0 + \beta_1 \ln Y_{it} + \beta_2 \ln Y_{jt} + \sum_{i=1}^{N} \beta_3^i V_{ijt}^i + \sum_{t=1}^{T} \gamma_t D_t \right) + \varepsilon_{ijt} \tag{4.6}$$

Using panel data time varying coefficient (TVC) estimates are obtained from moving window OLS, where the gravity model is estimated on shorter period and then reestimated N-times each time moving selected period by 1 quarter ahead, and PPML cross-section regressions. More precisely, (4.1), (4.2), (4.5) and (4.6) are estimated separately for each period and without time dummies. In order to obtain time-varying estimates based on aggregated data, Kalman filter is applied to the following state and space model (4.7):

---

[5] While Santos Silva and Tenreyro (2010) show that (pseudo) maximum likelihood estimator in Poisson regression may converge to a spurious maximum when a share of missing observations is important, it should not be a problem here as the sample used in this paper contains relatively small number of missing data.

$$\begin{aligned} \ln Z_t &= \beta_0 + \beta_1 \ln Y_t^{CZ} + \beta_2 \ln Y_t^{*} + sv1_t * V_t + \varepsilon_t \\ \mathrm{sv1_t} &= \beta_4 + \beta_5 sv1_{t-1} + \xi_t \end{aligned} , \qquad (4.7)$$

where Y_t^{cz} stands for Czech GDP and Y_t^{*} is foreign GDP computed as weighted average of partner-countries GDP using time-varying weights of respective trade flow (export, import or total trade). The same weights are used for exchange rate volatility.

Variance specification expression in both state and space equations contains unknown parameters to be estimated. Starting values are set to zero for all coefficients but β_1 and β_2. In line with the theory starting values for elasticities of GDP are set to unity.

4.2. Dynamic model

Static gravity equations often suffer from autocorrelation. Common practice suggests estimating dynamic version of the equation with lagged depended variable. This approach is not applied here due to difficulties with quantification of the impact on trade; an alternative dynamic model is proposed instead. Furthermore, econometric procedures explained above accounts for variation in time of volatility coefficient and are able to provide consistent estimates in presence of heteroscedasticity and zero-trade flows, however, they addresses only partially endogeneity and non-stationarity problems. This section discusses dynamic model which accounts for endogeneity and non-stationarity of the data.

Low level of bilateral exchange rate volatility may not impact trade between a pair of countries. At the same time tight trade linkages are likely to create favorable conditions for low bilateral exchange rate volatility. While the Granger test (section 3) suggests the direction of causality rather from exchange rate volatility to trade then the other way round, in principle, causality could be in both directions. An application of instrumental variable (IV) approach is a general solution to endogeneity problem in a gravity framework. Tenreyro (2007) proposes jointed probability to anchor the currency as an instrument for exchange rate volatility. Propensity to anchor is obtained from logit regression where probability to anchor to one of five currencies is based on gravity-type model including GDP, inflation, distance, other geographical and historical variables. This approach is only applicable for fully floating currencies and *a priori* works better for a large set of countries. Bénassy-Quéré and Lahrèche-Révil (1999) find that prior to the introduction of the euro Central and Eastern European countries were already more inclined to anchor their currencies to a basket where euro would be a dominant currency. These countries together with euro area countries constitute a large proportion of the sample selected for this paper impeding to use currency anchor as an instrument. Another useful instrument for exchange rate volatility is volatility of money supply (Frankel and Wei 1993, Clark et al., 2004)[6]. This approach is generally applicable for gravity equations estimated on yearly data, i.e., volatility is computed on quarterly or monthly series. In this paper weekly data are used to construct exchange rate volatility, but this frequency is not available for money supply. Furthermore, as show Devereux and Lane (2003), determinants of exchange rate volatility are not necessarily the same for developed and developing countries.

When the choice of an appropriate instrument is not trivial, (inter)linkages among the variables can be addressed explicitly in a vector autoregressive (VAR) framework. In a VAR model all variable can be considered as endogenous, i.e., allowing for endogenous relation not only between exchange rate volatility and trade, but between trade and GDP or exchange rate volatility and GDP. By construction VAR model includes lagged endogenous variables correcting for autocorrelation. More importantly VAR model accounts for non-stationarity of the data. A stationary variable enters into VAR without transformation. A non-stationary variable, prior to be included to the VAR, is differentiated unless it becomes stationary. Because the unit root test is sometime controversial and tends to over- or under-reject H0, in practice, estimation in levels with non-stationary variables is acceptable, once the whole model is stable.[7] Finally, when series are non-stationary but cointegrated vector error correction (VEC) model or cointegrated equation are applied.

Fidrmuc (2009) emphasizes non-stationarity problem as well as the existence of long run cointegration relation between trade and output and suggests estimating gravity model as cointegrated equation. His result shows that fixed effect model still performs quite well compared to FMOLS and DOLS estimates. To our knowledge, VAR/VEC model has a limited application in measuring the impact of exchange rate volatility on trade. VEC model is applied by Arize (1996) and Vergil (2002) for studying the impact of real exchange rate

[6] Balg and Metcalf (2010) report inconclusive result about determinants of exchange rate volatility based on standard deviation measuring divergence of equilibrium level (short run volatility). In the long run the authors find money supply is a solely determinant of exchange rate volatility. Long run volatility is estimated as variance from structural equation.

[7] When time period is long enough, the presence of the unit root in time series together with instability of the whole model leads to spurious regression. Cross-sectional moving-windows regression is immune to non-stationarity problem. However, parameters estimates are based on a very restricted set of information (available in this particular period) generating substantial instability in the estimated results.

volatility on real export. More frequently VAR/VEC framework is used with export demand equation which resembles to gravity equation. Casario (1996) estimates export and import functions to capture the effect of NAFTA on aggregated export and import trade flows between USA, Canada and Mexico. The selected model includes trade, GDP, exchange rate and prices. Algutacil and Orts (2003) estimate relation between trade and FDI using VAR framework.

Cointegration is tested using Maddala and Wu (1999) Johansen-Fisher panel cointegration and Johansen (1991, 1995) cointegration tests, as well as Pedroni (1999, 2004) residual cointegration test based on Engle-Granger (1987) framework and adjusted for panel data. Cointegrated relation was tested for non-stationary variables only. In general the tests are inconclusive about cointegration (see Table A4 and A5 in the annex). Since the primary focus of the paper is nominal exchange rate volatility which has no equilibrium effect on trade, simple VAR model is estimated, i.e., the error correction term is not included into the model (4.8).

$$\underset{(k\times 1)}{y_{ijt}} = \underset{(k\times k)}{A_1}\underset{(k\times 1)}{y_{ij,t-1}} + \ldots + \underset{(k\times k)}{A_\rho}\underset{(k\times 1)}{y_{ij,t-\rho}} + \underset{(k\times n)}{B}\underset{(n\times 1)}{x_i} + \underset{(k\times 1)}{\varepsilon_{ijt}}, \tag{4.8}$$

where y_{ijt} is a vector of endogenous variables, x_i is a vector of exogenous variables, *A* are matrices of coefficients on endogenous variables, *B* are matrices of coefficients on exogenous variables, and ε_{ijt} is vector of error terms.

Based on data properties model (4.8) is estimated in two versions. To stay as closer as possible to a gravity equation, endogenous variables enter into the VAR model without transformation: $y_{ijt} = \left[V_{ijt}, \ln Z_{ijt}, \ln Y_{it}, \ln Y_{jt}\right]$. Time trend is added to ensure stability of VAR model. Therefore, the vector of exogenous variables contains dummies for reporter-country and time trend: $x_i = \left[FE_i, TREND_i\right]$. In the second version of VAR model all endogenous variables, but exchange rate volatility, are estimated in log-difference; exchange rate volatility is taken in levels: $y_{ijt} = \left[V_{ijt}, \Delta\ln Z_{ijt}, \Delta\ln Y_{it}, \Delta\ln Y_{jt}\right]$. The vector of exogenous variables contains country-dummies only: $x_i = \left[FE_i\right]$.

It is important to note that together with data transformation changes the interpretation of estimations. In traditional log-linear equation the regression coefficients on variables in logarithms represent the elastisities. In a VAR model transformation in log-difference broadly corresponds to growth rate. Table 1 summarizes all estimated procedures described in section 4. Each specification is estimated (when it is possible) using aggregated volatility, i.e. one coefficient on exchange rate volatility for all country-pairs, as well as assuming variation by country in coefficients on exchange rate volatility.

Table 1: Summary of model specifications and applied econometric procedures

	Panel-38				Panel-12				Panel-CZ		CZ-AGR	
Definition of volatility →	V_{ijt}	V_{ijt-1}	V^{CZ}_{jt}	V^{CZ}_{jt-1}	V_{ijt}	V_{ijt-1}	V^{CZ}_{jt}	V^{CZ}_{jt-1}	V_{ijt}	V_{ijt-1}	V_{ijt}	V_{ijt-1}
Trade flow												
IMPORT ijt	*	*	*	*	*	*	*	*	*	*	*	*
EXPORT ijt	*	*	*	*	*	*	*	*	*	*	*	*
TTRADE ijt											*	*
Fixed effects												
Constant									*		*	
Time dummies - D_t	* [a]		* [a]		* [a]		* [a]		* [a]			
Fixed effects - FE_i	*				*							
Econometric procedure												
OLS	*	*	*	*	*	*	*	*	*	*	*	*
Poisson (PPML)	*	*	*	*	*	*	*	*	*	*	*	*
Moving window OLS	*	*	*	*	*	*	*	*	*	*		
Moving window PPML	*	*	*	*	*	*	*	*	*	*		
Kalman Filter											*	
VAR in levels	*				*				*		*	
VAR in differences	*				*				*		*	

Note: [a] except VAR, V^{CZ} is exchange rate volatility for the Czech Republic.

5. Quantification of the impact on trade

In the single regression and moving window regression approaches the computation of the size of the impact on trade is straightforward. It depends on the regression coefficient on exchange rate volatility (β_3) and on average volatility over the estimation period (V_{mean}). A percentage change in trade due to 100% increase in volatility is computed using the following formula:

$$\Delta Z = \left(\exp\left(\beta_3 \frac{V_{mean}}{100} \right) - 1 \right) * 100, \tag{5.1}$$

where β_3 refers to coefficient on exchange rate volatility.

In contrast to previous studies impact on trade is also computed using dynamic framework which allows estimating a change in trade accounting for lagged structure of the model. Impact on trade is computed using impulse response function derived from VAR model. In the dynamic model the impact on trade is captured by generating a shock to exchange rate volatility. The initial shock to exchange rate volatility is one standard deviation of errors in exchange rate volatility equation.

$$\Delta Z_{t+k} = \frac{IR_{t+k}^{\Delta \ln Z_{ijt}}}{Shock^{V_{ijt}}} * V_{mean} * 100 \tag{5.2}$$

Impulse response of trade up to period $t+k$ ($IR_{t+k}^{\Delta \ln Z_{ijt}}$) adjusted by the ratio of the initial shock ($Shock^{V_{ijt}}$) to the sample mean (V_{mean}) roughly corresponds to percentage change in trade (5.2). When VAR model is estimated in levels computation is based in the peak (minimum value) of instant impulse response. When in VAR model trade and GDP are taken in log-difference, accumulated impulse responses are used instead.

6. Results

Regression coefficients from static specification report the impact of exchange rate volatility on trade mostly negative and highly statistically significant (Table 2). In some cases (e.g., using Panel-CZ data) a positive impact is found by the OLS. Since this result is not supported by other regressions, it is likely being biased amid to numerous drawbacks of OLS estimator (detailed results based on PPML estimator see in Tables A1, A3, A5 A7 and results based on OLS regressions see in Tables A2, A4, A6, A8 in the annex). Overall magnitude of the impact varies across samples. Considering the result for all countries as the average, the sub-sample of transition economies has the below-average impact of exchange rate volatility in static estimations. This is probably explained by greater heterogeneity in this group. Furthermore, the result for the Czech Republic is clearly above average.

Table 2: Percentage change in trade due to 100% increase in volatility, %

				IMPORT		EXPORT	
				Vt	*Vt-1*	*Vt*	*Vt-1*
STATIC MODELS	Poisson (PPML)	V_{ijk}, *k=t, t-1*	P-38	-0.97	-0.92	-1.02	-1.02
			P-12	-0.52	-0.46	-0.54	-0.46
			P-CZ	-1.99	-1.92	-2.59	-2.63
			CZ-agr	*n.s.*	*n.s.*	-0.07	*n.s.*
		V^{CZ}_{jk}, *k=t, t-1*	P-38	-0.84	-0.85	-1.12	-1.16
			P-12	-0.33	-0.27	-0.43	-0.39
	OLS	V_{ijk}, *k=t, t-1*	P-38	-0.23	-0.16	-0.29	-0.20
			P-12	-0.12	-0.05	-0.21	-0.13
			P-CZ	-0.43	-0.28	-0.61	-0.44
			CZ-agr	*n.s.*	*n.s.*	-0.08	*n.s.*
		V^{CZ}_{jk}, *k=t, t-1*	P-38	*n.s.*	*0.12*	*0.05*	*0.10*
			P-12	*0.13*	*0.17*	*0.13*	*0.17*
TVC ESTIMATES	Poisson (PPML)	V_{ijk}, *k=t, t-1*	P-38	-1.10	-1.08	-1.17	-1.17
			P-12	-1.04	-0.98	-0.95	-0.91
			P-CZ	-2.14	-2.06	-2.76	-2.69
		V^{CZ}_{jk}, *k=t, t-1*	P-38	-1.66	-1.67	-1.91	-1.94
			P-12	-0.58	-0.55	-0.89	-0.86
	OLS	V_{ijk}, *k=t, t-1*	P-38	-0.80	-0.58	-0.72	-0.72
			P-12	-0.72	-0.59	-0.43	-0.97
			P-CZ	-1.30	-0.90	-0.93	-1.27
		V^{CZ}_{jk}, *k=t, t-1*	P-38	-0.71	-0.68	-0.72	-0.71
			P-12	*n.s.*	*n.s.*	*n.s.*	*n.s.*
	Kalman Filter	V_k, *k=t, t-1*	CZ-agr	-0.08	-	-0.08	-
DYNAMIC MODEL	VAR	V_{ijt}, in levels, min IR	P-38	-2.50	(3)	-3.14	(3)
			P-12	-2.89	(2)	-3.16	(3)
			P-CZ	*n.s.*	(-)	-3.25	(5)
			CZ-agr	*n.s.*	(-)	*n.s.*	(-)
		V_{ijt}, in diff, short run, min IR	P-38	-2.36	(3)	-2.55	(3)
			P-12	-3.85	(3)	-2.82	(3)
			P-CZ	*n.s.*	(-)	-3.48	(3)
			CZ-agr	*n.s.*	(-)	*n.s*	(-)
		V_{ijt}, in diff, long run, AIR	P-38	-2.12	(12)	-2.28	(12)
			P-12	-3.59	(12)	-2.57	(12)
			P-CZ	*n.s.*	(-)	-2.43	(12)
			CZ-agr	*n.s.*	(-)	*n.s.*	(-)

Note: V_t and V_{t-1} denote results based on common coefficient on volatility for all countries. V^{cz}_t *and* V^{CZ}_{t-1} stand for results computed using volatility coefficient for the Czech Republic (specification with volatilities varying by country). Columns V_t and V^{CZ}_t summarize results using specification with contemporaneous volatility. Columns V_{t-1} and V^{CZ}_{t-1} show results based on specification with lagged volatility. In TVC models impact on trade is reported as average impact. Results for individual periods see in the annex. The final number includes both significant and insignificant periods except when volatility coefficient is insignificant in all periods. Numbers in parenthesis accompanying results based on dynamic models refer to (i) a period where impulse response (IR) function achieves its minimum (min) for VAR in levels and short run impact for VAR in differences or (ii) number of periods considered as long run (LR) for VAR in differences and long run impact based on accumulated impulse responses (AIR). The impact on trade is not reported when the corresponding coefficient or (accumulated) impulse response is not significant at 10 % level (n.s.).

Dynamic version of the gravity model indicates that impact on trade is, on the contrary, above average in transition economies. At the same time there is less variation in results compared to static model. The impact on Czech trade estimated on sub-sample Panel-CZ or aggregated data is in many cases insignificant in dynamic model. Once it is significant, it is close to results for a sub-sample of transition economies, as well as to the average estimated impact of volatility on trade.

The choice of depended variable does not change the main conclusion, since results for exports are broadly comparable with results for imports. An average impact on trade by estimation procedure is summarized in Table 3.

Table 3: Average impact on trade, %

	IMPORT		EXPORT	
	Vt	*Vt-1*	*Vt*	*Vt-1*
Static models	-0.7	-0.6	-0.7	-0.8
TVC estimates	-1.1	-1.0	-1.2	-1.2
Dynamic models	-2.9		-3.1	
ALL MODELS	**-1.6**	-0.8	**-1.6**	-1.0

Note: Average impact based on table 2 excluding positive and insignificant impact. Average for dynamic models does not include results based on aggregated data.

Static estimates, including TVC estimates, find a negative impact of exchange rate volatility on trade somewhere between 0.6% and 1.2%. This result is broadly in line with Babecká-Kucharčuková et al. (2012). Using simulations based on static gravity equation estimates the authors find an increase in trade of 1.3% after exchange rate volatility disappears between exchange rates of selected new member states, including the Czech Republic, and EA12. Dynamic models suggest higher impact attaining between 2.9% and 3.1%. Results from VAR model based on aggregated sample are not accounted owing to large confidence bands of estimated impulse response functions.

Conclusion

Exchange rate volatility has negative and significant impact on trade. The magnitude of the impact is stronger when dynamic structure of the model is assumed. According to results based on static models 100% increase in bilateral exchange rate volatility leads to decrease in trade between 0.6% and 1.2%. Impact on trade is about 3% based on dynamic models (2.9%-3.1%).

References:

Anderson J, van Wincoop E (2003): Gravity with gravitas: a solution to the border puzzle. *American Economic Review*, 93 (March): 170–192.

Arize A C (1996): Real exchange-rate volatility and trade flows: The experience of eight European economies. *International Review of Economics & Finance*, 5(2): 187-205.

Babecká-Kucharčuková O, Babecký J, Raiser M (2012): Gravity Approach for Modelling International Trade in South-Eastern Europe and the Commonwealth of Independent States: The Role of Geography, Policy and Institutions. *Open Economies Review*, 23(2): 277–301.

Balg B A, Metcalf H (2010): Modeling Exchange Rate Volatility. *Review of International Economics*, 18(1): 109–120.

Baum, C F, Caglayan M (2010) On the sensitivity of the volume and volatility of bilateral trade flows to exchange rate uncertainty. *Journal of International Money and Finance*, 29(1): 79-93.

Bénassy-Quéré A, Lahrèche-Révil A (1999) : L'euro comme monnaie de référence à l'est et au sud de l'Union européenne. *Revue Economique*, 50(6): 1185-1200.

Casario M (1996): North American Free Trade Agreement Bilateral Trade Effects. *Contemporary Economic Policy*, 14(1): 36-61.

Clark P B, Tamirisa N T, Wei S-J, Sadikov A M, Zeng L (2004): A New Look at Exchange Rate Volatility and Trade Flows. International Monetary Fund. Occasional paper No.235. Washington, DC.: IMF.

Côté A (1994): Exchange rate volatility and trade: a survey. Bank of Canada Working Paper 94–95.

De Nardis S, De Santis R, Vicarelli C (2008) : The Euro's Effects on Trade in a Dynamic Setting. *European Journal of Comparative Economics*, Cattaneo University (LIUC), 5(1): 73-85.

Devereux M B, Lane P R (2003): Understanding bilateral exchange rate volatility. *Journal of International Economics*, 60(1): 109-132.

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

Esquivel G, Larraín F B (2002): The Impact of G-3 Exchange Rate Volatility on Developing Countries. G-24 Discussion Paper Series, No. 16.

Fontagné L (1999) : Spécialisation et asymétrie des chocs en union monétaire. *Revue française d'économie*, 14(2): 107-162.

Frankel J A, Wei S J (1993): Trade Blocs and Currency Blocks. Working Paper No. 4335, Cambridge, Massachusetts: National Bureau of Economic Research.

Granger C W J (1969): Investigating Causal Relations by Econometric Models and Cross-Spectral Methods. *Econometrica*, 37: 424-438.

Havránek T (2010): Rose Effect and the Euro: Is the Magic Gone? Review of World Economics (Weltwirtschaftliches Archiv), Springer, 146(2): 241-261.

Im K S, Pesaran M H, Shin Y (2003): Testing for Unit Roots in Heterogeneous Panels. *Journal of Econometrics*, 115: 53-74.

Johansen S (1991): Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models. Econometrica, 59: 1551-1580.

Johansen S (1995): Likelihood-based Inference in Cointegrated Vector Autoregressive Models, Oxford: Oxford University Press.

Levin A, Lin C F, Chu C (2002): Unit Root Tests in Panel Data: Asymptotic and Finite-Sample Properties. *Journal of Econometrics,* 108: 1-24.

MacKinnon J G, Haug A A, Michelis L (1999): Numerical Distribution Functions of Likelihood Ratio Tests for Cointegration. *Journal of Applied Econometrics*, 14: 563-577.

Maddala G S, Wu S (1999): A Comparative Study of Unit Root Tests with Panel Data and A New Simple Test. *Oxford Bulletin of Economics and Statistics*, 61: 631-52.

McKenzie M (1999): The impact of exchange rate volatility on international trade flows. *Journal of Economic Surveys*, 13: 71–106.

McKenzie M, Brooks R (1997): The impact of exchange rate volatility on German-US trade flows. *Journal of International Financial Markets, Institutions and Money*, 7(1): 73-87.

Pedroni P (1999): Critical Values for Cointegration Tests in Heterogeneous Panels with Multiple Regressors. *Oxford Bulletin of Economics and Statistics*, 61: 653-70.

Pedroni P (2004): Panel Cointegration; Asymptotic and Finite Sample Properties of Pooled Time Series Tests with an Application to the PPP Hypothesis. *Econometric Theory*, 20: 597-625.

Rose A K (2000): One money, one market: Estimating the effect of common currency on trade. *Economic Policy*, 15(30): 7–46.

Rose A K, Engel C (2000): Currency unions and international integration. NBER Working Paper No 7872, September.

Santos Silva J M C, Tenreyro S. (2006): The log of gravity. *The Review of Economics and Statistics*, 88: 641–658.

Santos Silva J.M.C., Tenreyro S (2010): On the existence of the maximum likelihood estimates in Poisson regression. *Economic Letters,* 107(2): 310-312.

Scrimgeour D (2002): Exchange rate volatility and currency union: New Zealand evidence. *Journal of Policy Modeling*, 24(7-8): 739-749.

Siliverstovs B, Schumacher D (2009): Estimating gravity equations: to log or not to log? *Empirical Economics*, Springer, 36(3): 645-669.

Tenreyro S (2007): On the trade impact of nominal exchange rate volatility. *Journal of Development Economics*, 82(2): 485-508.

Vergil H (2002): Exchange Rate Volatility in Turkey and Its Effect on Trade Flows. *Journal of Economic and Social Research,* 4 (1): 83-99.

Annexes

Table A1: List of countries

	TE (12)		EA-core (11)		EU non-EA (6)
BY	Belarus	AT	Austria	BG	Bulgaria
HR	Croatia	BE	Belgium	DK	Denmark
CZ	Czech Republic	FI	Finland	LV	Latvia
HU	Hungary	FR	France	LT	Lithuania
KZ	Kazakhstan	DE	Germany	SE	Sweden
PL	Poland	GR	Greece	GB	United Kingdom
RO	Romania	IE	Ireland		
RU	Russian Federation	IT	Italy		**OTHER (9)**
SK	Slovak Republic	NL	Netherlands	BR	Brazil
SI	Slovenia	PT	Portugal	CA	Canada
TR	Turkey	ES	Spain	CN	China, P.R.: Mainland
UA	Ukraine			IN	India
				JP	Japan
				KO	Korea, Republic of
				NO	Norway
				CH	Switzerland
				US	United States

Note: SI has joined the EA in 2007:1.

Table A2: Autocorrelation

	Autocorrelation				Partial autocorrelation			
	LnM_{ijt}	LnX_{ijt}	$LnGDP_{it}$	V_{ijt}	LnM_{ijt}	LnX_{ijt}	$LnGDP_{it}$	V_{ijt}
1	0.954	0.954	0.972	0.430	0.954	0.954	0.972	0.430
2	0.922	0.922	0.944	0.366	0.136	0.125	-0.022	0.222
3	0.893	0.893	0.916	0.434	0.032	0.038	-0.01	0.278
4	0.865	0.865	0.888	0.287	0.019	0.013	-0.02	0.003
5	0.833	0.832	0.859	0.268	-0.055	-0.058	-0.021	0.044
6	0.804	0.801	0.831	0.234	-0.005	-0.01	-0.016	-0.008
7	0.775	0.772	0.802	0.245	0	0.002	-0.016	0.086
8	0.747	0.744	0.773	0.225	-0.007	-0.004	-0.015	0.036
9	0.717	0.714	0.745	0.2	-0.028	-0.03	-0.015	0.028
10	0.689	0.684	0.716	0.215	-0.003	-0.011	-0.016	0.039
11	0.66	0.656	0.688	0.197	-0.019	-0.006	-0.012	0.025
12	0.633	0.628	0.659	0.19	-0.002	-0.009	-0.016	0.027
13	0.603	0.598	0.631	0.178	-0.046	-0.038	-0.018	0.009
14	0.575	0.569	0.603	0.196	-0.005	-0.006	-0.017	0.052
15	0.547	0.542	0.575	0.182	-0.007	-0.007	-0.014	0.018
16	0.52	0.515	0.547	0.167	-0.006	0	-0.011	0.013

Note: Panel-38.

Table A3: Granger causality test

	Panel-38		Panel-12		Panel-CZ		CZ-AGR	
Null Hypothesis:	F-Stat.	Prob.	F-Stat.	Prob.	F-Stat.	Prob.	F-Stat.	Prob.
V_{ijt} does not Granger Cause $\Delta Ln(M_{ijt})$	54.6241	2.00E-24	65.5709	4.00E-29	12.2202	5.00E-06	11.4045	0.0002
$\Delta Ln(M_{ijt})$ does not Granger Cause V_{ijt}	1.13819	0.3204	1.10823	0.3302	0.09612	0.9084	2.46636	0.1004
V_{ijt} does not	57.0921	2.00E-25	20.8621	9.00E-10	7.81828	0.0004	3.97923	0.0283

Null Hypothesis:	Panel-38 F-Stat.	Panel-38 Prob.	Panel-12 F-Stat.	Panel-12 Prob.	Panel-CZ F-Stat.	Panel-CZ Prob.	CZ-AGR F-Stat.	CZ-AGR Prob.
Granger Cause $\Delta Ln(X_{ijt})$								
$\Delta Ln(X_{ijt})$ does not Granger Cause V_{ijt}	0.42743	0.6522	0.61364	0.5414	1.54725	0.2132	1.15698	0.3269
Number of obs.	53286		16575		1406		38	

Note: 2 lags.

Table A4: Johansen Fisher panel cointegration and Johansen cointegration tests

No. of CE(s)	Statistic from trace test	Prob.	Statistic from max-eigen test	Prob.	Included obs.
Panel-38[a]					54872
None	12164	0.0000	9761.	0.0000	
At most 1	5296.	0.0000	4611.	0.0000	
At most 2	4358.	0.0000	4358.	0.0000	
Panel-12[a]					17328
None	3786.	0.0000	2986.	0.0000	
At most 1	1716.	0.0000	1480.	0.0000	
At most 2	1414.	0.0000	1414.	0.0000	
Panel-CZ[a]					1444
None	214.3	0.0000	194.7	0.0000	
At most 1	90.77	0.0901	69.28	0.6335	
At most 2	114.8	0.0017	114.8	0.0017	
CZ-AGR					38
None	21.34193	0.3366 [b]	13.51477	0.4061 [b]	
At most 1	7.827162	0.4840 [b]	5.849178	0.6327 [b]	
At most 2	1.977984	0.1596 [b]	1.977984	0.1596 [b]	

Note: a - Fisher statistics, probabilities are computed using asymptotic Chi-square distribution, b - MacKinnon-Haug-Michelis (1999) p-values. 1 lag

Table A5: Pedroni (Engle-Granger based) residual cointegration test

	H1: common AR coefs. (within-dimension)				H1: individual AR coefs. (between-dimension)	
	Panel statistic		Panel statistic (weighted)		Group statistic	
	Statistic	Prob.	Statistic	Prob.	Statistic	Prob.
Panel-38						
v-Statistic	27.71	0.0000	-0.34	0.6319		
rho-Statistic	-74.85	0.0000	-71.85	0.0000	-60.73	0.0000
PP-Statistic	-94.10	0.0000	-90.12	0.0000	-108.50	0.0000
ADF-Statistic	-55.15	0.0000	-48.47	0.0000	-51.85	0.0000
Panel-12						
v-Statistic	16.63	0.0000	0.14	0.4435		
rho-Statistic	-37.67	0.0000	-39.38	0.0000	-32.37	0.0000
PP-Statistic	-50.39	0.0000	-49.93	0.0000	-59.15	0.0000
ADF-Statistic	-32.24	0.0000	-26.26	0.0000	-27.41	0.0000
Panel-CZ						
v-Statistic	1.19	0.1167	-1.05	0.8540		
rho-Statistic	-7.21	0.0000	-9.35	0.0000	-6.50	0.0000
PP-Statistic	-9.72	0.0000	-11.90	0.0000	-11.96	0.0000
ADF-Statistic	-4.75	0.0000	-3.94	0.0000	-3.25	0.0006

Note: H0: No cointegration, 1lag,

Table A6: Coefficients on V_{ijt} from panel regressions

	Poisson				OLS			
	V_{cz}		V		V_{cz}		V	
IMPORT								
P38	-76.8	***	-89.0	***	5.9	**	-20.8	***
P12	-25.0	***	-39.0	***	9.4	***	-8.7	***
PCZ			-179.4	***			-38.8	***
EXPORT								
P38	-102.9	***	-93.0	***	5.0		-26.1	***
P12	-32.1	***	-40.4	***	9.9	***	-15.7	***
PCZ			-234.9	***			-54.3	***

Note: ***, ** and * denote significance of the coefficient on exchange rate volatility at 1%, 5%, and 10% level, respectively.

Table A7: Coefficients on V_{ijt-1} from panel regressions

	Poisson				OLS			
	V_{cz}		V		V_{cz}		V	
IMPORT								
P38	-75.0	***	-80.7	***	10.301	***	-13.9	***
P12	-19.1	***	-32.6	***	12.4	***	-3.7	***
PCZ			-169.8	***			-24.8	***
EXPORT								
P38	-102.4	***	-89.4	***	8.9	***	-18.3	***
P12	-27.6	***	-32.5	***	11.9	***	-9.5	***
PCZ			-232.6	***			-39.4	***

Note: ***, ** and * denote significance of the coefficient on exchange rate volatility at 1%, 5%, and 10% level, respectively.

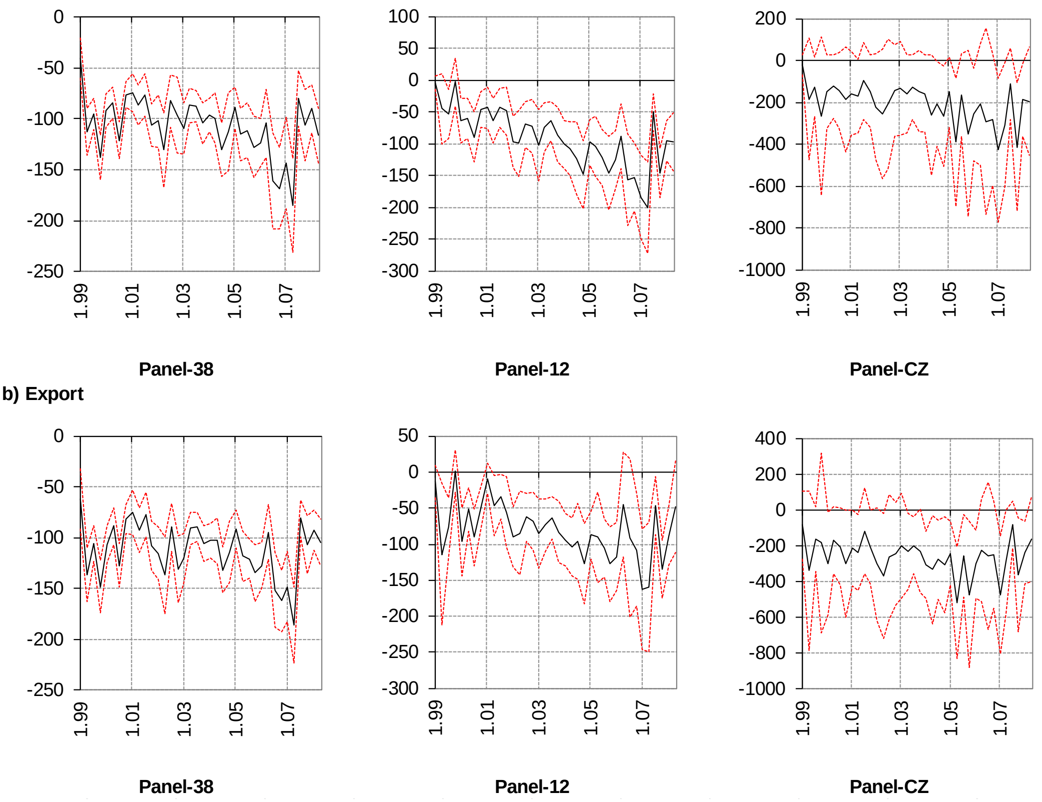
Table A8: Coefficients on exchange rate volatility based on aggregated data

	Poisson			OLS		
	V_t		V_{t-1}	V_t		V_{t-1}
IMPORT	-3.77		5.65	-5.07		3.17
EXPORT	-7.53	**	0.55	-9.10	*	-2.51
TTRADE	-5.45		3.20	-7.28		0.39

Note: ***, ** and * denote significance of the coefficient on exchange rate volatility at 1%, 5%, and 10% level, respectively.

Chart A1: TVC on exchange rate volatility. Poisson regression, V_t

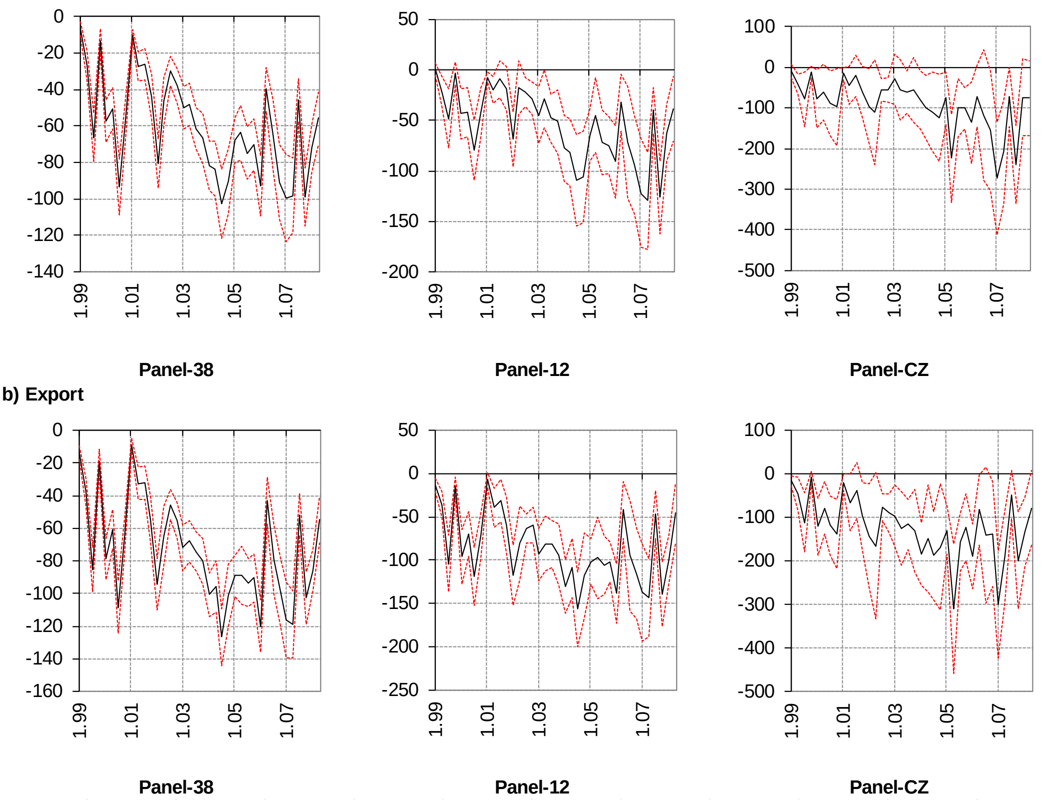
a) Import



Note: Confidence intervals are computed as ± 2 S.E.

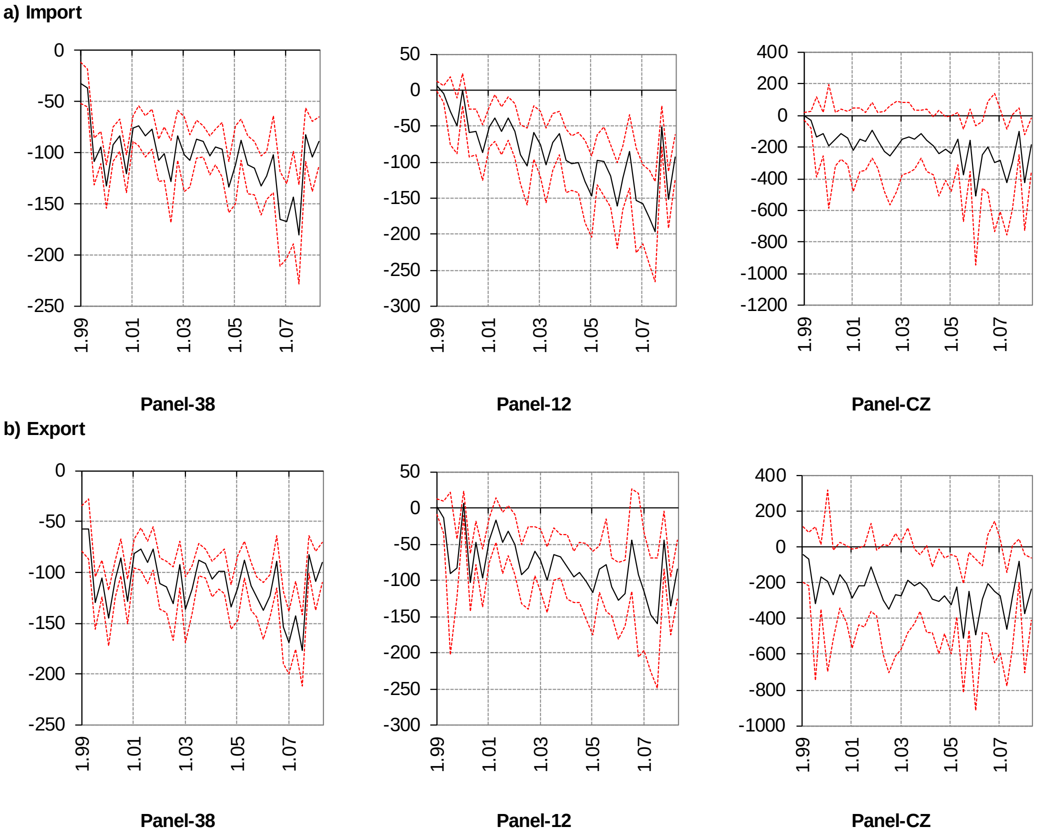
Chart A2: TVC on exchange rate volatility. OLS regression, V_t

a) Import



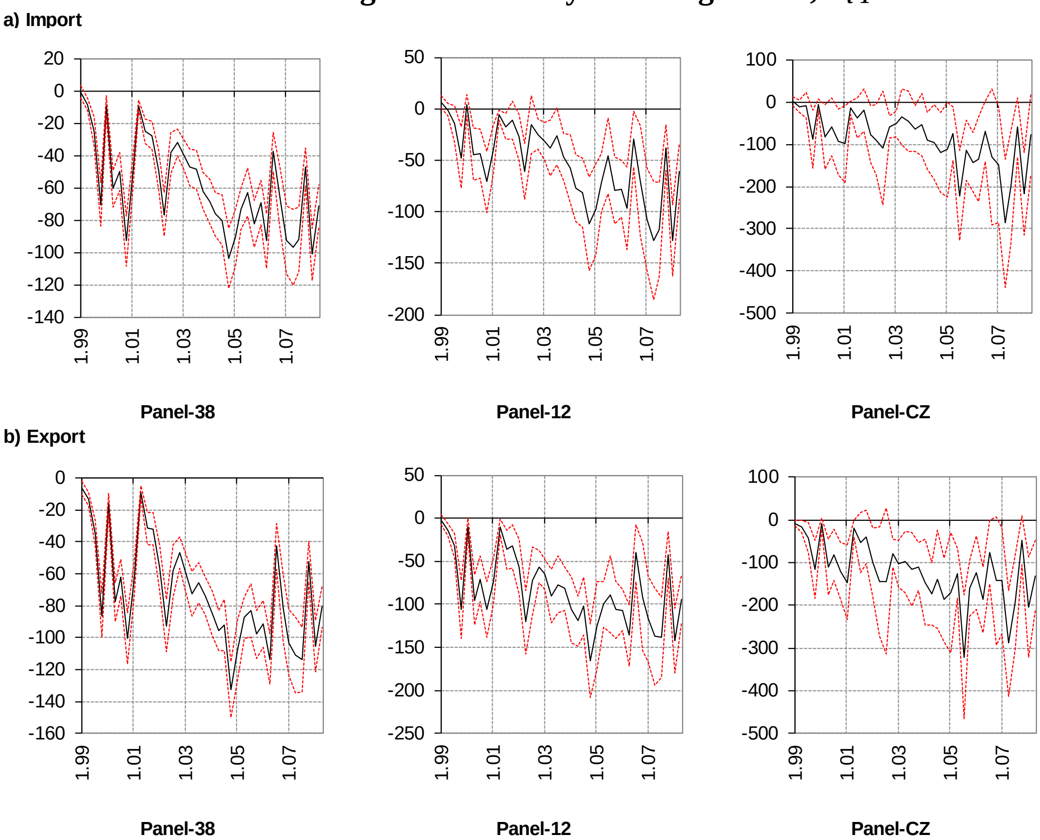
Note: Confidence intervals are computed as ± 2 S.E.

Chart A3: TVC on exchange rate volatility. Poisson regression, V_{t-1}



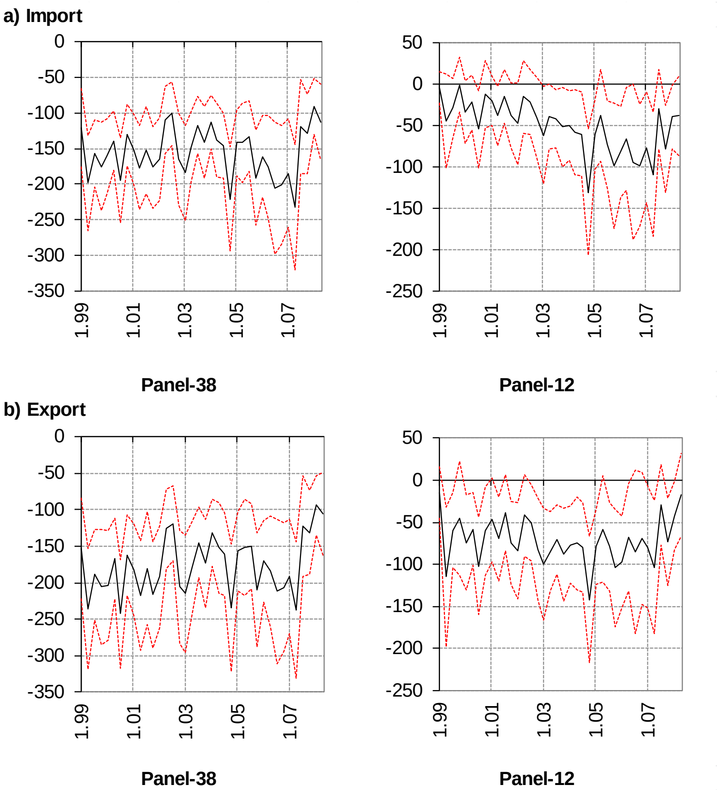
Note: Confidence intervals are computed as ± 2 S.E.

Chart A4: TVC on exchange rate volatility. OLS regression, V_{t-1}



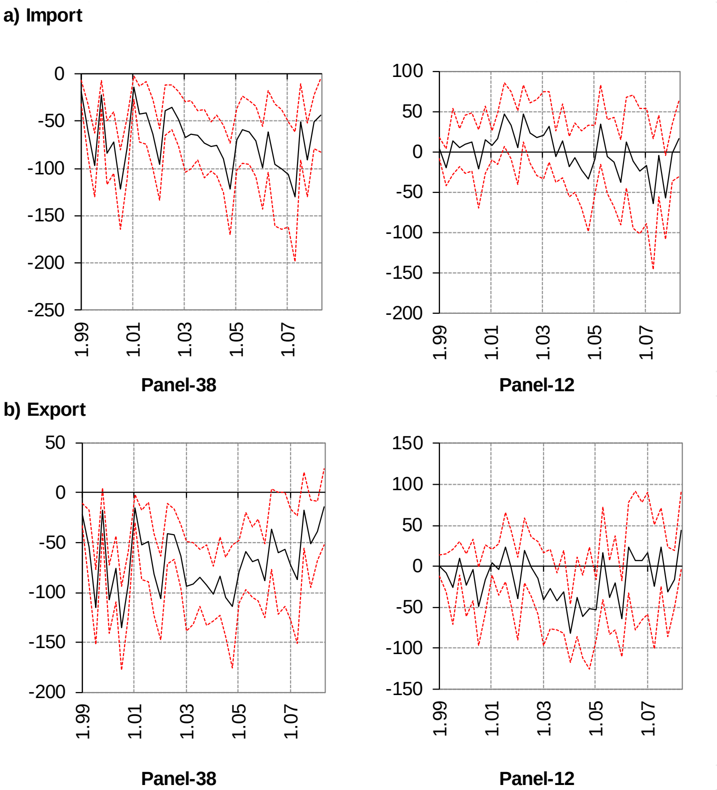
Note: Confidence intervals are computed as ± 2 S.E.

Chart A5: TVC on exchange rate volatility. Poisson regression, V^{cz}_t



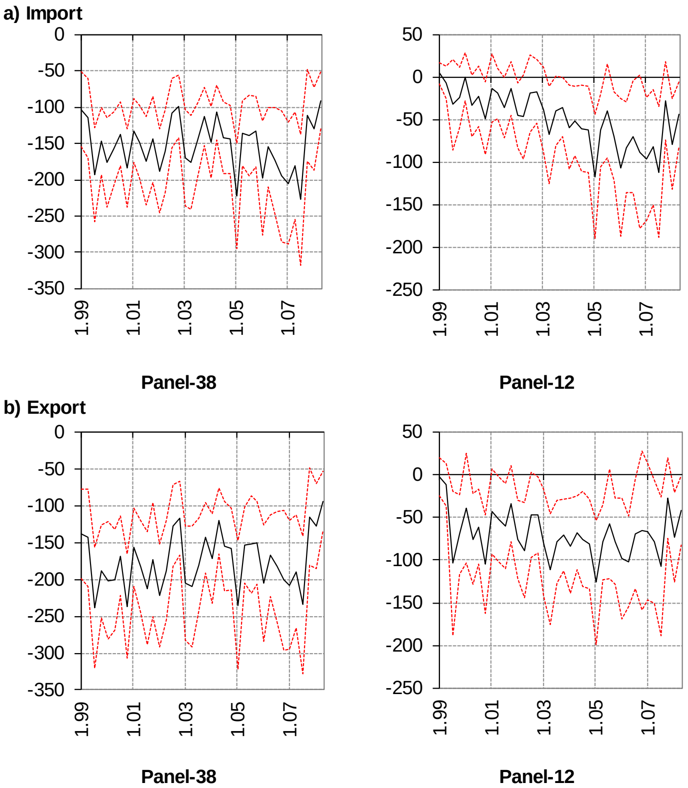
Note: Confidence intervals are computed as ± 2 S.E.

Chart A6: TVC on exchange rate volatility. OLS regression, V^{cz}_t



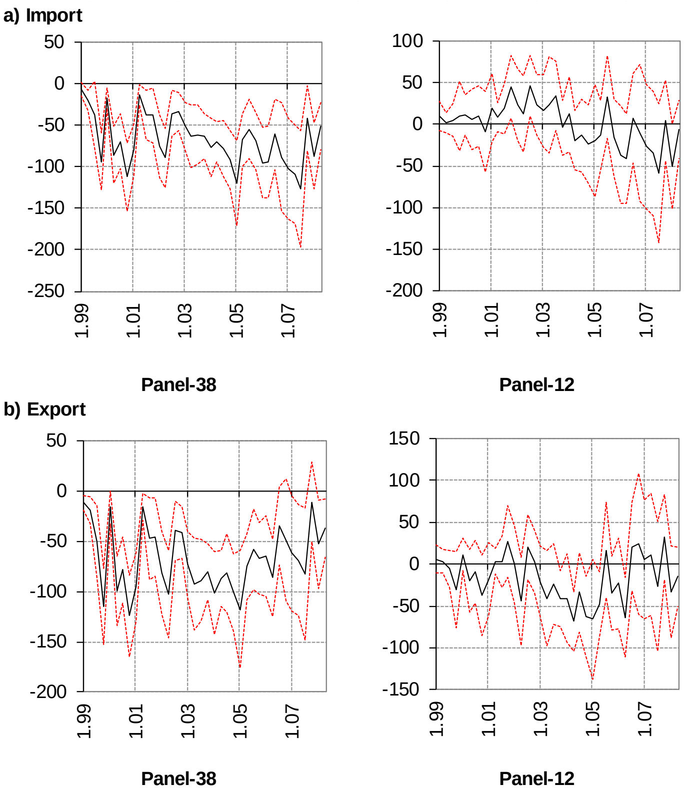
Note: Confidence intervals are computed as ± 2 S.E.

Chart A7: TVC on exchange rate volatility. Poisson regression, V^{cz}_{t-1}



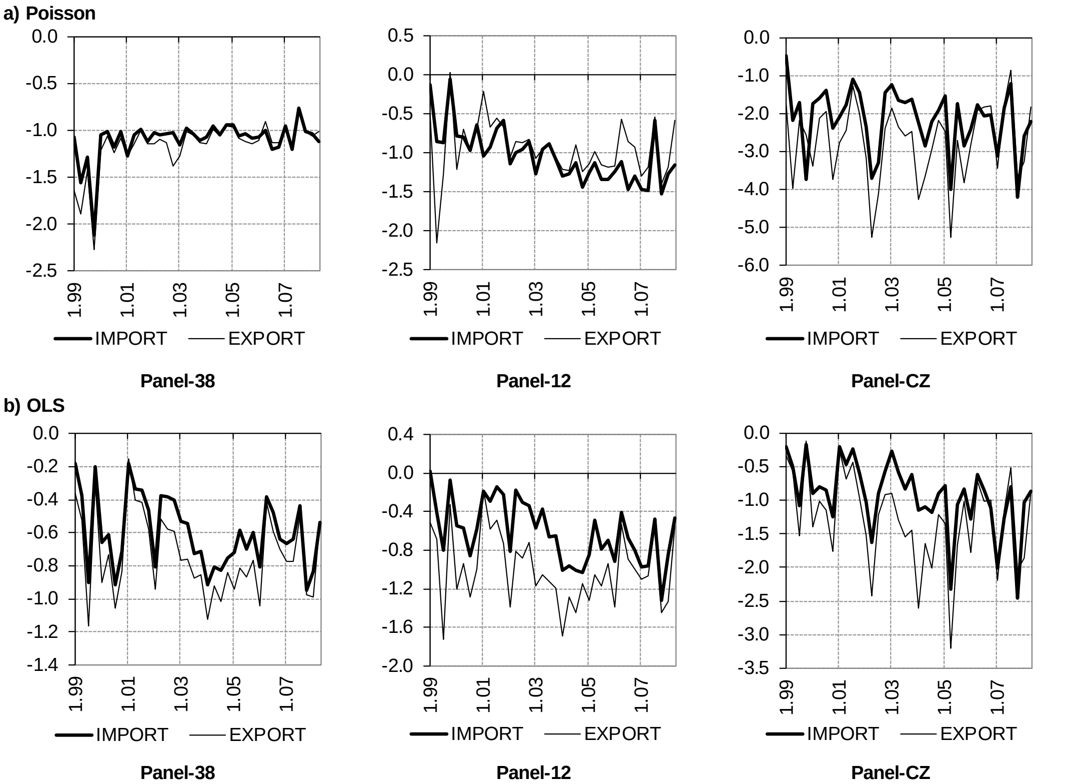
Note: Confidence intervals are computed as ± 2 S.E.

Chart A8: TVC on exchange rate volatility. OLS regression, V^{cz}_{t-1}



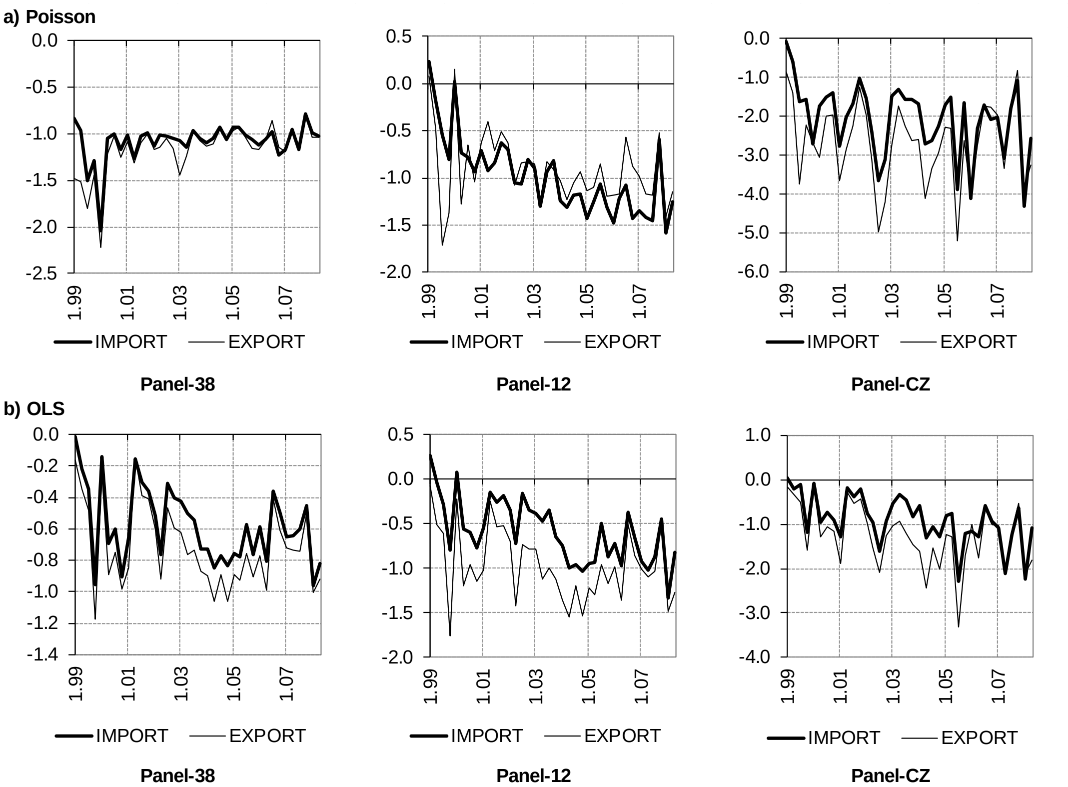
Note: Confidence intervals are computed as ± 2 S.E.

Chart A9: Impact on trade. TVC, V_t, %



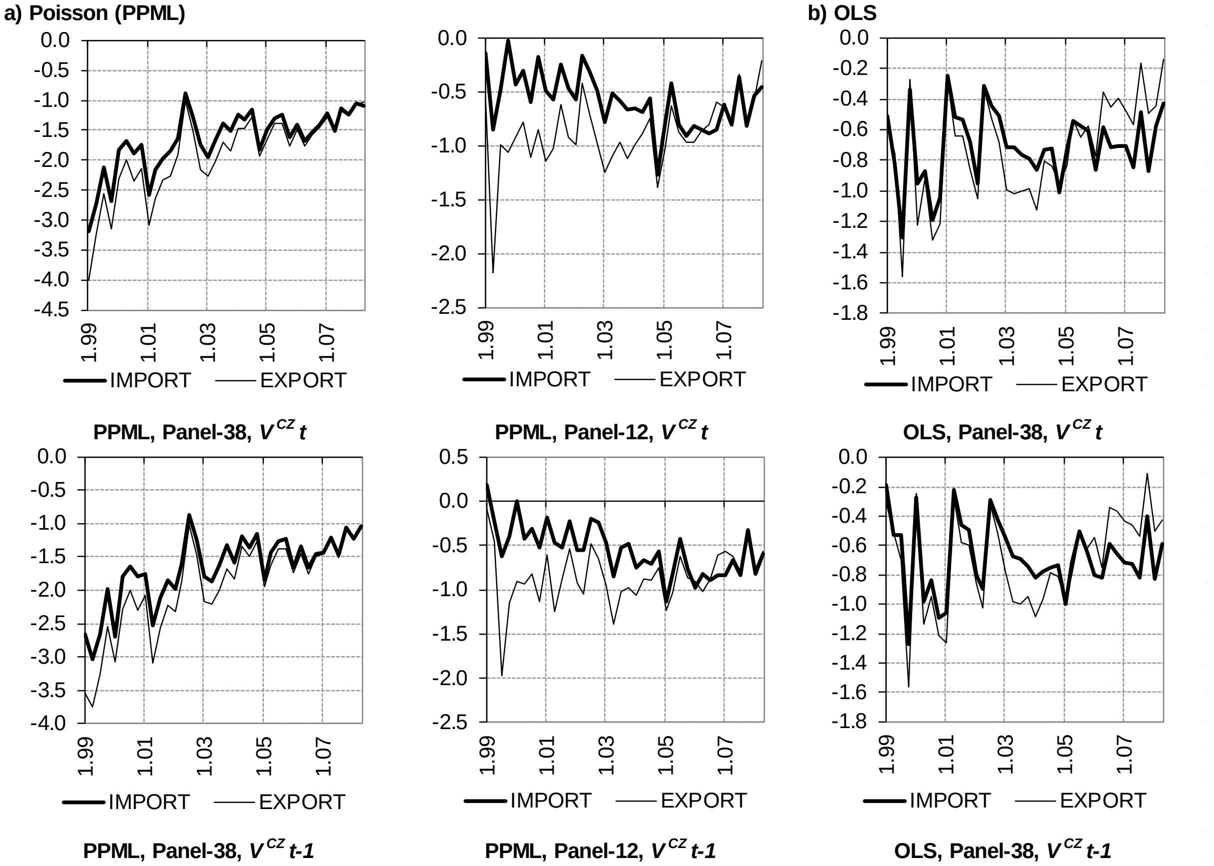
Note: Confidence intervals are computed as ± 2 S.E.

Chart A10: Impact on trade. TVC, V_{t-1}, %



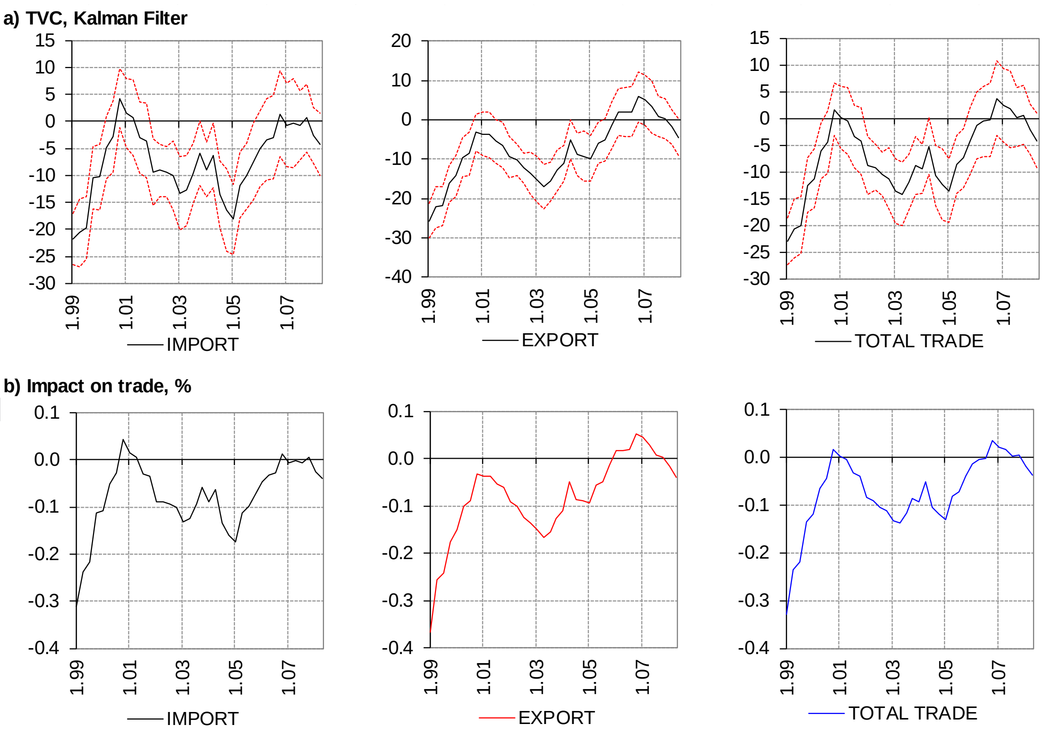
Note: Confidence intervals are computed as ± 2 S.E.

Chart A11: Impact on trade. TVC, V^{cz}, %



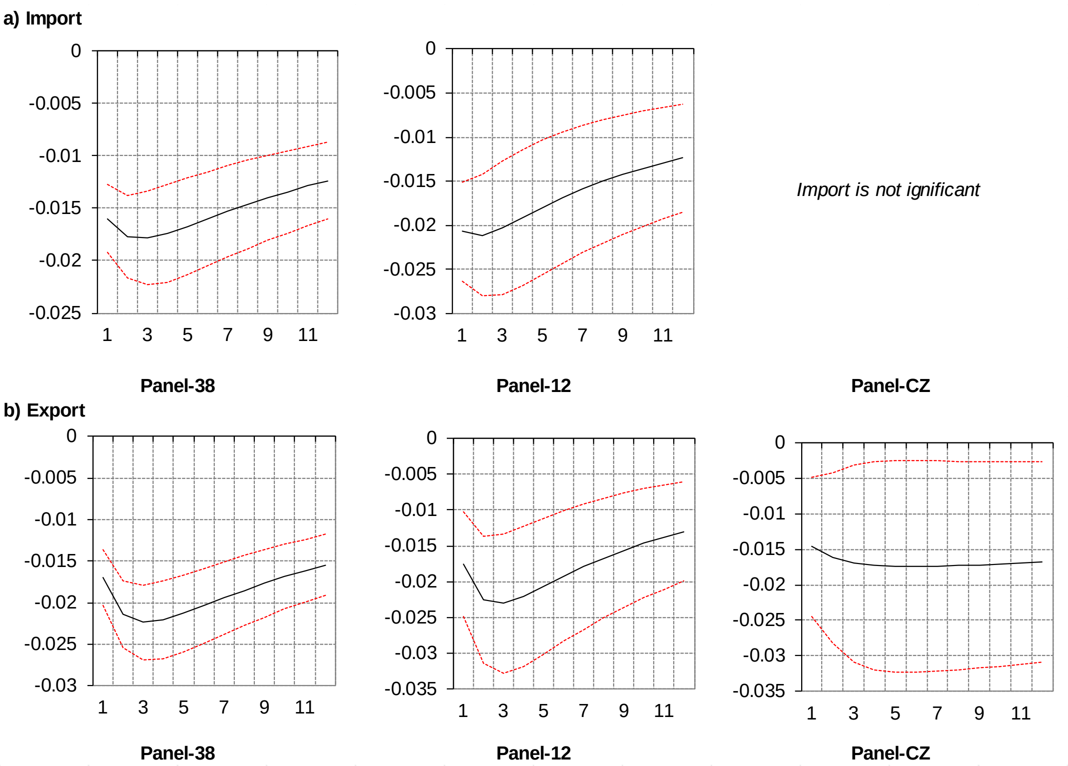
Note: Confidence intervals are computed as ± 2 S.E.

Chart A12: TVC estimates based on CZ-AGR sample



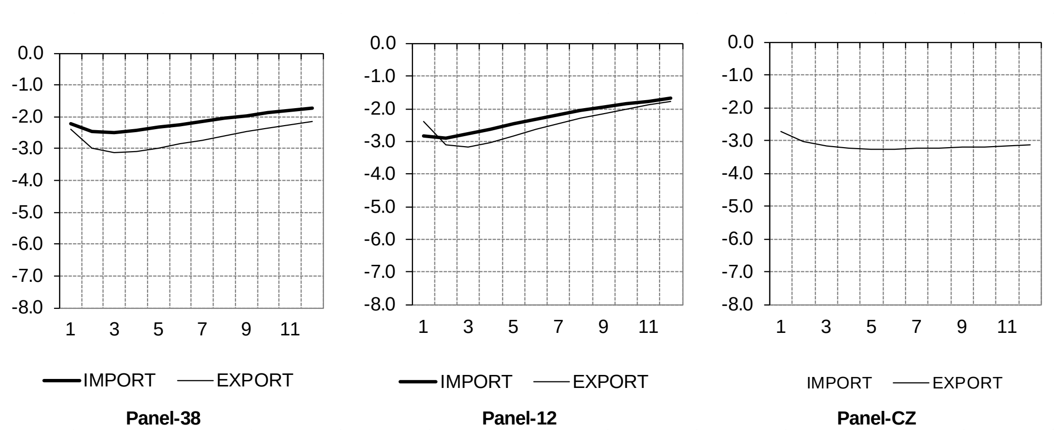
Note: Confidence intervals are computed as ± 2 S.E.

Chart A13: IR of trade to a shock to exchange rate volatility



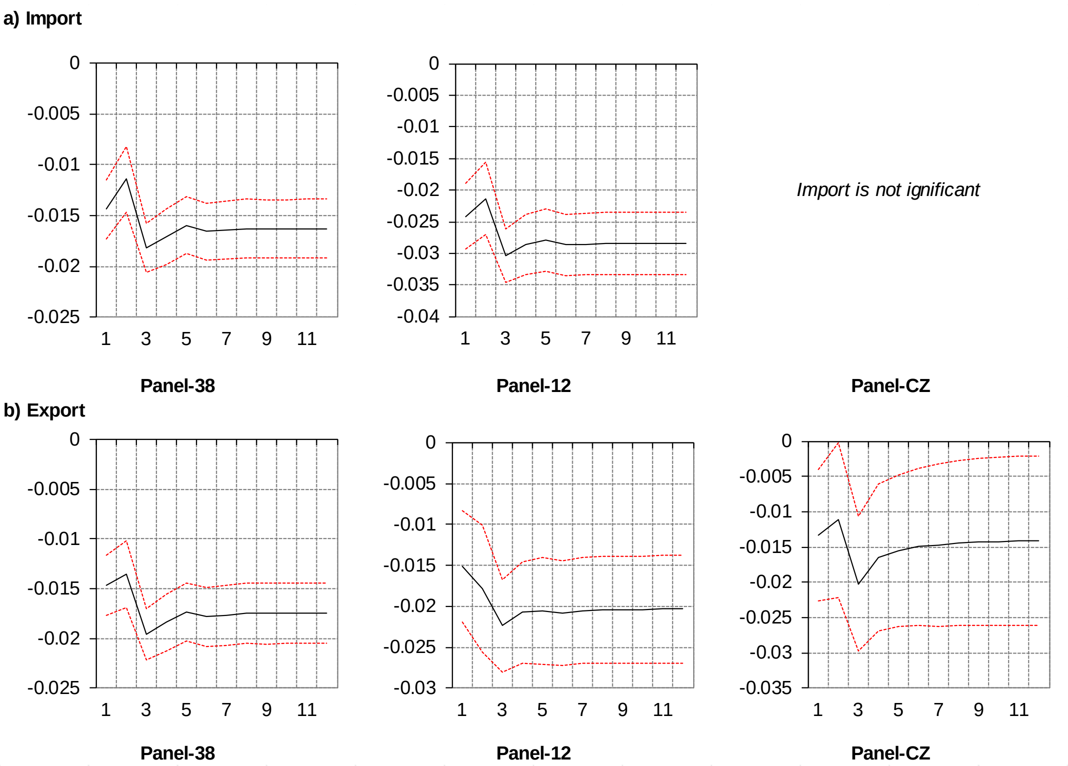
Note: Confidence intervals are computed as ± 2 S.E. Generalized impulse responses. VAR in levels. Endogenous variables' ordering: $[V_{ijt}, \ln Z_{ijt}, \ln GDP_{it}, \ln GDP_{jt}]$.

Chart A14: Impact on trade based on VAR model in levels, %



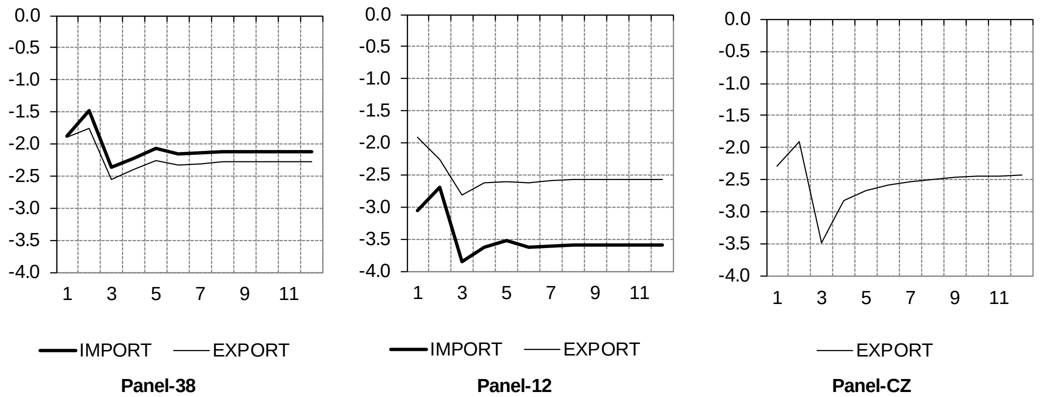
Note: Percentage change in trade is plotted on vertical axis. Horizontal axis shows periods (quarters). Computation is based on statistically significant accumulated impulse responses. Endogenous variables' ordering: $[V_{ijt}, \ln Z_{ijt}, \ln GDP_{it}, \ln GDP_{jt}]$.

Chart A15: AIR of trade to a shock to exchange rate volatility



Note: Confidence intervals are computed as ± 2 S.E. Generalized impulse responses. Endogenous variables' ordering: $\left[V_{ijt}, \Delta \ln Z_{ijt}, \Delta \ln GDP_{it}, \Delta \ln GDP_{jt}\right]$.

Chart A16: Impact on trade based on VAR in difference, %



Note: Percentage change in trade is plotted on vertical axis. Horizontal axis shows periods (quarters). Computation is based on statistically significant accumulated impulse responses. Endogenous variables' ordering: $\left[V_{ijt}, \Delta \ln Z_{ijt}, \Delta \ln GDP_{it}, \Delta \ln GDP_{jt}\right]$.

IES Working Paper Series

2014

1. Diana Zigraiova, Petr Jakubik: *Systemic Event Prediction by Early Warning System*
2. Pavla Blahova, Karel Janda, Ladislav Kristoufek: *The Perspectives for Genetically Modified Cellulosic Ethanol in the Czech Republic*
3. Oxana Babecká Kucharčuková: *The impact of exchange rate volatility on trade: Evidence for the Czech Republic*

All papers can be downloaded at: http://ies.fsv.cuni.cz

Univerzita Karlova v Praze, Fakulta sociálních věd
Institut ekonomických studií [UK FSV – IES] Praha 1, Opletalova 26
E-mail : ies@fsv.cuni.cz

http://ies.fsv.cuni.cz