MODELING UNCERTAINTY IN PARTIAL EQUILIBRIUM MODELS THROUGH A PANEL VAR

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ABSTRACT: A Panel VAR model is proposed to estimate the underlying model that governs the baseline projections on macroeconomic drivers in Partial Equilibrium (PE) models. The panel VAR is then used to provide forecasts and a confidence interval by Monte Carlo simulation methods, that further on will feed the PE model to obtain alternative future paths for agricultural markets.

KEY WORDS: *PE model, stochastics, VAR, forecast, uncertainty.*

1. INTRODUCTION

Partial Equilibrium Models (PE) are used to evaluate ex-ante the impact on agricultural markets of specific policies in the medium-run (up to 10 years). This is done by comparing the results of the PE simulation that includes the policy shocks, with a 'baseline' that represents the future path of the markets in absence of that policy. Projections obtained with the PE simulation are conditional on the future values of exogenous variables. Among these, macroeconomic variables, such as GDP growth, inflation and exchange rates, or oil prices, play an essential role, as they enter different supply and demand equations in the PE model. Burrell & Nii-Naate (2013) initiated a methodology to incorporate uncertainty in macroeconomic drivers in 10 regions (also yields) into the AGLINK-COSIMO model which is used in two yearly reports: OECD-FAO "Agricultural Outlook" and the European Commission "Prospects for the EU agricultural markets and income". In their original approach, random draws are generated from a multivariate Normal distribution with covariance estimated from one year ahead projection errors. For further projection horizons, errors are temporarily accumulated, while an ad-hoc down-weighting is used in some variables to avoid unrealistic negative values. For each draw, an alternative value for the macroeconomic variable at the baseline for different time horizons is obtained, and the PE model is solved. The objective of this paper is to present some work in progress that explores an alternative methodology for stochastic partial equilibrium models. In particular, the proposal tries to exploit the regularities observed among the variables themselves rather than the projection errors.

2. METHODOLOGY AND DATA

2.1. Overview

In the current methodology the dynamic and long-run interrelationships between variables are neglected, leading to some implausible sets of macroeconomic conditions, which in turn, may cause convergence failure in the PE solution. A Vector Autoregressive Model (VAR) would allow to restrict the joint evolution of macro-variables. Basically, a VAR is a multi-equational model, where each endogenous variable depends on its own past and the past of the rest of the variables in the system. VAR models have been used since the seminal work by Sims (1980) as a tool for economic forecasting and understanding of the dynamic interdependencies using a minimal set of restrictions. When variables are I(1) (i.e. integrated of order 1), that is, non-stationary but whose trend can be removed by differencing, they can also be co- integrated (Engle and Granger, 1987) i.e. they keep a meaningful long-run equilibrium relationship. In this case, a VAR in levels or differences would be misspecified, and a Vector Error Correction Model (VECM), that incorporates both, short and long-run linkages, is more appropriate.

An intherent problem of VARs is overparameterization that can exhaust degrees of freedom in single country models. Alternatively, panel VARs have been developed for situations when time exceeds the cross-unit dimension. The simplest approach in this context is Least Squares Dummy Variable (LSDV), which introduces a country fixed effect in each of the equations, while leaves the dynamics constant across units. In recent years, panel or multicountry VAR models have been developed, in particular, in macroeconomic analysis to examine economic issues in interdependent economies (see Canova and Ciccarelli (2013) for a survey). Increasing degrees of flexibility (accompanied by complexity in estimation) can be achieved by, for instance, allowing for lagged interdependencies across countries, what implies normally using Bayesian techniques.

Our goal in this paper, however, is less ambitious. We aim at estimating a Panel VAR model that takes into account the dynamic and long-run interdependencies of the macroeconomic variables of interest, respecting their time series properties (non-statitionarity). We try to replicate an underlying model that could generate forecasts as close as possible to the projections in the baseline, and use that model to provide the error bands for the forecasts. In computing such error bands, we use Monte Carlo simulation methods which take coefficients uncertainty into account. 500 draws have been used, and for each of them, a Variance-Covariance matrix of the residuals and a vector of coefficients is obtained, for which new forecasts are generated (see Doan, 2010, p.37, for a detailed explanation).

2.2. Data

Historical data for the period 1996 to 2013 (T=18) and ten countries (n=10)[1] for four macroeconomic variables and oil prices come from the OECD Economic Outlook (2014) (see Table 1), and the baseline data for the period 2014-2023 comes from AGLINK's last baseline. All variables are converted into logs.

[1] Countries are: Australia, Brazil, Canada, China, India, Japan, New Zealand, Russia, USA and EU15.

Table 1. Description of variables.

Acronym	Description
GDPI	Gross domestic product, volume, at 2005 PPP, US Dollar
GDPD	Gross domestic product, deflator, market prices
CPI	Private final consumption expenditure deflator
XR	Exchange rate, national currency per US Dollar
XP	Crude oil price, fob, spot Brent, US Dollars

3. RESULTS

A first step in the specification of a VAR model is an analysis of the univariate properties of the series through unit roots tests and if the series are found to be integrated of order 1 (I(1)) as it is usually the case with macroeconomic variables, cointegration tests need to be applied. Both tests suffer from poor size and power properties when applied to time series of moderate length, and this has prompted the development of panel tests. We restrict ourselves to two panel unit root tests: Im, Pesaran and Shin (2003) (IPS) and Hadri (2000); and one for panel cointegration test (Westerlund, 2007). Equivalent tests without the panel dimension are applied for the oil price. Unit roots tests show a clear evidence in favour of the presence of a unit root in every variable. The panel cointegration test by Westerlund (2007) tests the null of no cointegration through the significance of the error correction term. The test is flexible to accommodate unit-specific parameters, but it is restricted to pairs of variables. In most of the pairs among our variables, we find a lack of cointegration or very weak evidence. Strong evidence of cointegration is found between real GDP and exchange rate, and only weak between GDPD and CPI, CPI and exchange rate.

Provided the little evidence on cointegration, we proceed with a panel VAR instead of a VECM, while following the result on unit roots, the VAR is specified in first differences. In this first attempt, only country fixed effects are included, although future work should contemplate more general specifications. Oil price is considered as exogenous and the remaining four macro variables, as endogenous. Two lags, selected with AIC are included, and oil price also includes contemporaneous changes. Accordingly, the final sample size is 150 observations (15 years×10 countries).

Static forecasts, from one to 10 periods ahead are generated, for the period 2014-2023, using two alternative paths for oil price: i) the baseline projections; ii) a random walk. A graphical comparison between static forecasts (undoing differences and logs) and the baseline shows a remarkable likeness between them even when simulated rather than baseline oil prices are employed in forecasting. Table 4 summarizes the deviations between Panel VAR forecasts and baseline projections. Across macroeconomic variables, main divergences are found in Exchange Rate, with a mean deviation of 5.8% when simulated oil prices are used, and 2.6% when the baseline data is used instead. Across countries, main differences are found in Russia for both deflators and exchange rate. Exchange rate in Russia seems especially problematic, as a deviation of 19%-20% is found.

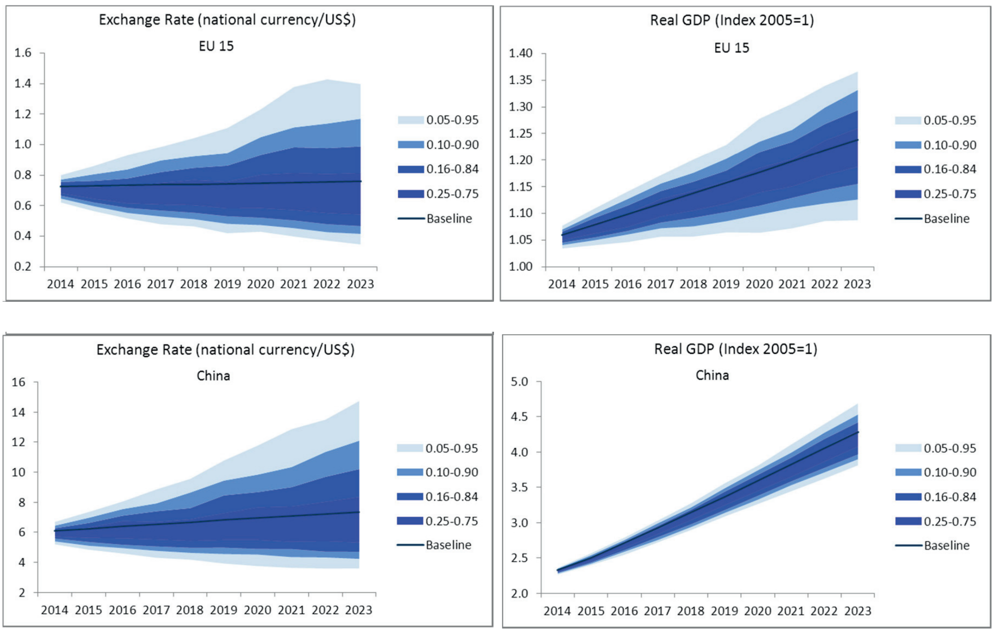
Table 4. Mean deviation of the Panel VAR model forecasts over baseline projections (%).

	Oil price simulated				Oil price baseline			
	GDPI	GDPD	CPI	XR	GDPI	GDPD	CPI	XR
AUS	1.7	1.3	0.6	8.6	2.4	0.6	0.8	7.6
BRA	2.3	4.0	2.9	1.9	3.0	2.5	2.4	2.8
CAN	1.0	0.7	1.2	7.5	2.0	1.6	1.4	6.5
CHN	3.7	3.5	2.3	4.4	2.5	2.0	2.7	3.0
EU15	2.4	2.3	0.4	3.9	3.4	3.6	0.5	3.0
IND	0.7	1.6	1.3	3.0	1.1	1.4	1.0	1.7
JPN	0.9	5.7	4.6	2.7	0.9	6.9	4.8	2.8
RUS	0.8	19.3	12.7	19.0	0.6	17.6	12.0	20.6
USA	4.6	2.9	1.0	1.6	5.7	4.7	1.3	2.5
Mean	2.0	4.6	3.0	5.8	2.4	4.5	3.0	5.6

Note: Absolute deviations between forecast (F) and baseline (B) data, for each forecast horizon(h) are calculated, and then averaged, for each country c: .

Given the proximity beween the Panel VAR forecasts and the PE model baseline, we proceed with the calculation of the confidence interval of forecasts errors by Monte Carlo simulation. As an example, Graph 1 shows the baseline and 90% confidence interval for exchange rate and real GDP in China and the EU15.

Graph 1. Confidence interval of the baseline based on static forecasts generated by a Panel VAR



Note: the bands have been scaled to equal the median of simulated values to the baseline projection

4. CONCLUSIONS

In absence of a confidence band around the macroeconomic baseline projections used in PE models (AGLINK-COSIMO in particular), a Panel VAR model is proposed in order to simulate error bands around forecasts. Even with the simplest approach, the VAR model generates forecasts that are close to the baseline projections used in the AGLINK model, and error bands seem to avoid unrealistic negative values obtained in some of the macro variables with the current stochastic PE approach.

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