JEL classification: C11, C13, C15, C33
Keywords: Panel Bayesian VAR, simulations, exchange rate pass-through, emerging economies

Exchange Rate Pass-Through in Central and Eastern Europe: A Panel Bayesian VAR Approach*

Valeriu NALBAN—Bucharest University of Economics Studies (PhD student)
(valeriu.nalban@fin.ase.ro)

Abstract

In this paper we estimate average and individual countries' exchange rate pass-through to producer and consumer price indices in four Central and Eastern Europe countries (Romania, the Czech Republic, Hungary and Poland) within a Panel Bayesian VAR model. This method makes it possible to efficiently combine static and dynamic interrelations with any possible heterogeneity within the units. The resulting average long-run pass-through coefficients are about 0.5 for producer prices and 0.3 for consumer prices (with around 0.25 in the short run for producer prices and no immediate pass-through for consumer prices), with the estimates for Hungary and the Czech Republic generally situated above the group average and Romania and Poland below the average. Sub-sample estimates showed that starting in 2008 pass-through enlarged slightly, given the increased macroeconomic distress during this period, while the countries in the study display a higher endogenously determined degree of homogeneity.

1. Introduction

The nominal exchange rate is a macroeconomic variable of significant importance for small open economies. Therefore, understanding and quantifying the effects of exchange rate fluctuations is essential for economic policymakers. The exchange rate pass-through usually refers to the percentage change in domestic prices resulting from a 1% change in the nominal exchange rate. Pass-through can be studied along the distribution chain: starting with importers, exchange rate shocks also affect domestic intermediate goods producers and eventually retailers and final consumers. These indirect effects supplement the direct influence of imported inflation on the consumer price index, since imported goods are included in the consumption basket, as discussed in Karagöz *et al.* (2010). The magnitude of pass-through is an important indicator for central banks, suggesting specific features of the macroeconomic transmission mechanism. More precisely, the extent and timing of pass-through have implications for economic analysis and the forecasting framework, and implicitly for monetary policy decisions, especially in the case of inflation-targeting countries. It is also important for policy design in the context of the fulfilment of the Maastricht criteria and potential adoption of the euro by Central and Eastern European (CEE) countries.

There are a large number of factors affecting the dimension and speed of exchange rate pass-through to domestic prices. According to Krugman (1987), exchange

* The author would like to thank Pietro Dallari for providing an initial version of the Panel Bayesian VAR estimation codes, the participants at the 2014 INFER workshop in Timișoara, and two anonymous referees. This work was partially co-financed from the European Social Fund through Sectoral Operational Programme Human Resources Development 2007–2013, project no. POSDRU/159/1.5/S/134197. Any remaining errors are the author's sole responsibility.

rate pass-through is incomplete because of "pricing-to-market" behavior: producers allow profit margins rather than domestic currency prices to fluctuate. Other imperfections like downward price rigidity, incomplete information and imperfect competition are usually cited as important. The magnitude of pass-through also depends on nominal exchange rate volatility, the persistence of its shocks, the country's openness and import penetration, and aggregate demand volatility, as analyzed in McCarthy (2007). Another recent strand of literature focuses on asymmetries and non-linearities of pass-through; see Przystupa and Wróbel (2009) for Poland and Cozmâncă and Manea (2010) for Romania.

With respect to the evolution of exchange rate pass-through coefficients in emerging markets, a consensus emerged in the literature, namely that these became smaller and were still on a declining trend before the crisis of the late 2000s. Evidence in support of this affirmation is found in Razafimahefa (2012), Karagöz *et al.* (2010) and Coulibaly and Kempf (2010). Among the most cited reasons for falling exchange rate pass-through during that period are the adoption of inflation targeting and more credible monetary policies, a less inflationary environment and increased globalization and competition. However, Nogueira Jr. and León-Ledesma (2011) and Ben Cheikh (2013) found evidence of increased pass-through during the recent crisis period in Mexico and in the peripheral euro-area countries due to the high macroeconomic instability associated with that episode.

Exchange rate pass-through in emerging countries in general and in CEE states in particular is a relatively thoroughly explored field of study. However, the record of panel analyses is quite limited. The available studies usually employ individual countries' vector autoregression models (VARs) on level or stationary data. Apart from presenting a survey of empirical results found with respect to nine CEE countries, Beirne and Bijsterbosch (2011) use five-variable cointegrated VARs and impulse responses from vector error correction models to show that exchange rate pass-through to consumer prices averages about 0.5, but it is higher for countries that have adopted some form of fixed exchange rate regime. Jimborean (2011) did not find a statistically significant exchange rate pass-through to producer and consumer prices in the ten new European Union (EU) member states in a dynamic panel data model. Karagöz *et al.* (2010) use a panel VAR for six non-EU countries to estimate a mean exchange rate pass-through of 0.22 for producer prices and 0.31 for consumer prices before 2001 and only 0.075 and 0.04, respectively, after 2001. A similar framework is used in Alpaslan and Demirel (2014) to conclude that exchange rate pass-through is lower in Asian countries than in Latin America and Turkey, and that the effects on producer prices are more pronounced than on consumer prices. Overall, the results are heterogeneous with respect to the econometric methodology employed, the economy under investigation, the time span of the observable data and the variables considered.

In this paper we include a group of four small open economies in the CEE region with (managed) floating exchange rate regimes: Romania (RO), the Czech Republic (CZ), Hungary (HU) and Poland (PL). All economies are part of the EU and are planning to adopt the euro in the future (though no exact schedule has been established). All of them are post-communist countries that underwent individual transition periods in the 1990s and early 2000s and are presently believed to share a common economic model. The monetary policy strategy pursued by the national central banks is inflation targeting; however, different periods of adoption (the Czech Republic and Poland in 1998, Hungary in 2001 and Romania in 2005) are likely to give the central banks varying levels of credibility. Other aspects that are relevant to the exchange rate pass-through effect indicators that are country-specific are the level of openness (Hungary and the Czech Republic are more open) and the level of domestic credit dollarization (higher in Hungary and Romania). Jimborean (2011) provides a closer analysis of homogeneity/heterogeneity among new EU member states with respect to some relevant macroeconomic variables.

Given some of the similarities mentioned above and the countries' common geographical position, as well as the reduced dimension of qualitative economic time series for the four countries, we employ a panel Bayesian VAR model, a method which make it possible to simultaneously consider individual characteristics of the units and common features shared by all members. As the estimates might be inconsistent if members display a high degree of heterogeneous dynamics, as Pedroni (2013) and others have warned, we do not consider adding other countries. For example, during the last ten years Slovenia, Slovakia, Bulgaria and the Baltics (Latvia, Estonia and Lithuania) had fixed exchange rate regimes and were either part of the ERM (exchange rate mechanism) system or had already adopted the euro.

Canova and Ciccarelli (2009, 2013) notice that while panel VAR models simultaneously capture static and dynamic interrelations, these take into account any possible dynamic heterogeneity within the units. Pedroni (2013) mentions the advantages of panel models, as their specific structure compensates for short temporal dimensions for individual units, making it possible to reveal not only the average relationship, but also to improve individual members' inference. Adding a Bayesian framework to panel VARs further mitigates the small-sample problem common for emerging economies and facilitates inference *via* powerful simulation algorithms.

Even if there are major indicators of heterogeneity among the four CEE countries, we stress that the Panel Bayesian VAR model is still a proper econometric approach to follow. First, as mentioned in Pedroni (2013), part of the heterogeneity is accounted for by allowing the inclusion of fixed effects (with totally flat priors in our case). Second, although we use a priori the hypothesis that the units' coefficients share a common mean, the resulting degree of pooling is stochastic and in the end is determined endogenously by the data, an observation attributable to Canova and Cicarelli (2009). Third, as compared to other studies that use panel methods, the number of units is lower, while the sample is shorter and the data are more comparable (collected under common Eurostat methodologies), thus rendering a lower degree of heterogeneity among the units' variables in the present paper. Moreover, we estimate an alternative specification which omits monetary policy shocks, given that the interest rate data is likely to constitute a significant proportion of the database disparateness.

The contribution of this paper to the literature on exchange rate pass-through in CEE countries consists in the joint estimation of individual countries and average effects using a Panel Bayesian VAR model. Also, we update the sample with the most recent observations to cover the period from January 2001 to June 2014, during which the four economies became more integrated into the EU, and reduce it to essentially a single monetary regime (with the exception of Romania). In addition, we study the stability of the pass-through coefficients following the recent crisis by estimating the model on a subsample starting in 2008. Furthermore, the robustness of the model to the exclusion of interest rate data is carefully analyzed.

This paper is structured as follows: Section 2 describes the methodological aspects of Panel Bayesian VAR models and the Gibbs sampler algorithm used for drawing from the conditional posterior distributions. Section 3 describes the data in the baseline specification. The results are presented in Section 4, where we also conduct a crisis subsample estimation and a comparative analysis of the baseline model with respect to a specification that omits monetary policy shocks. Section 5 concludes the paper.

2. The Model

In order to estimate the effects of exchange rate shocks on price indices in the four countries, we employ a structural Panel Bayesian VAR model. This approach allows us to efficiently combine country-specific and cross-sectional information while also mitigating the small-sample problem without imposing homogeneous dynamics within a pooled VAR. The model assumes the individual countries' coefficients are heterogeneous, but also that they are random draws from a common distribution. However, as discussed in Canova and Cicarelli (2009), the resulting level of pooling is stochastic and is ultimately endogenously decided by the data, thus allowing the inclusion of some heterogeneous cross-sectional data. Next we describe the technical details, closely following the expositions in Jarocinski (2010) and Canova and Dallari (2013). We mention a similar econometric approach employed in the present analysis, but the economic problem under investigation is rather distinct: the former paper studies the monetary policy transmission mechanism in Eastern and Western Europe, using sign restrictions to identify the structural shocks, while the latter paper examines the importance of tourism flows for Mediterranean countries.

Consider country-specific VAR(p) models:

$$\mathbf{y_{n,t}} = \mathbf{B_n^{1'} y_{n,t-1}} + \mathbf{B_n^{2'} y_{n,t-2}} + \dots + \mathbf{B_n^{p'} y_{n,t-p}} + \mathbf{\Gamma_n' z_{n,t}} + \mathbf{u_{n,t}} \tag{1}$$

where p denotes lag length, $n = 1,2,...,N$ indexes countries, $t = 1,2,...,T$ indexes time,[1] $\mathbf{y_{n,t}}$ is a $M \times 1$ vector of endogenous variables, $\mathbf{z_{n,t}}$ is a $Q \times 1$ vector of deterministic and exogenous variables, $\mathbf{u_{n,t}}$ is $M \times 1$ vector of residuals, and $\mathbf{B_n^i}, i = 1,..., p$, and $\mathbf{\Gamma_n}$ are coefficient matrices. The system in (1) is rewritten as:

$$\mathbf{Y_n} = \mathbf{X_n B_n} + \mathbf{Z_n \Gamma_n} + \mathbf{U_n} \tag{2}$$

where $\mathbf{Y_n}$ and $\mathbf{U_n}$ are obtained by stacking the observations in $\mathbf{y_{n,t}}$ and $\mathbf{u_{n,t}}$, with dimensions $T \times M$; $\mathbf{X_n}$ stacks the observations in $\mathbf{y_{n,t-1}, y_{n,t-2}, ..., y_{n,t-p}}$ and has dimensions $T \times K$, $K = Mp$; $\mathbf{Z_n}$ is the $T \times Q$ stacked version of $\mathbf{z_{n,t}}$; $\mathbf{B_n} = \left\lfloor \mathbf{B_n^{1'}, ..., B_n^{p'}} \right\rfloor$ and $\mathbf{\Gamma_n}$ are $K \times M$ and $Q \times M$ coefficient matrices. Next, we denote with lower

[1] Here we assume T is the same for all units in order to have samples of equal lengths for each country.

case letters the vectorized versions of the corresponding upper-case letter matrices: $\mathbf{y_n} = vec(\mathbf{Y_n})$, $\mathbf{b_n} = vec(\mathbf{B_n})$ and $\boldsymbol{\gamma}_\mathbf{n} = vec(\boldsymbol{\Gamma}_\mathbf{n})$.

The $\mathbf{b_n}$ country-specific coefficients are a priori assumed to come from a common distribution:

$$\mathbf{p}\left(\mathbf{b_n} \mid \overline{\mathbf{b}}, \tau, \mathbf{O_n}\right) = \mathbf{N}\left(\overline{\mathbf{b}}, \tau \times \mathbf{O_n}\right) \tag{3}$$

where $\overline{\mathbf{b}}$ is the common prior mean and $\tau \times \mathbf{O_n}$ is the variance-covariance matrix, restricted to being diagonal. While the mean is common, the variance is unit-specific, allowing for an optimal balance between homogeneity and heterogeneity. This specification is usually denoted as "exchangeable prior", as in Jarocinski (2010), since the units share the same prior mean. We consider a non-informative prior for the common mean in order to let the data speak:

$$p(\overline{\mathbf{b}}) \propto 1 \tag{4}$$

In (3) τ controls the tightness of the assumption that the coefficients share a joint mean, so its magnitude indicates how much the section-specific coefficients $\mathbf{b_n}$ differ from the common mean $\overline{\mathbf{b}}$. As τ goes to 0, the model is shrunk towards full pooling and $\mathbf{b_n}$ are identical and equal to $\overline{\mathbf{b}}$, while as τ increases, the model is broken into *N* independent VAR models. Since we attempt to estimate τ, the model acquires a hierarchical structure. As we use a rather heterogeneous set of time series, without any a priori knowledge of the degree of country-specific uniqueness, we consider a non-informative prior distribution for τ and let the data endogenously select a data-consistent degree of pooling. Specifically, we follow Gelman (2006) and use a simple uniform prior, which still guarantees conjugacy:

$$p(\tau) \propto \tau^{-\frac{1}{2}} \tag{5}$$

$\mathbf{O_n}$ in (3) is a scaling factor that has the form shown in (6). It specifies the variance of the coefficient on variable k in the equation of endogenous variable m as:

$$\mathbf{O_n}(m,k) = var\left[\mathbf{b_n}(m,k)\right] = \frac{\hat{\sigma}_{n,m}^2}{\hat{\sigma}_{n,k}^2}; \;\; m = 1, ..., M; k = 1, ..., K \tag{6}$$

where $\hat{\sigma}_{n,j}^2$ is the variance of the error term in a univariate p order autoregression of VAR series *j* of country *n*. The specification in (6) is inspired by the Minnesota-type prior as implemented in Doan *et al.* (1984), adjusting the size of the coefficients according to the volatilities of the endogenous variables. With this functional form for $\mathbf{O_n}$, $\mathbf{b_n}$ capture each unit's individual time series characteristics, taking into account and preserving a portion of heterogeneity presented in the data. Jarocinsky (2010) refers to (3) as the first stage of the hierarchy and to (4), (5) and (6) as the second stage of the hierarchy.

The residuals in (2) are $\mathbf{i.i.d.}\,\mathbf{N}\left(\mathbf{0}, \boldsymbol{\Sigma}_\mathbf{n}\right)$ and for the variance-covariance matrices we use standard diffuse priors of the form:

$$p(\boldsymbol{\Sigma}_{\mathbf{n}}) \propto |\boldsymbol{\Sigma}_{\mathbf{n}}|^{-\frac{1}{2}(M+1)}$$

Similar to the common mean, we consider a non-informative prior for deterministic/exogenous variable coefficients:

$$p(\boldsymbol{\gamma}_{\mathbf{n}}) \propto 1$$

These coefficients have the natural interpretation of fixed effects, are unit-specific and assimilate a part of the cross-country heterogeneity inherent in the data.

As the employed priors are conjugate, there exist closed-form solutions for the conditional posterior densities for the parameters of interest $\boldsymbol{\Theta} \equiv \lfloor \mathbf{b}_{\mathbf{n}}, \bar{\mathbf{b}}, \boldsymbol{\gamma}_{\mathbf{n}}, \boldsymbol{\Sigma}_{\mathbf{n}}, \tau \rfloor$. The posterior distributions are computed using the Gibbs sampler algorithm described below.

Denoting with $\boldsymbol{\Theta}/\alpha$ the vector of $\boldsymbol{\Theta}$ excluding the α coefficient, the conditional posterior of $\mathbf{b}_{\mathbf{n}}$ has the following form:

$$\mathbf{p}(\mathbf{b}_{\mathbf{n}} \mid \mathbf{Y}, \boldsymbol{\Theta}/\mathbf{b}_{\mathbf{n}}) = \mathbf{N}(\tilde{\mathbf{b}}_{\mathbf{n}}, \tilde{\boldsymbol{\Delta}}_{\mathbf{n}}) \tag{7}$$

where

$$\tilde{\boldsymbol{\Delta}}_{\mathbf{n}} = \left(\boldsymbol{\Sigma}_{\mathbf{n}}^{-1} \otimes \mathbf{X}_{\mathbf{n}}^{'}\mathbf{X}_{\mathbf{n}} + \tau^{-1}\mathbf{O}_{\mathbf{n}}^{-1}\right)^{-1}$$

$$\tilde{\mathbf{b}}_{\mathbf{n}} = \tilde{\boldsymbol{\Delta}}_{\mathbf{n}} \times \left(\left(\boldsymbol{\Sigma}_{\mathbf{n}}^{-1} \otimes \mathbf{X}_{\mathbf{n}}^{'}\right)(\mathbf{y}_{\mathbf{n}} - \mathbf{Z}_{\mathbf{n}}\boldsymbol{\gamma}_{\mathbf{n}}) + \tau^{-1}\mathbf{O}_{\mathbf{n}}^{-1}\bar{\mathbf{b}}\right)$$

The conditional posterior distribution of the common mean $\bar{\mathbf{b}}$ is also normal:

$$\mathbf{p}(\bar{\mathbf{b}} \mid \mathbf{Y}, \boldsymbol{\Theta}/\bar{\mathbf{b}}) = \mathbf{N}\left(\tilde{\bar{\mathbf{b}}}, \tilde{\bar{\boldsymbol{\Delta}}}\right) \tag{8}$$

where

$$\tilde{\bar{\boldsymbol{\Delta}}} = \left(\sum_{\mathbf{n}} (\tau \mathbf{O}_{\mathbf{n}})^{-1}\right)^{-1}$$

$$\tilde{\bar{\mathbf{b}}} = \tilde{\bar{\boldsymbol{\Delta}}} \times \sum_{\mathbf{n}} (\tau \mathbf{O}_{\mathbf{n}})^{-1} \mathbf{b}_{\mathbf{n}}$$

Next, the posterior distribution of $\boldsymbol{\gamma}_{\mathbf{n}}$ is:

$$\mathbf{p}(\boldsymbol{\gamma}_{\mathbf{n}} \mid \mathbf{Y}, \boldsymbol{\Theta}/\boldsymbol{\gamma}_{\mathbf{n}}) = \mathbf{N}(\tilde{\boldsymbol{\gamma}}_{\mathbf{n}}, \tilde{\boldsymbol{\Gamma}}_{\mathbf{n}}) \tag{9}$$

where

$$\tilde{\boldsymbol{\Gamma}}_{\mathbf{n}} = \left(\boldsymbol{\Sigma}_{\mathbf{n}}^{-1} \otimes \mathbf{Z}_{\mathbf{n}}^{'}\mathbf{Z}_{\mathbf{n}}\right)^{-1}$$

$$\tilde{\boldsymbol{\gamma}}_{\mathbf{n}} = \tilde{\boldsymbol{\Gamma}}_{\mathbf{n}} \times \left(\boldsymbol{\Sigma}_{\mathbf{n}}^{-1} \otimes \mathbf{Z}_{\mathbf{n}}^{'}\right)(\mathbf{y}_{\mathbf{n}} - \mathbf{X}_{\mathbf{n}}\mathbf{b}_{\mathbf{n}})$$

The conditional posterior distribution of residuals' variance-covariance matrices is inverse-Wishart:

$$\mathbf{p}(\boldsymbol{\Sigma}_{\mathbf{n}} \mid \mathbf{Y}, \boldsymbol{\Theta}/\boldsymbol{\Sigma}_{\mathbf{n}}) = \mathbf{iW}\left((\mathbf{Y}_{\mathbf{n}} - \mathbf{X}_{\mathbf{n}}\mathbf{B}_{\mathbf{n}} - \mathbf{Z}_{\mathbf{n}}\boldsymbol{\Gamma}_{\mathbf{n}})^{'}(\mathbf{Y}_{\mathbf{n}} - \mathbf{X}_{\mathbf{n}}\mathbf{B}_{\mathbf{n}} - \mathbf{Z}_{\mathbf{n}}\boldsymbol{\Gamma}_{\mathbf{n}}), T\right) \tag{10}$$

Finally, the posterior distribution of the tightness parameter τ is inverse-Gamma:

$$\mathbf{p}(\tau \mid \mathbf{Y},\mathbf{\Theta}/\tau) = \mathbf{iG}\left(\frac{NKM\ \mathbf{-1}}{\mathbf{2}}, \frac{\sum_{\mathbf{n}}\left(\mathbf{b_n} - \bar{\mathbf{b}}\right)' \mathbf{O_n^{-1}}\left(\mathbf{b_n} - \bar{\mathbf{b}}\right)}{\mathbf{2}}\right) \tag{11}$$

Starting from some arbitrary values, like ordinary least square (OLS) estimates, it is easy to repeatedly draw from (7), (8), (9), (10) and (11) to obtain a sample from the posterior. In practice, a large number of draws is needed for a good approximation and convergence of the posterior distributions and it is usually recommended to burn a fraction of initial draws in order to minimize the influence of starting values and to keep only each 100th draw in order to get rid of any autocorrelation.

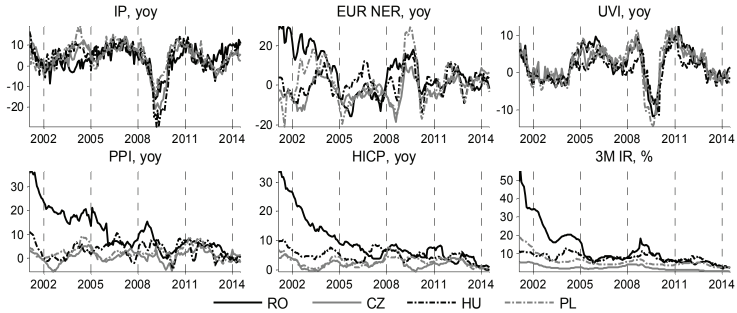
For each retained draw, coefficients can be used to compute the impulse response functions. Here we use Cholesky factorization for disentangling structural shocks from reduced-form residuals, as explained below. The exchange rate pass-through coefficients are computed as the cumulative response of price index inflation (i.e. producer or consumer) after a certain number of months to the exchange rate shock, divided by the cumulative response of the exchange rate over the same period to the exchange rate shock.[2] Aside from the individual pass-through coefficients (given by the impulse response functions computed using the individual countries' coefficients, $\mathbf{b_n}$), we compute the average pass-through (given by the impulse response functions computed using common coefficients, $\bar{\mathbf{b}}$), which can be interpreted as a weighted average, with tightly estimated country models receiving more weight relative to imprecise estimates.

3. Data

We consider a standard dataset for studying exchange rate pass-through in open economies, similar to the one used in the seminal paper of McCarthy (2007). The baseline specification consists of the Brent oil price (this variable is common for all countries), the industrial production (IP) index (seasonally adjusted), the euro nominal exchange rate (EUR NER) expressed in national currency units per one euro such that a rise indicates depreciation, the unit value index (UVI) as a proxy for import prices, the producer price index (PPI), the harmonized index of consumer prices (HICP), and three-month money market interest rates (3M IR). All series except the interest rates are transformed into a 12-period log difference (i.e. annual growth rates, year-on-year) to induce stationarity. Although non-stationarity is not an issue in the Bayesian framework, as posterior distributions have the same proprieties for both stationary and non-stationary models, unlike classical econometrics,

[2] For estimation we use annual growth-rate data and, in order to estimate the cumulative effects, we compute the implied fixed base indices by chain-linking the respective year-on-year responses (i.e. we recover the variable's level at the end of any month following the shock). This is analogous to the usual approach with monthly growth-rate data, but we favour the annual rates because: these are not so noisy (giving more meaningful estimates) and better capture the economic events that took place (like the recent crisis); some variables are more relevant in annual terms (like inflation rates, as the central banks target some annual inflation rate); there is no need to induce arbitrariness when seasonally adjusting or including seasonal dummies in the estimation, etc.

Figure 1 Observable Data



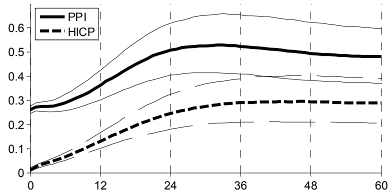
where asymptotic distributions are non-standard under unit roots, we prefer to use log-differenced data, as such data are less sensitive to the likely structural breaks and instabilities in the time series we use. For an alternative specification, we exclude the interest rate series in order to evaluate the marginal importance of monetary policy shocks. The sources of the data are Eurostat and the Energy Information Administration (for the oil price), and the sample covers the January 2001–June 2014 period.[3] The main reason for this rather short sample is given by data availability (particularly the unit value index series) and consistency (the NACE Rev. 2 recalculated industrial production index is not available for all countries prior to 2000).

The data are displayed in *Figure 1* and show a great degree of correlation in the case of industrial production and the unit value index (both before and after the crisis). The nominal exchange rates are also related, even if the fluctuations differ in magnitude. The price indices and interest rates seem to be rather independent across units, being driven mostly by idiosyncratic rather than regional forces.

When using Cholesky factorization for recovering the structural shocks, the order of the variables is as declared above, i.e. slow-moving variables are placed first, while fast-moving ones are arranged last, similar to McCarthy (2007). The oil price is intended to capture the supply-side shocks, while the industrial production indices capture the domestic demand shocks, the former variable being contemporaneously affected only by its own innovations. The nominal exchange rate is allowed to be affected in the same month only by the supply and demand shocks, while the other variables' effects appear with a lag. The ordering of the price indices imitates the distribution chain, with each stage of production being affected by the prices set in previous phases. Import price shocks simultaneously affect producer and consumer prices. Next, producer prices influence only consumer prices in the same period, while consumer prices do not induce contemporaneous changes in the indices situated in the previous stages. The interest rate is ordered last, meaning that the central bank can react to supply, demand, exchange rate and any stage prices shocks in the same month, while the effects of a modified interest rate upon the other variables is only lagged. Overall, the specification is consistent with the relevant

[3] The data were extracted on 21 September 2014. For some periods the interest rate for Hungary was missing, so we considered the monthly averages of the available daily quotations for these dates, which were taken from the National Bank of Hungary database.

Figure 2 Average Exchange Rate Pass-Through (median and 68% confidence bands)



literature, while at the same time representing a logical progression of the shocks, as stated in Beirne and Bijsterbosch (2011).

In the baseline model we consider that $\boldsymbol{\gamma}_\mathbf{n}$ consists of constants only, implying country-specific fixed effects. The lag length is agnostically chosen to be 3 $(p = 3)$. This is somehow more than the standard information criteria suggest when implementing individual OLS VARs, but we prefer adding more dynamics to the system.

4. Results

In what follows, we focus on exchange rate pass-through into domestic currency producer prices (proxied by PPI) and consumer prices (proxied by HICP). Apart from the average results, we also discuss the individual countries' results. The obtained pass-through coefficients are calculated as the cumulative response of PPI or HICP to the exchange rate shock divided by the cumulative response of the exchange rate to the exchange rate shock, for horizons between one and 60 months. We consider the average effect of the first three months to be the short-run pass-through coefficient, and the average of the second year (13–24 months) and of the fifth year (49–60 months) estimates to represent the medium- and long-run pass-through, respectively.

4.1 Panel Bayesian VAR Results

For the average pass-through, the derived impulse response functions are computed using $\overline{\mathbf{b}}$ coefficients, while for individual countries we use $\mathbf{b}_\mathbf{n}$ coefficients. In order to approximate the posterior distribution of the Panel Bayesian VAR parameters, we employ the Gibbs sampler described in Section 2, running 150,000 draws, burning the first 50,000 draws and retaining each 100^{th} iteration. This ensures the convergence and no autocorrelation of the simulated draws.[4] The results are based on the draws' median, while for confidence bands we use the 16^{th} and 84^{th} percentiles (i.e. 68% confidence bands).

The average CEE exchange rate pass-through to PPI and HICP is presented in *Figure 2*. The average response of producer prices is larger than the response of consumer prices at all horizons, especially at the short- and medium-term horizons. This result is compatible with the production chain structure and was also found in

[4] In order to check the convergence of the draws, we computed the exchange rate pass-through coefficients using the first and last 40% of the posterior draws and we did not find visual evidence of any differences between these (the results are robust to any reasonable splitting proportions of the posterior draws). Some formal statistical tests confirm the corresponding means are not statistically different.

Figure 3 Individual Countries' Exchange Rate Pass-Through (median and 68% confidence bands)

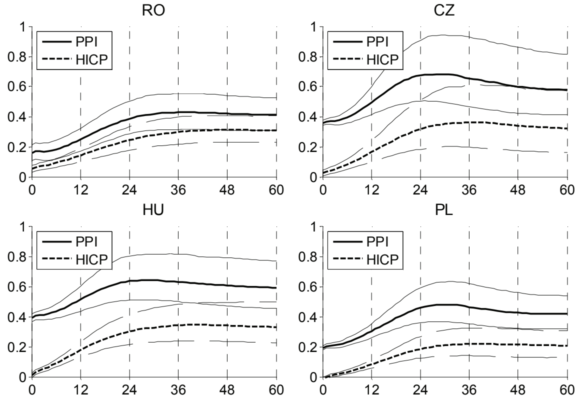
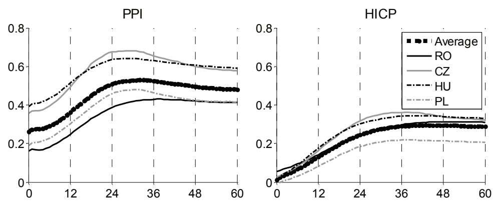


Figure 4 Average and Individual Countries' Median Exchange Rate Pass-Through



McCarthy (2007) for developed countries and in Ca'Zorzi *et al.* (2007) for CEE countries. Also, a low PPI and no HICP responses in the short run are consistent with the New Keynesian evidence of sticky prices, a fact that implies monetary non-neutrality and renders monetary policy capable of influencing real variables.

In the short run the pass-through to PPI is about 0.27, with a 68% confidence band of [0.25; 0.29]. It increases during the first two years, averaging 0.44 in the medium term (with [0.35; 0.53] confidence band). The long-run pass-through is around 0.49 (with [0.38; 0.61] confidence band), close to the medium-run effect. In the case of HICP, the pass-through increases during the first three years, starting from a low but statistically significant 0.02 coefficient ([0.01; 0.03] confidence band) in the first three months, reaching an average of 0.19 ([0.14; 0.24] confidence band) during the second year (13–24 months) and stabilizing at 0.29 ([0.21; 0.40] confidence band) in the long run.

Coefficients of country-specific exchange rate pass-through to national producer and consumer prices are displayed in *Figure 3* with 68% confidence bands, while *Figure 4* overlaps the average and individual median estimates (presented in *Figure 2* and *Figure 3*). The country-specific shapes are similar to the average results. Overall, Romania and Poland display the smallest pass-through coefficients to PPI (and are situated below the average), while the Czech Republic and Hungary display the largest (and are situated above the average). In the case of HICP, only Polish pass-through is positioned below the group mean. A higher pass-through of nominal exchange rate shocks calls for more vigilant monitoring of domestic currency price

Table 1 Average and Individual Median Exchange Rate Pass-Through Coefficients (68% confidence interval in square brackets)

	PPI				
	Average	**Romania**	**Czech Rep.**	**Hungary**	**Poland**
short-run (1–3 months)	**0.27 [0.25; 0.29]**	0.17 [0.11; 0.22]	0.37 [0.35; 0.39]	0.40 [0.38; 0.43]	0.20 [0.19; 0.22]
medium-run (13–24 months)	**0.44 [0.35; 0.53]**	0.32 [0.23; 0.41]	0.59 [0.46; 0.77]	0.58 [0.48; 0.71]	0.38 [0.31; 0.47]
long-run (49–60 months)	**0.49 [0.38; 0.61]**	0.42 [0.31; 0.53]	0.59 [0.42; 0.88]	0.60 [0.46; 0.78]	0.42 [0.32; 0.55]
	HICP				
	Average	**Romania**	**Czech Rep.**	**Hungary**	**Poland**
short-run (1–3 months)	**0.02 [0.01; 0.03]**	0.06 [0.04; 0.08]	0.03 [0.01; 0.06]	0.03 [0.01; 0.04]	0.00 [-0.01; 0.01]
medium-run (13–24 months)	**0.19 [0.14; 0.24]**	0.19 [0.14; 0.26]	0.24 [0.14; 0.37]	0.24 [0.18; 0.33]	0.13 [0.09; 0.19]
long-run (49–60 months)	**0.29 [0.21; 0.40]**	0.31 [0.23; 0.40]	0.33 [0.17; 0.58]	0.34 [0.23; 0.50]	0.21 [0.13; 0.31]

evolution by the economic authorities. On the other hand, a larger pass-through strengthens the exchange rate channel transmission mechanism and renders it an effective monetary policy tool.

A closer look suggests the median PPI responses are slightly higher in Poland as compared to Romania in the short and medium run (five percentage points), but are similar starting with the fifth year following the shock. For the Czech Republic and Hungary, for which the estimates are above the group mean, the pass-throughs are roughly similar at any horizon.

Only Romanian HICP reacts on impact (with around 6%), suggesting slightly different behavior of final goods retailers: they start including the exchange rate fluctuations in their products' prices already in the same month the shock occurred, compared to the other three economies, where retailers' profit margins initially absorb the shock. Despite a larger initial impact, Romanian HICP pass-through stabilizes in the long run at similar to the levels displayed by its peers, at around 0.30. The Polish HICP does not react on impact, but increases gradually during the first three years to about 0.20. Again, Hungary and the Czech Republic display the highest and similar pass-through coefficients, maintaining a five-percentage-points gap with respect to the group average in the medium to long term. However, median estimates are surrounded by larger confidence bands, suggesting higher uncertainty in the case of Czech and Hungarian data (thus, these countries' individual results receive lower weights in the average results). *Table 1* summarizes the estimated short-run (average of 1–3 months), medium-run (average of 13–24 months) and long-run (average of 49–60 months) exchange rate pass-through coefficients.

Beirne and Bijsterbosch (2011) estimate individual VAR models and find generally higher exchange rate pass-through coefficients to HICP, especially for shorter horizons, where we estimate essentially no pass-through. Stronger effects of exchange rate shocks on consumer prices were also reported in Ca'Zorzi *et al.* (2007). However, when taking into account the estimated level of uncertainty (*via*

Table 2 Openness and Volatility of Real Exchange Rates (RER)

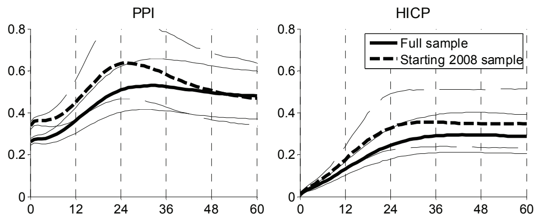
	Romania	Czech Rep.	Hungary	Poland
Openness, 2001Q1–2014Q2	76.6	111.6	131.7	69.9
Openness, 2008Q1–2014Q2	75.3	135.8	162.3	85.3
RER standard deviation, PPI based, full sample	7.5	3.9	3.9	7.8
RER standard deviation, PPI based, starting 2008	3.7	3.6	3.1	7.5
RER standard deviation, HICP based, full sample	7.4	6.2	6.9	10.2
RER standard deviation, HICP based, starting 2008	5.3	7.0	6.6	10.1

the confidence bands), the results cannot be considered totally and significantly different. Moreover, the results in the above-mentioned works are similar to ours in terms of relative effects: pass-through effects are estimated to be higher in Hungary and the Czech Republic as compared to Poland (both references) and Romania (only the former reference includes Romanian data). On the other side, using a dynamic panel data model Jimborean (2011) concludes that the exchange rate pass-throughs to producer and consumer prices are not significant in the new EU member states (including all four countries analyzed in the present paper), mentioning also a great degree of heterogeneity in the estimates. Overall, the results found in the relevant literature that are different from ours might be caused by different econometric methodologies, slightly different datasets and different sample periods and frequencies.

As mentioned and analyzed in McCarthy (2007) and Ca'Zorzi *et al.* (2007), the more open a country is, the more an exchange rate shock is transmitted into domestic prices. The ratios of imports plus exports to gross domestic product as an indicator of openness are displayed in *Table 2* for both the 2001Q1–2014Q2 period and the 2008Q1–2014Q2 subsample. The Panel Bayesian VAR results are compatible with the theoretical positive correlation between the pass-through and openness levels, with Hungary and the Czech Republic being more trade-integrated and receiving higher estimated pass-through coefficients when compared to Poland and Romania.

Using cointegrated VAR models, Coricelli *et al.* (2006) explain the differences in exchange rate pass-through coefficients among some new EU member states *via* the degree of monetary policy accommodation implemented by the national central banks. Accordingly, in Hungary and Slovenia the real exchange rate is less volatile, so monetary policy is claimed to be more accommodative, resulting in larger exchange rate pass-throughs. Conversely, Poland and the Czech Republic present larger fluctuations in the real exchange rate and, consequently, lesser effects of the exchange rate on domestic prices. Sample standard deviations of real exchange rates displayed in *Table 2* (for the full sample and for a subsample starting in 2008) sustain the evidence documented in Coricelli *et al.* (2006) regarding the inverse correlation between the magnitude of exchange rate pass-through and the volatility of the real exchange rate: Romania and Poland, for which the exchange rate effects are generally below average, present greater volatility of their real exchange rates (calculated using both PPI and HICP) as compared to the countries with above-average effects, i.e. Hungary and the Czech Republic.

Figure 5 Average Exchange Rate Pass-Through Estimated on the Full Sample and the Sample Starting with 2008 (median and 68% confidence bands)



4.2 Pass-Through Coefficients since 2008

While the full-sample estimates are likely to provide the "true" exchange rate pass-through prevailing under "average economic conditions", as the full sample contains a more complete business cycle (both economic boom and crisis phases), the financial crisis occurring in the second half of the sample might have induced significant changes to price setters' behavior. Jimborean (2011) found a significant break in the new EU members' time series corresponding to the recent crisis (but overall the pass-through effects are evaluated as being rather stable). In order to evaluate the exchange rate pass-through associated with the more recent period, we re-estimate the Panel Bayesian VAR model using the second part of the sample from the baseline specification, i.e. only observations from January 2008–June 2014.[5] We again stress that the Bayesian framework allows for consistent estimation even using this rather short and increased-volatility sample (however, the resulting confidence bands are wider, causing more uncertainty over the corresponding estimates).

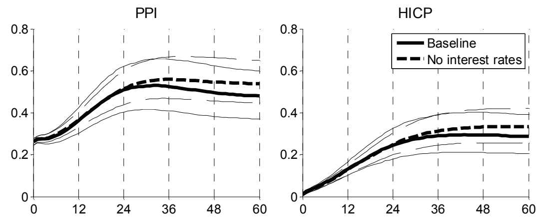
The average pass-throughs are plotted in *Figure 5* together with the baseline full-sample results analyzed previously.[6] The two confidence bands are partially overlapping, with the exception of the PPI response during the first six months, where the recent observations sample shows statistically significant higher pass-through. The median pass-through to PPI difference reaches a maximum gap of about 15 percentage points at the end of second year following the shock, being higher after the crisis, but the gap narrows in the long-run. In the case of consumer prices, the median pass-through coefficients are identical in the short run but are again higher for the shorter sample in the medium to long term (but the differences do not seem to be significant). Using a time-varying parameter VAR model, Franta *et al.* (2014b) found only a marginally larger (but not significantly larger) response of inflation to exchange rate shocks in the Czech Republic.

Recent literature contributions suggest the exchange rate pass-through is likely to be higher during the crisis of the late 2000s. Nogueira Jr. and León-Ledesma (2011) and Ben Cheikh (2013) suggest that in periods of economic distress, increased instability, lower predictability and loss of confidence, firms have more incentives to incorporate exchange rate movements into their prices rather than margins, inducing a higher sensitivity of domestic prices and, correspondingly, a higher pass-through.

[5] A time-varying parameter specification along the lines of Canova and Cicarelli (2013) would be more appealing; this is a topic left for future research.

[6] Individual countries' pass-throughs change similarly to the average ones (not shown).

Figure 6 Average Exchange Rate Pass-Through Estimated In the Baseline and No Interest Rate Models (median and 68% confidence bands)



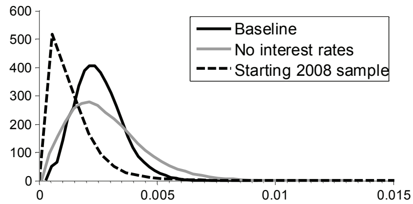
However, this effect can be partially counterbalanced by lower inflationary pressures coming from a negative output gap during the slowdown phase. In the context of the Czech central bank reaching the zero lower bound constraint, Franta *et al.* (2014a) claim exchange rate shocks are propagated faster and stronger, as the interest rate cannot be adjusted in order to absorb part of a shock (it cannot technically decrease below zero and cannot increase since the monetary policy should still be stimulative). Currently, only the Czech National Bank faces the zero lower bound constraint (in addition, in November 2013 it announced a commitment to weaken the koruna to a certain level in order to avoid deflation), but other countries' interest rates are also at historical lows.

The estimated higher pass-through to both producer and consumer prices during the recent crisis period are compatible with the theoretical reasons presented above. Some further arguments are provided by increased openness (except in the case of Romania) and generally lower volatility of real exchange rates during the 2008–2014 period, as presented in *Table 2* (these outcomes are according to McCarthy, 2007, and Coricelli *et al.,* 2006, respectively, as noted in a previous section). A higher pass-through implies domestic prices are more vulnerable to exchange rate shocks, but also that the exchange rate is more powerful as a monetary policy instrument.

4.3 The Model's Robustness to Interest Rate Data and Monetary Policy Shocks

In order to check the robustness of the baseline Panel Bayesian VAR model, we estimate an alternative specification which excludes the interest rate data, a variable which introduces some additional heterogeneity given that an inflation targeting strategy was implemented later in Romania; the levels of central banks' credibility varied across time and countries; and the Czech central bank reached the zero lower bound recently and also committed to depreciate the domestic currency. Monetary policy shocks are also omitted in Beirne and Bijsterbosch (2011) and Alpaslan and Demirel (2014). The resulting pass-through coefficients are plotted in *Figure 6* along with the baseline estimates. The estimated median pass-throughs are roughly identical in the short and medium run, indicating a high level of robustness, and are about five percentage points higher when the interest rates are excluded in the case of both PPI and HICP only in the long run. In addition, in the alternative specification the 68% confidence bands are narrower and partially incorporated into the baseline model ones, suggesting the results are estimated with marginally higher precision for the lower-dimension dataset, most likely due to a slightly reduced level of heterogeneity among units.

Figure 7 Posterior Density of $\sqrt{\tau}$



In *Figure 7* we display the estimated posterior distribution of $\sqrt{\tau}$, which is analyzed in Jarocinski (2010) as a measure of endogenously determined units' degree of homogeneity: a lower value for this hyperparameter implies a lower variance of the individual coefficient priors and, consequently, a higher level of similitude between the countries taken as a group. The peaks of the baseline model and the alternative model, which excludes interest rates, are similar, suggesting the estimated degree of homogeneity of the four CEE countries is roughly uniform. A slightly heavier left tail in the alternative specification is to some degree in agreement with the corresponding marginally narrower confidence bands for the pass-through coefficients reported in *Figure 6*. This result of only a small gain in homogeneity when omitting the interest rates is somewhat unexpected if one takes into account the diverse dynamics among the interest rate series (see *Figure 1*). However, the interest rates seem to be consistent with the respective countries' other variables in the dataset (e.g. a high interest rate in Romania is consistent with high inflation rates of both producer and consumer prices), yielding a roughly similar level of overall homogeneity. Moreover, a higher peakedness and lighter tails (i.e. the distribution is sharper) in the baseline model implies τ is estimated with less uncertainty/higher confidence.

Figure 7 also contains the posterior distribution of $\sqrt{\tau}$ estimated with the crisis sample. Its peak is significantly lower (pushing the model towards full pooling) as compared to the baseline full sample estimate,[7] implying the countries became more integrated and synchronized during and after the crisis. This evidence is supported by the global nature of the recent financial and economic crisis, which affected the four economies roughly simultaneously, through similar channels, and had rather uniform impacts.

5. Conclusions

In this paper we employ a Panel Bayesian VAR model for a group of four Central and Eastern European countries, namely Romania, the Czech Republic, Hungary and Poland, in order to estimate exchange rate pass-through coefficients to producer (PPI) and consumer (HICP) price indices. This method is particularly useful at efficiently combining country-specific and cross-sectional information, mitigating at the same time the small sample problem (which due to the limited time dimension is particularly relevant in the case of emerging economies). In order to deal with

[7] However a warning regarding the reduced number of observations in the crisis subsample, which delivered higher uncertainty for the pass-through coefficients in *Figure 5*, must be mentioned.

the units' heterogeneity, we assume the presence of some fixed effects and allow a data-driven endogenous selection of the tightness hyperparameter that governs the assumption of the common prior distribution for the individual countries' coefficients. Overall, the priors are specified such that conjugacy is preserved, making it possible to take repeated draws from marginal conditional posterior distributions *via* the Gibbs sampler.

The seven-variable baseline model is estimated with data from January 2001––June 2014 and Cholesky factorization for disentangling structural shocks, using a standard identification scheme that imitates the pricing chain. The CEE countries' average exchange rate pass-through to producer prices is larger than that to consumer prices at all horizons: about 0.27 versus roughly no response in the short run and 0.5 versus 0.3 in the long run, respectively. This result is compatible with the distribution chain structure assumed when ordering the variables. Individual countries' coefficients are generally below the group mean for Romania (except HICP) and Poland, while the Czech Republic and Hungary display higher pass-throughs, indicating the need for closer monitoring of nominal exchange rate shocks and volatility, as well as potentially more effective exchange rate transmission channels. The relative levels of pass-through effects are consistent with the countries' degrees of openness and real exchange rate volatilities (as an indicator of monetary policy accommodation).

The estimations using the subsample starting in 2008 show the average median exchange rate pass-through generally increased slightly since the financial crisis started (only the short-run PPI response is significantly higher), implying that the national central banks should take into account that the effects of nominal exchange rate fluctuations on domestic prices prevailing during episodes of increased macroeconomic distress and instability may be stronger than those estimated under "average economic conditions" (given by the full sample estimates). The resulting posterior distribution of the tightness hyperparameter in the subsample estimation is significantly lower, in accordance with the increased synchronization of the CEE countries since the onset of the crisis.

The baseline model is robust to the exclusion of the interest rate data, as the estimated exchange rate pass-throughs are almost identical, being only marginally larger in the long run. As such, a priori prospects of the benefit coming from increased homogeneity of the dataset proved to be limited to only slightly narrower confidence bands for the estimated pass-through coefficients.

REFERENCES

Alpaslan B, Demirel B (2014): Exchange Rate Pass-Through Effect on Prices and Inflation Targeting: A Comparison of Emerging Market Economies. *University Library of Munich, MPRA Paper, no. 53726*.

Beirne J, Bijsterbosch M (2011): Exchange rate pass-through in central and eastern European EU Member States. *Journal of Policy Modeling*, 33:241–254.

Ben Cheikh N (2013): The Pass-Through of Exchange Rate in the Context of the European Sovereign Debt Crisis. *FIW Working Paper*, no. 123.

Ca'Zorzi M, Hahn E, Sanchez M (2007): Exchange rate pass-through in emerging markets. *European Central Bank, Working Paper Series*, no. 739.

Canova F, Ciccarelli M (2009): Estimating Multicountry VAR Models. *International Economic Review*, 50(3):929–959.

Canova F, Ciccarelli M (2013): Panel Vector autoregressive Models. A Survey. *European Central Bank, Working Paper Series*, no. 1507.

Canova F, Dallari P (2013): How Important is Tourism for the International Transmission of cyclical fluctuations? Evidence from the mediterranean. *European Central Bank, Working Paper Series*, no. 1553.

Coricelli F, Jazbec B, Masten I (2006): Exchange rate pass-through in EMU acceding countries: Empirical analysis and policy implications. *Journal of Banking & Finance*, 30(5):1375–1391.

Coulibaly D, Kempf H (2010): Does Inflation Targeting Decrease Exchange Rate Pass-through in Emerging Countries? *Centre d'Economie de la Sorbonne, Working Paper*, no. 49.

Cozmâncă BO, Manea F (2010): Exchange Rate Pass-Through into Romanian Price Indices. A VAR Approach. *Romanian Journal for Economic Forecasting*, 3:26–52.

Doan T, Litterman R, Sims C (1984): Forecasting and Conditional Projection Using Realistic Prior Distributions. *Econometric Reviews*, 3:1–100.

Franta M, Holub T, Král P, Kubicová I, Šmídková K, Vašíček B (2014a): The Exchange Rate as an Instrument at Zero Interest Rates: The Case of the Czech Republic. *Czech National Bank, CNB Research and Policy Notes*, no. 3.

Franta M, Horvath R, Rusnak M (2014b): Evaluating changes in the monetary transmission mechanism in the Czech Republic. *Empirical Economics*, 46(3):827–842.

Gelman A (2006): Prior distributions for variance parameters in hierarchical models. *Bayesian Analysis*, 1(3):515–533.

Jarocinski M (2010): Responses to Monetary Policy Shocks in the East and the West of Europe: A Comparison. *Journal of Applied Econometrics*, 25:833–868.

Jimborean R (2011): The Exchange Rate Pass-Through in the New EU Member States. *Banque de France Document de Travail*, no. 341.

Karagöz M, Demirel B, Bozdağ E (2010): Does Inflation Targeting Reduce Pass-through Effect? *European Journal of Economic and Political Studies*, 21.

Krugman P (1987): Pricing to Market when the Exchange Rate Changes. In: Arndt S, Richardson JD (Eds): *Real Financial Linkages Among Open Economies*. MIT Press, Cambridge, pp. 49–70.

McCarthy J (2007): Pass-Through of Exchange Rates and Import Prices to Domestic Inflation in Some Industrialized Economies. *Eastern Economic Journal*, 33(4):511–537.

Nogueira RP Jr, León-Ledesma MA (2011): Does exchange rate pass-through respond to measures of macroeconomic instability? *Journal of Applied Economics*, XIV(1):167–180.

Pedroni P (2013): Structural Panel VARs. *Econometrics*, 2:180–206.

Przystupa J, Wróbel E (2009): Asymmetry of the exchange rate pass-through: An exercise on the Polish data. *University Library of Munich, MPRA Paper*, no. 17660.

Razafimahefa I (2012): Exchange Rate Pass-Through in Sub-Saharan African Economies and its Determinants. *International Monetary Fund Working Paper*, no. 141.