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Keywords: Bayesian Vector-Autoregression, Structural Vector-Autoregression, External Shocks, Emerging Markets

JEL classification: F37, F43

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The Effects of External Shocks on Business Cycles in Emerging Asia: A Bayesian-VAR Model*

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January 17, 2011

Abstract

In this paper, we analyze the effects of external shocks on countries in emerging Asia. For this purpose, we estimate a Bayesian vector autoregressive model (BVAR) with an informative prior on the steady state, with variables representing world economic activity, financial conditions, Chinese GDP and an aggregate GDP index of eight East Asian countries. We show that almost half of the forecast error variance in emerging Asia's real GDP growth can be explained by external factors. We also conduct an estimation of a classical VAR model using maximum likelihood estimation and a traditional BVAR. An out-of-sample forecast evaluation shows that the BVAR with an informative prior on the steady-state outperforms both, the classical VAR and the traditional BVAR. Finally, we simulate a double dip scenario for the world economy and a muted growth path for the Chinese economy using conditional forecasts and show that the economic outlook in emerging Asia highly depends on the growth path of the world economy and remarkably little on business cycle fluctuations in China.

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1 Introduction

The economic performance of most countries in East Asia (henceforth Emerging Asia) has been overwhelming in the wake of the Asian Crisis in 1998. Even in the recent great recession, most of the countries in the region, unlike the industrialized countries, only had to pocket a short period of output loss. Some countries, like Indonesia, did not record any recession at all. Many observers have claimed that emerging Asia fully decoupled from the industrialized nations in the last decade, and there is some evidence to support this. In the *Asia Economic Monitor*, the Asian Development Bank (ADB (2010)) shows that the Asian recovery from the great recession has been driven by the region's own economic demand — especially by the tremendous rebound in intraregional trade. The region is also less dependent on foreign capital than before. The impact of the European debt crisis has been minimal: bond yields have fallen but capital continues to flow in. However, it is often claimed that the region is still exposed to external shocks, since it depends to a large degree on exports. Export-to-GDP-ratios of the countries have reached levels up to 200 percent.[1] Several countries in the region continue to undervalue their currencies, making it difficult to move away from industrialized world's demand and toward domestic consumption. Monetary and fiscal stimulus packages have largely driven Asia's blistering growth in 2010, but if the United States and the Eurozone continue to face muted growth rates, it is uncertain what emerging Asia's growth path will look like in the near future.

This paper is a contributes to shedding light on the possible outcomes of the economic activity in emerging Asia if external conditions worsen. In fact, this paper contributes to the discussion of how much the countries in emerging Asia can be expected to decouple. In order to answer this question, we estimate a Bayesian Vector Autoregressive model (BVAR) with an informative prior on the steady state, i.e., the mean-adjusted BVAR suggested by Villani (2005). The reason for our choice of methodology is straightforward. Due to structural changes in the countries being analyzed, e.g., increasing openness, liberalization, and institutional changes, econometric estimation is limited to a short period of time. A classical VAR typically suffers from a generous parameterization, causing a loss in estimation precision, particularly if the estimation is based on a short data sample. In a standard Bayesian VAR, this problem is mitigated by imposing an informative prior

[1] We are aware that Singapore and Hong Kong are exceptions because of their small country size. Nevertheless, the other countries in the sample also exhibit higher-than-average export-to-GDP ratios.

on the dynamic coefficients of the model. However, by applying the model suggested by Villani (2005), we also impose an informative prior on the constant of the model. This should yield an additional gain in estimation precision since the prior makes it more likely that forecasts will converge to levels judged sensible by the forecasters.[2]

The remainder of the paper is organized as follows. In Section 2, we review the literature that is related to our analysis. In Section 3, we derive the baseline model used for the estimation. In Section 4, we present the results of our analysis. In this section, we first conduct an impulse-response analysis and a variance decomposition. We then compare a standard VAR, a traditional BVAR, and the mean-adjusted BVAR with one another in terms of out-of-sample forecast performance. Finally, we provide scenarios for emerging Asia based on conditional forecasts. Section 5 briefly concludes.

2 Literature Review

The belief that external shocks have an important impact on Emerging Market Economies (EME) goes back to Calvo et al. (1993). Using a structural VAR, they find that external shocks explain a large fraction of the variance in the real exchange rate in Latin American countries during the period 1988 - 1991. Based upon this study, Canova (2005) investigates how U.S. shocks are transmitted to eight Latin American countries. He uses a VAR model with sign restrictions on the impulse responses and finds that a monetary policy shock in the U.S. is transmitted fairly quickly to Latin American countries. Genberg (2005) analyzes the impact of external shocks on inflation in "small" Asian countries, using a theoretical model and a classical VAR approach. He finds that external shocks explain much of the variance in inflation in six Asian countries, namely Taiwan, Hong Kong SAR, Singapore, Thailand, the Philippines, and Korea, nearly all of which is accounted for by the United States, not China. In addition, during the period 1999-2002, movements in inflation are well explained by external shocks. Kim (2001) develops a structural VAR, estimating the effects of U.S. monetary policy shocks on the non-U.S. G-7 countries.[3] He finds that spillover effects of U.S. monetary policy shocks on the non-U.S. G-7 countries are rather negligible. This coincides with the idea that EME are more vulnerable to external shocks than large and developed economies. A study close related to ours is the study by Mackowiak (2007), in which he analyzes the impact of

[2]See Österholm and Zettelmeyer (2008).

[3]See, for comparison, also Kim (1999) and Kim and Roubini (2000).

external shocks on EME using a structural VAR model. He finds that U.S. monetary policy shocks affect interest rates and the exchange rate in a typical emerging market country quickly and strongly. Sato et al. (2009) analyze the impact of external shocks for east Asian countries from the perspective of a currency union using a structural VAR. They find that the influence of a U.S. shock is still playing a dominant role in real output fluctuations in the East Asian region. Additionally, through trade and investment, also China has become a regional key-country candidate.

In this paper, we use a methodology similar to the methodology used in the study by Österholm and Zettelmeyer (2008) and Beechey and Österholm (2008), both of which use the methodology of Villani (2005) with an informative prior on the steady state. As we do, Österholm and Zettelmeyer (2008) also find that the mean-adjusted BVAR outperforms both the standard BVAR and the traditional VAR with respect to out-of-sample forecast performance. The method of using an informative prior in BVAR models has recently also been used by other researchers. Christoffel et al. (2010) run the BVAR with data for the European Monetary Union against the New Area Wide Model (NAWM) of the ECB[4], a small VAR, and a large scale BVAR, and compare all models with respect to out-of-sample forecast performance. They find that the BVAR with an informative prior outperforms the NAWM, especially at a longer forecast horizon.

3 The Model

3.1 Methodology

With a Bayesian estimation, a prior probability density function is specified for the parameters to be estimated. The specification is based on non sample information. A prior probability distribution is considered informative when the main part of the probability mass is centered relatively tight around a particular value. Accordingly, the distribution is considered non informative when this is not the case. Sample information is summarized in the likelihood function. From the combination of these two probability density functions, an updated density function is derived for the parameters. The specific shape of this posterior probability density function depends on the sample observations.

The general Bayesian VAR model has the following form:

[4]The NAWM is a large-scale DSGE model that has been designed for use in the macroeconomic projections conducted at the European Central Bank.

$$G(L)x_t = \mu + \eta_t, \tag{1}$$

where $G(L) = I - G_1 L - \cdots - G_p L^p$ is a lag polynomial of order p, x_t is an $(n \times 1)$ vector of stationary macroeconomic variables, and η_t is an $(n \times 1)$ vector of i.i.d. error terms fulfilling $E(\eta_t) = 0$ and $E(\eta_t \eta_t') = \Sigma$.
However, with the general VAR model (1) it is difficult to come up with a prior distribution for μ. This problem has typically been solved by imposing a non informative prior on these parameters. Indeed, it is possible to specify an analogous informative prior if the parameterization of the model is altered in a particular way. Consider the following model:

$$G(L)(x_t - \Psi) = \eta_t, \tag{2}$$

where $G(L)$, x_t, and η_t are defined as above. This model is a special case of the so-called mean-adjusted VAR model used by Villani (2005).[5] It is non-linear in its parameters. Now Ψ represents the steady-state of the variables in the system. That is why it is relatively easy to come up with an informative prior distribution for these parameters. The principle form of the prior that we impose on each Σ, G_1, ..., G_p and Ψ is as follows:

$$p(\Sigma) \propto |\Sigma|^{-(n+1)/2},$$

$$vecG \sim N_{pn^2}(\theta_G, \Omega_G),$$

$$\Psi \sim N_n(\theta_\Psi, \Omega_\Psi).$$

The prior on Σ is non informative, whereas the multivariate normal distributions are informative. The priors on G and Ψ are assumed to be independent from each other. The corresponding joint posterior distribution is analytically intractable. However, the posterior distribution of each set of coefficients conditional on the remaining coefficients is tractable. Applying the Gibbs sampling numerical method, as suggested by Smith and Roberts (1993), to these conditional posteriors generates a sample of draws from the intractable joint posterior. The corresponding full conditional posterior distributions are as follows.

[5] We will refer to model (2) as the mean-adjusted VAR in the following.

Conditional posterior for Σ:

$$\Sigma | G, \Psi, X_t \sim IW(E'E, T),$$

Conditional posterior for G:

$$vecG | \Sigma, \Psi, X_t \sim N_{n^2p}(\overline{\theta}_G, \overline{\Omega}_G),$$

Conditional posterior for Ψ:

$$\Psi | \Sigma, G, X_t \sim N_n(\overline{\theta}_\Psi, \overline{\Omega}_\Psi),$$

where $X_t = \{x_1, ..., x_t\}$, T is the length of the data sample and E, $\overline{\theta}_G$, $\overline{\Omega}_G$, $\overline{\theta}_\Psi$, and $\overline{\Omega}_\Psi$ are defined as in Villani (2005). Iteratively sampling from this three-block Gibbs sampler, always conditioning on the most recent draw of coefficients, yields an empirical distribution converging to the target joint posterior distribution.

The prior on the dynamic coefficients is also a multivariate normal distribution. We impose a slightly modified version of the Minnesota prior suggested by Litterman (1986). In the traditional Minnesota prior, means on the first own lag of variables modeled in levels are set to one. However, we set them to 0.9 to make the prior theoretically consistent with the mean-adjusted model (2). All remaining means are set to zero, i.e., means on the first own lag of variables modeled in differences, means on all higher-order lags, and means on all cross-coefficients. The coefficients are assumed to be independent from one another so that all covariances in Ω_G are zero. The prior standard deviation for the coefficient on lag l of variable j in equation i equals

$$\delta_{ij}^l = \lambda_b / l \text{ if } i = j,$$

and

$$\delta_{ij}^l = \theta \lambda_b \hat{\sigma}_i \lambda_e^{I_i(j)} / l \hat{\sigma}_j \text{ if } i \neq j,$$

where $\lambda_b > 0$, $0 < \theta \leq 1$ and $0 < \lambda_e \leq 1$. Overall tightness is determined by λ_b. Hyperparameter θ assures that the coefficients on lags of variables other than the dependent variable are distributed more tightly around zero. The reason for this is that all variables are assumed to be affected stronger by own lags. Hyperparameter λ_e determines how much more tightly a coefficient is distributed around zero if the respective variable is assumed to have no impact on the dependent variable. $I_i(j)$ is the corresponding exogeneity indicator. It equals one if variable j is assumed to be exogenous in equation

i and zero otherwise. Parameter $\hat{\sigma}_i$ ($\hat{\sigma}_j$) is the estimated standard error of the residuals in an unrestricted univariate autoregression of variable i (j). The residuals account for the fact that variables in the data are scaled differently.

3.2 Empirical Implementation

As pointed out by Mackowiak (2007), important external factors driving the business cycles in EME are U.S. monetary policy shocks and real economic activity in the United States. In order to account for the increasing integration in the world economy, we decide to use an index of world economic activity in our estimation. The 3-month treasury bill rate can be seen as a world interest rate. In order to include general financial conditions, we choose the Chicago Board of Trade Volatility Index (VIX), which can be interpreted as risk perception. We also include the real GDP growth of China in our estimation to account for the emerging Asia's dependence on China. After determining the order of integration, the vector of stationary macroeconomic variables is given by:

$$\mathbf{x}_t = \begin{pmatrix} \Delta y_t^{world} \\ i_t^{US} \\ VIX_t \\ \Delta GDP_t^{CH} \\ \Delta y_t^{ASIA} \end{pmatrix}, \tag{3}$$

where Δy_t^{world} is the growth rate of world GDP, i_t^{US} is the 3-month treasury bill rate, VIX_t is the trade volatility index, ΔGDP_t^{CH} is the growth rate of Chinese GDP, and Δy_t^{ASIA} is the growth rate of GDP in emerging Asia.

The data used in our estimation are quarterly data collected from various sources. We calculate world GDP using disaggregated data for 48 countries and weight it with GDP at market prices to obtain a world real GDP index. The U.S. 3-month treasury bill rate is the money market rate, taken from the International Financial Statistics (IFS) database, provided by the IMF. The VIX is taken from the Chicago Board Options Exchange. The time series for Chinese real GDP is a series constructed by Abeysinghe and Rajaguru (2003). It is constructed using the year-on-year changes of real GDP and rewriting it to quarter-on-quarter changes. For the real GDP data for Hong Kong, South Korea, Malaysia, and Thailand, we use time series provided by the IFS. The first three are volume indices with the base year 2000. The latter is denominated in Thai bahts at constant prices with the base year

1998. The time series for real GDP for Indonesia is taken from the OECD database Main Economic Indicators. The time series is denominated in Indonesian Rupiah at constant prices with the base year 2000. The data for the remaining countries are collected from national sources. Real GDP for Taiwan is taken from the DGBAS at 2006 prices in new Taiwanese dollars, for Singapore data are taken from the Department of Statistics in Singapore dollars at 2006 prices and data for the Philippines are taken from the National Statistics Coordination Board at 1985 prices in Philippine pesos. Seasonally adjusted data are only directly available for Indonesia, Singapore, and the Philippines. The time series of the remaining countries have been seasonally adjusted using the ratio-to-moving-average approach that is employed by Datastream.[6]

In order to conduct the estimation of model (2), specific priors have to be chosen for the steady state values of Ψ and G. The means and standard deviations of the priors and the posteriors for the unrestricted Bayesian VAR are presented in Table 1.

Table 1: Prior and posterior distributions of the unrestricted VAR

		Prior		Posterior	
		Mean	95 % conf. interval	Mean	95 % conf. interval
World GDP	Δy_t^{world}	2.5	[2.0; 3.0]	2.68	[2.48; 2.88]
3-m treasury bill rate	i_t^{US}	4.0	[3.0; 5.0]	3.75	[4.20; 3.28]
VIX	VIX_t	20.0	[10.0; 30.0]	20.83	[19.13; 22.53]
Real GDP China	ΔGDP_t^{CH}	8.25	[7.0; 9.5]	9.13	[8.79;9.47]
EA growth rate	Δy_t^{ASIA}	5.5	[3.5; 7.5]	4.42	[3.93;4.91]

Source: Authors' calculations.
Notes: The values for world GDP, real GDP China and the EA growth rate are expressed in percent at annualized rates. The data for the U.S. 3-m treasury bill rate is expressed in percent.

World GDP is assumed to have a steady-state growth rate of 2.5 percent and is assumed to follow a relatively tight distribution, since deviations from the long-run trend are usually rather small. This value is in line with the medium-term projections in the IMF World Economic Outlook. The steady-state prior for the 3-month treasury bill rate is chosen to be 4 percent, which corresponds to the U.S. inflation target and an equilibrium real interest

[6] This approach first takes the ratio of the data to a centered one-year moving-average each quarter, excluding the first two and last two quarters, and then uses the five-year centered moving-average of this ratio to adjust the original data. The first two and last two quarters of the data are adjusted by the adjacent five-year moving-averages (See Harris and Yilmaz (2008)).

rate of approximately 2 percent each.[7] We do not have prior information from theory for the trade volatility index. We therefore take a somewhat longer sample and take the mean average of that longer sample as prior information. Additionally, we impose a rather diffuse prior with a wide distribution around the prior mean. The steady-state of real GDP in China is set to 8.25 percent, which corresponds to the growth interval forecast in Holz (2005), who analyzes the growth potential of China until 2020. The steady-state real GDP growth rate of Emerging Asia is chosen to be 5.5 percent, which is an average value of the sample from 1993 to 2010 excluding the sharp recession associated with the Asian crisis.

We choose the following values for the hyperparameters: $\lambda_b = 0.1$, $\theta = 0.5$, and $\lambda_e = 0.1$. We employ a lag order of four. In order to obtain the sample from the joint posterior distribution of the coefficients, we employed 10,000 iterations of the Gibbs sampler. We identified independent standard normal shocks based on the estimated reduced form shocks, using a standard Cholesky decomposition of the variance-covariance matrix. That is, we used the relationships $\Sigma = PP'$ and $\varepsilon_t = P^{-1}\eta_t$ with the variables ordered as in (3). For each variable the shock magnitude equates one standard deviation.

4 Results

4.1 Impulse Responses and Variance Decompositions

The responses in Figure 1 have been estimated on the basis of the model with block exogeneity, where the coefficients for the dynamic impact of Asian GDP on the remaining variables have been given a tighter prior distribution according to hyperparameter λ_e. It can be seen in figure 1 that an upturn in world GDP has a significant positive hump-shaped impact on the interest rate and on China's and Emerging Asia's GDP.[8] An increase of world GDP of 0.5 percentage points results in an increase of real GDP of 0.4 in an average Emerging Asia country whereas the impact seems to be slightly smaller for China. A tightening of financial conditions has a negative impact on real GDP in Emerging Asia. After both a contractive interest rate shock and a worsening in financial conditions (an increase in the VIX), the responses are significant and persistent. Interestingly, a worsening in financial conditions has an even stronger negative impact on China than on emerging Asia.

[7] See Österholm and Zettelmeyer (2008) and Clarida et al. (1999).

[8] Note: Shocks are in columns, responding variables are in rows. The confidence bands are 50 % and 95 %.

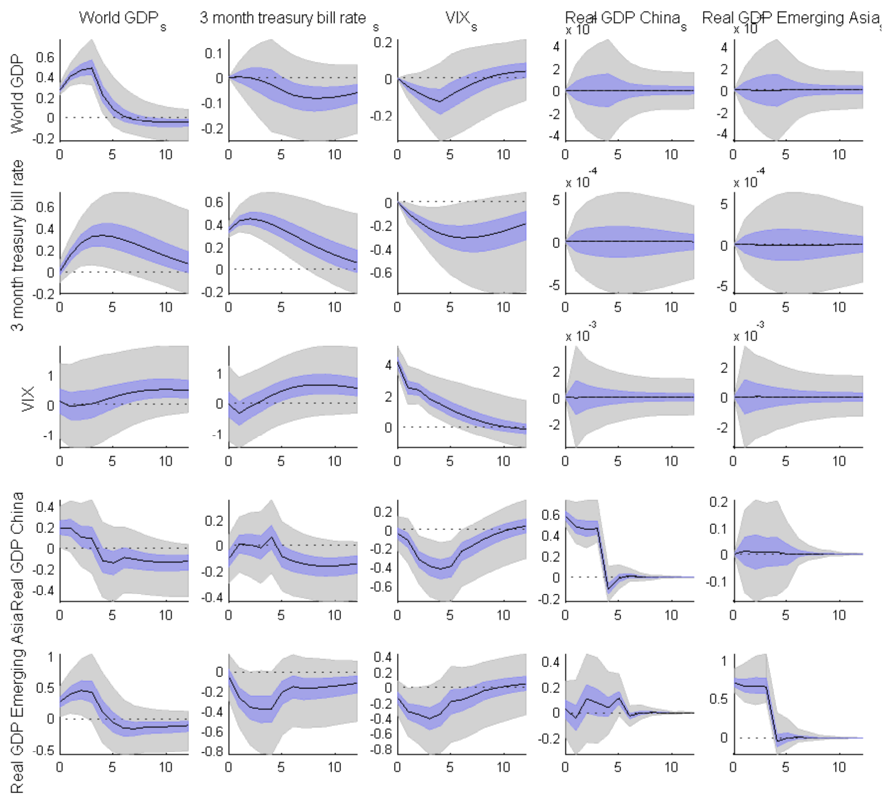

Figure 1: Impulse response functions of the Bayesian VAR with informative priors

The impact of China's GDP on economic activity in Emerging Asia seems to be rather limited in the model. Real GDP responds with a few lags and its impact is rather muted. A 0.5 percentage points increase in China's GDP results in only a 0.2 percentage point increase in emerging Asia's GDP. The impulse-response analysis shows that economic activity in Emerging Asia depends to a large extent on external factors such as world output and financial conditions.

In order to analyze how much external shocks contribute to growth in emerging Asia, we compute a variance decomposition, illustrated in figure 2.[9] Almost half of the forecast error variance in emerging Asia's real GDP growth can be explained by external factors. Shocks from world GDP contribute about 25 percent over the medium term. The U.S. short-term inter-

[9]Note: Shocks are in columns, responding variables are in rows. The confidence bands are 50 % and 95 %.

est rate and financial conditions contribute about 15 percent each, whereas China's real GDP just adds less than 10 percent.

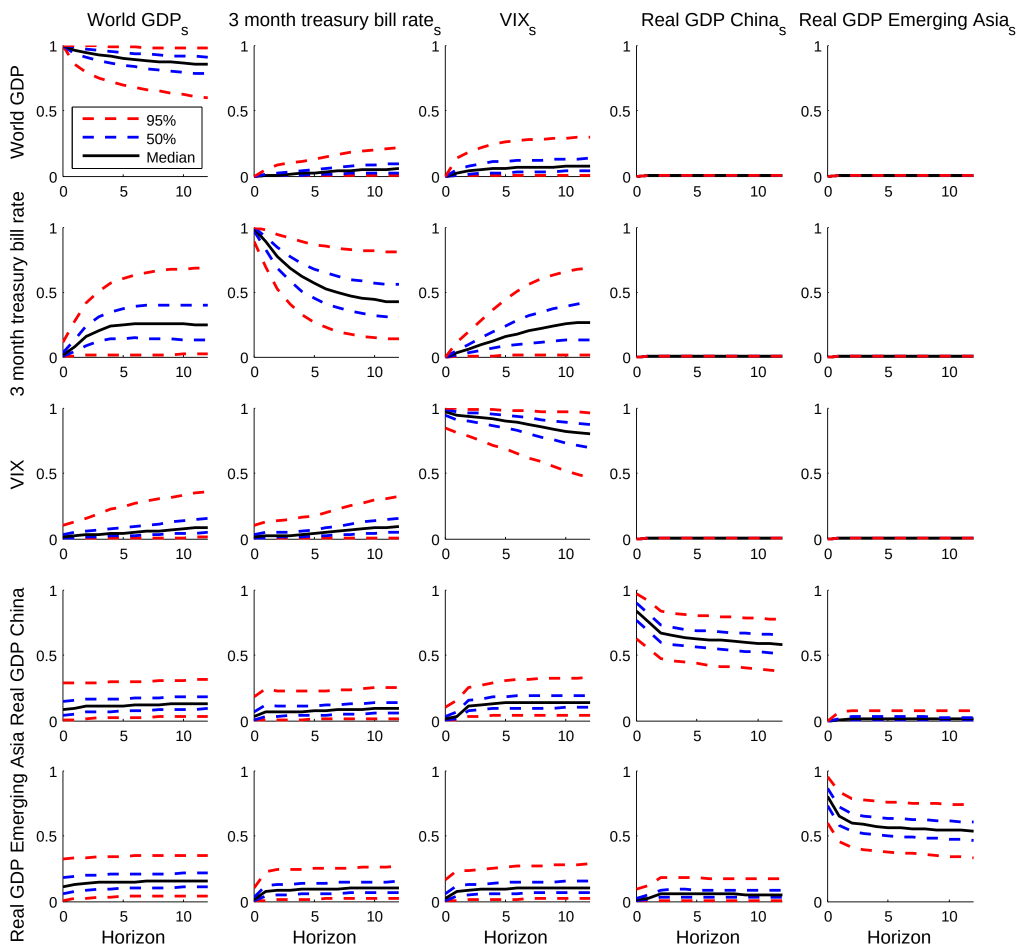

Figure 2: Variance decomposition of the Bayesian VAR with informative priors

4.2 Out-of-Sample Forecasts

In order to obtain some evidence on the superiority of the mean-adjusted BVAR, we compare the model with the corresponding standard VAR and traditional Bayesian VAR in terms of out-of-sample forecast accuracy. The forecasting performance of the models is evaluated using the horizon h root mean squared error (RMSE), given by

$$RMSE_h = \sqrt{N_h^{-1} \sum_{t=1}^{N_h} (x_{t+h} - \hat{x}_{t+h,t})^2} \tag{4}$$

where x_{t+h} is the actual value of variable x at time $t+h$ and $\hat{x}_{t+h}$ is an h step ahead forecast of x implemented at time t.

We want to evaluate the forecasting performances for all quarterly horizons between one and 12. Therefore, we first estimate all three models using data from 1993:Q2 to 2003:Q3 and generate forecasts over all 12 horizons. Then we consecutively extend the estimation sample by one quarter and do the same until the estimation sample comprises 2006:Q4. Thereafter we forecast over consecutively shorter periods since from this point on there would be no data to compare the longer forecasts with. We get 13 forecasts and therewith 13 squared errors at the 12 quarter horizon, 14 squared errors at the 11 quarter horizon, 15 squared errors at the 10 quarter horizon, and so on. At the one-quarter horizon, we finally get 24 squared errors. Using all of these, we compute the corresponding mean squared errors for all 12 horizons.

In order to get a clear picture of the comparative performance of all three models, *relative* RMSEs are computed for all horizons h, which are defined as

$$RR_h = \frac{RMSE_{ma,h}}{RMSE_{alternative,h}}, \tag{5}$$

where $RMSE_{ma,h}$ is the RMSE of the mean-adjusted model at horizon h and $RMSE_{alternative,h}$ is the RMSE of the traditional BVAR or the standard VAR, as the case may be. Figure 3 shows the relative RMSEs at horizons 1-12 for all variables in the system except for the volatility index, which is not interpretable by implication. Including the volatility index in the computation does not change the quality of the overall results in any way, which are explicated in the sequel.[10] The blue (green) line illustrates the relative RMSE of the traditional BVAR (classical VAR) at each forecasting horizon for each variable. So whenever this line is below the level of one, the performance of the corresponding model is worse than the mean-adjusted BVAR. Hence, the constant red line at the level of one can be regarded

[10]The results for the volatility index can be provided on request.

as representing the forecasting performance of the mean-adjusted BVAR. Consequently, the following simple rule applies: the higher the line, the better the performance of the respective model.

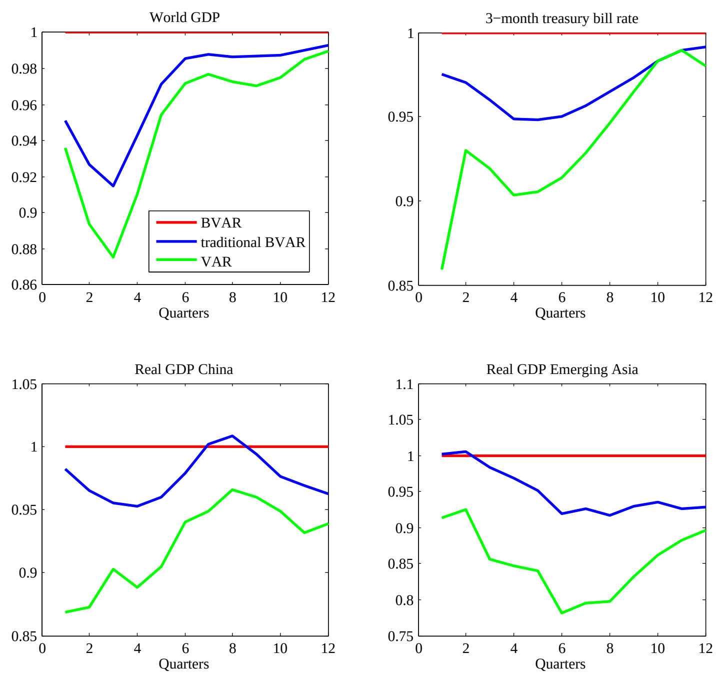

Figure 3: Relative root mean squared erros of the models

The general picture is unambiguous: the mean-adjusted BVAR by far outperforms the traditional BVAR, which again by far outperforms the classical VAR.[11] There are three insignificant exceptions. (1) For the 3-month treasury bill rate, the traditional BVAR and the classical VAR perform equally well at horizons of ten and eleven quarters. (2) For China's GDP the traditional BVAR performs slightly better than the mean-adjusted BVAR at horizons of seven and eight quarters. (3) For emerging Asia's GDP, the traditional BVAR again performs slightly better than the mean-adjusted BVAR at horizons of one and two quarters. Nevertheless the overwhelming advantage of the mean-adjusted BVAR is evident. This implies that in all parts of our analysis — i.e., the impulse response functions and forecast error variance decompositions from above as well as the scenario analysis in the following subsection — the results can be expected to be much more

[11] This holds also true for the volatility index.

accurate than if the estimations were based on more conventional models.

The unconditional forecasts (of the endogenous variables) for the mean-adjusted BVAR are presented in Figure 4. It can be seen that, according to our model, world GDP growth will fall to three percent for the three years to come. Over the same period, U.S. short term interest rates are expected to continuously rise back up to two percent, to levels seen before the crisis. China's and Emerging Asia's GDP both behave similarly to world GDP. Their growth rates stabilize at a lower level than at present. However, an "overshooting" in the wake of the crisis is more pronounced.

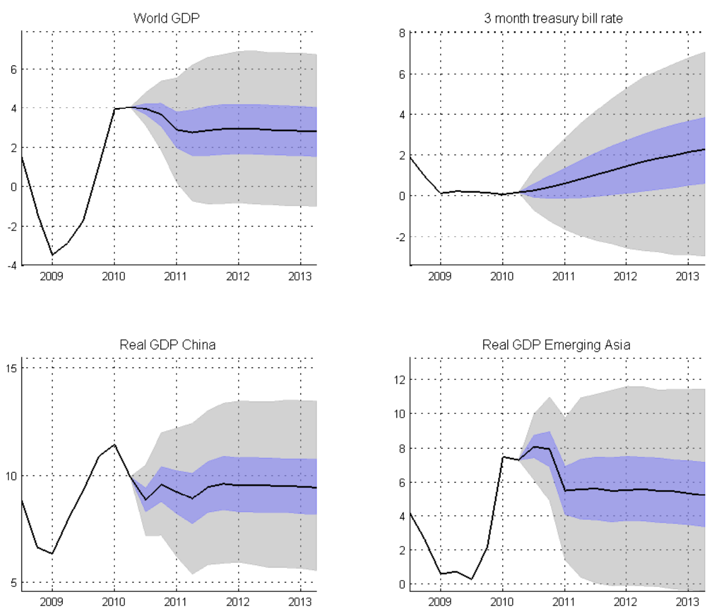

Figure 4: Unconditional forecasts of the mean-adjusted BVAR

4.3 Scenarios Based on Conditional Forecasts

In this section, we implement two conditional forecasts scenarios for emerging Asia's GDP that are based on prespecified paths for a subset of the endogenous variables. Foremost, we simulate the impact of a double dip in the world economy that is associated with a continuing phase of low interest rates, and a decelerated economic activity in China. Subsequently, we simulate the effects of a growth slowdown in China on emerging Asia's GDP.

4.3.1 Effects of a Double Dip in the World Economy

Using the mean-adjusted BVAR model, we produce forecasts conditional on prespecified paths for a subset of the endogenous variables. In the first scenario, we assume that world GDP growth remains muted for the forecasting horizon. Additionally, we assume that the Federal Reserve keeps the interest rate at a low level until the end of the forecast horizon. We let China's GDP and emerging Asia's GDP respond endogenously to the slowdown in world GDP. According to the model, economic stagnation of world GDP would result in a deceleration of GDP in China to a growth rate of about 6 percent (figure 5). GDP growth would recover immediately, however, and reach growth rates of 8 to 9 percent after 2 quarters already.

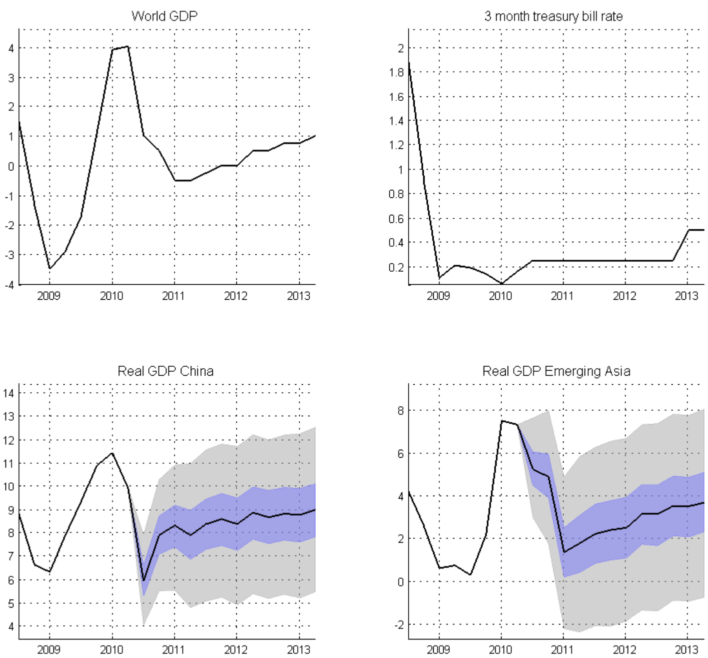

Figure 5: Simulation of a double dip of the world economy

The impact of a deceleration in world economic activity on emerging Asia would be more severe. Real GDP growth would slow down for 4 consecutive quarters and hit bottom at 1 percent. The recovery would be rather sluggish, and at the end of the forecast horizon, real GDP growth will reach just a little more than 3 percent. The results illustrate that the countries in Emerging Asia seem to be more exposed to shocks in the world economy than China is.

4.3.2 Effects of a Growth Slowdown in China

In the second scenario, we assume that the Chinese economy looses momentum and faces a period of economic weakness. We assume a deceleration of China's GDP to a growth rate of 5 percent. The model shows a slight deceleration in the GDP growth of emerging Asia (figure 6). However, the slowdown is far less pronounced than in the double dip scenario mentioned above. Economic growth would slowly converge to its steady-state level by the end of the forecast horizon. The model suggests that the influence of China on the rest of the region is rather limited and contradicts the popular view that intraregional connections are fundamental for the economic development of East Asia.

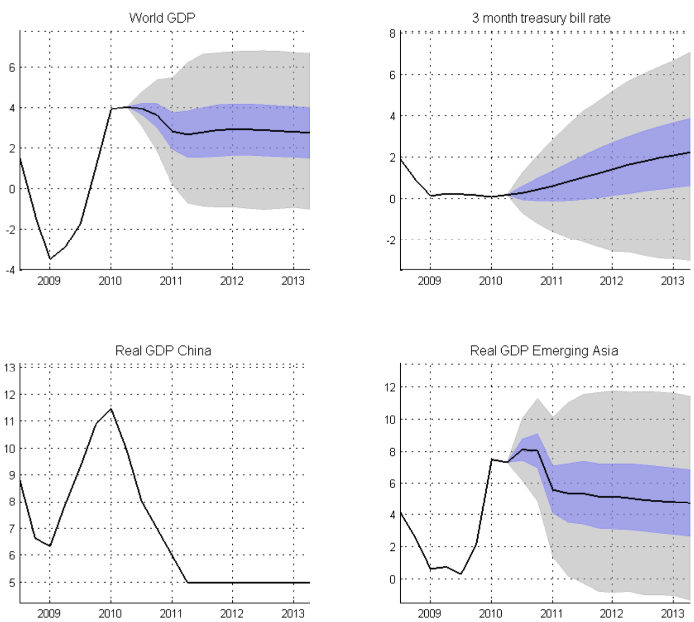

Figure 6: Simulation of a slowdown in Chinese GDP

5 Concluding Remarks

In this paper, we have analyzed the impact of external shocks on countries in Emerging Asia. We used a Bayesian VAR model with an informative prior on the steady state. The mean-adjusted BVAR by far outperforms the traditional BVAR, which in turn by far outperforms the classical VAR with respect to out-of-sample forecast performance. The BVAR model has the smallest root mean squared error for every variable for almost every forecast horizon, such that in all parts of our analysis — i.e., the impulse response functions and forecast error variance decompositions as well as the scenario analysis — the results can be expected to be much more accurate than if the estimations were based on more conventional models. Using the mean-adjusted BVAR model, we evaluated the impulse response function and a forecast error variance decomposition and found that almost half of the forecast error variance in emerging Asia's real GDP growth can be explained by external factors. World GDP still seems to have an extraordinarily high influence on the region. Contrarily, according to the model, changes in China's GDP seem to have a smaller influence on economic activity in emerging Asia. A slowdown in China's GDP growth has very little effect on the emerging Asia when aggregate world growth remains stable. This opposes the popular view, that intraregional connections are fundamental for the economic development of East Asia and that the region "decoupled" from aggregate world demand.

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6 Appendices

6.1 Figures

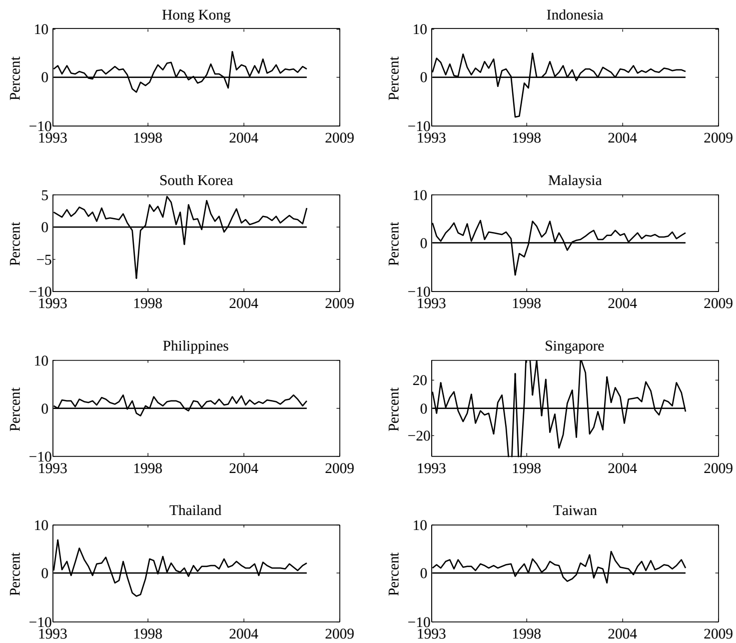

Figure 7: Quarterly growth rates for countries used in the estimation

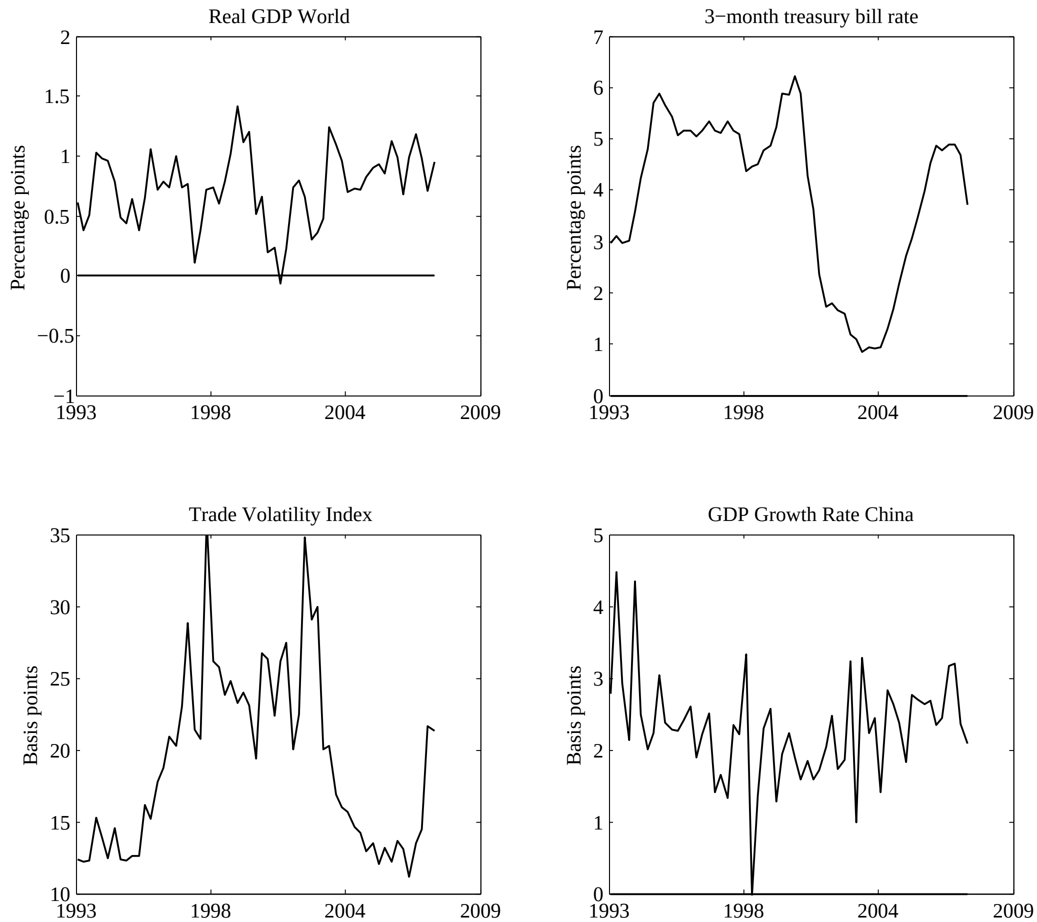

Figure 8: External variables used in the estimation

6.2 Tables

Table 2: Root Mean Squared Error for BVAR with Informative Steady State

Horizon	Δy_t^{world}	i_t^{US}	VIX	ΔGDP_t^{CH}	Δy_t^{ASIA}
1Q	0.23	0.35	4.27	0.70	0.68
2Q	0.50	0.85	5.67	0.88	0.91
3Q	0.79	1.30	6.07	1.05	1.20
4Q	1.25	1.74	8.44	1.29	1.49
5Q	1.75	2.12	9.36	1.30	1.53
6Q	2.02	2.41	9.65	1.17	1.63
7Q	2.17	2.61	9.68	1.16	1.79
8Q	2.18	2.74	9.77	1.21	1.80
9Q	2.17	2.79	9.77	1.33	1.82
10Q	2.16	2.78	9.86	1.41	1.81
11Q	2.22	2.76	10.11	1.52	1.81
12Q	2.29	2.72	10.52	1.62	1.89

Source: Authors' calculations.

Table 3: Root Mean Squared Error for Traditional BVAR

Horizon	Δy_t^{world}	i_t^{US}	VIX	ΔGDP_t^{CH}	Δy_t^{ASIA}
1Q	0.24	0.36	4.36	0.71	0.67
2Q	0.54	0.87	5.82	0.92	0.90
3Q	0.86	1.35	6.38	1.10	1.22
4Q	1.33	1.83	8.71	1.35	1.53
5Q	1.80	2.24	9.61	1.36	1.60
6Q	2.05	2.54	9.88	1.19	1.77
7Q	2.20	2.73	9.94	1.16	1.94
8Q	2.21	2.84	10.08	1.20	1.96
9Q	2.20	2.87	10.13	1.34	1.96
10Q	2.19	2.83	10.20	1.44	1.93
11Q	2.24	2.79	10.47	1.56	1.95
12Q	2.30	2.74	10.89	1.68	2.03

Source: Authors' calculations.

Table 4: Root Mean Squared Error for Maximum Likelihood VAR

Horizon	Δy_t^{world}	i_t^{US}	VIX	ΔGDP_t^{CH}	Δy_t^{ASIA}
1Q	0.25	0.41	4.93	0.80	0.74
2Q	0.56	0.91	6.35	1.01	0.98
3Q	0.90	1.41	6.86	1.16	1.39
4Q	1.37	1.92	8.96	1.45	1.75
5Q	1.83	2.34	10.04	1.44	1.81
6Q	2.08	2.63	10.48	1.24	2.08
7Q	2.22	2.80	10.61	1.22	2.25
8Q	2.24	2.89	10.65	1.25	2.25
9Q	2.23	2.89	10.62	1.38	2.18
10Q	2.21	2.83	10.66	1.48	2.09
11Q	2.25	2.78	10.79	1.62	2.04
12Q	2.31	2.77	11.19	1.72	2.10

Source: Authors' calculations.