Exploring A Macroeconometric Framework for Forecasting and Structural Anlaysis

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10 June, 2011

Executive Summary

- Nowadays, central banks and government bureaus have become accustomed to modern macroeconometric techniques. Often, outputs from different benchmark models (empirical, structural, short term or long term) are manipulated to suit the needs for forecasting and *ex ante* policy impact analysis. This exercise attempts to build a macroeconometric model of the Hong Kong economy that could supplement standard analytics practiced in government agencies.

- The model is an extension of Chow (1998) with two major modifications: (i) the inclusion of fiscal reserves as a proxy of government policy variable, and (ii) the introduction of a correction term that facilitates mean reversion in variables. The correction term instigates a regime structure that is driven by the growth cycles of the HK economy.

- The model, coined the Threshold-BVAR, turns out to be the better predictor of overall real economic activity, but is less accurate on inflation and unemployment forecasts.

- Forecast evaluation is conducted on an equal footing basis – a 1 to 4 quarters ahead forecasts are generated from each model in the 1stQ of 2001-2010 utilizing up to the 4thQ figures in the previous year – so no single model has an advantage in terms of information asymmetry. This is done repeatedly for the 10 years which requires re-estimation of the model and updating of forecasts.

- The forecast figures do not take into account possible forecast revisions, say, done in the 3rdQ of a particular year (this can be done, but revised forecasts of competing models are not completely available). Note also that this is out-of-sample forecasting and not in-sample fitting.

- The Threshold-BVAR model beat the Chow model in short term quarterly Real GDP forecast over the 10 year horizon.

- The Real GDP growth forecast for 2011 is +6.67%. Inflation and unemployment rate forecasts are +4.23% and 3.47%, respectively. (Obviously, effect of the 311 Earthquake has not been discounted by the model.)

Table1: Forecast comparison of Real GDP annual growth rates (%) by quarters

Year	Quarter	Threshold-BVAR	Chow Model	Actual RGDP
2001	Q1	3.21	2.13	**2.67**
	Q2	3.94	2.09	**1.51**
2002	Q1	-0.67	-0.66	**-0.99**
	Q2	0.50	0.68	**0.53**
2003	Q1	4.46	2.36	**4.14**
	Q2	4.71	0.95	**-0.86**
2004	Q1	5.73	4.32	**7.70**
	Q2	11.28	8.65	**12.00**
2005	Q1	5.18	4.24	**6.16**
	Q2	7.04	4.32	**7.09**
2006	Q1	6.04	5.82	**9.00**
	Q2	5.24	4.71	**6.13**
2007	Q1	4.24	4.79	**5.64**
	Q2	6.30	7.34	**6.12**
2008	Q1	7.04	5.88	**7.16**
	Q2	8.75	7.84	**4.22**
2009	Q1	-1.88	-7.19	**-7.94**
	Q2	0.65	-5.30	**-3.39**
2010	Q1	6.89	7.46	**8.09**
	Q2	5.45	8.32	**6.44**
Remarks	(1) Shaded cells are the most accurate. (2) Red cells are the most accurate in 1-quarter ahead predictions. Blue cells are the most accurate in 2-quarter ahead predictions.			

Table2: Forecast comparison of Real GDP annual growth rates (%) by years

Year	Frequency	Threshold-BVAR	Chow Model	HKSAR Govt	Actual RGDP
2001	FY	3.65	1.71	5.5	**0.50**
2002	FY	1.65	1.55	1.0	**1.84**
2003	FY	4.79	-0.27	3.0	**3.00**
2004	FY	7.69	3.85	6.0	**8.47**
2005	FY	6.74	3.54	4.5 – 5.5	**7.08**
2006	FY	5.69	3.50	4.0	**7.02**
2007	FY	5.26	5.48	4.5 – 5.5	**6.39**
2008	FY	7.17	5.89	4.0 – 5.0	**2.31**
2009	FY	0.74	-5.67	2.0 – 3.0	**-2.67**
2010	FY	6.36	7.29	4.0 – 5.0	**6.82**

- The major issue of the second part of the analysis is to convert the forecasting model (a reduced form model) into a structural model from which interpretations can be made about the interacting variables.

- Conversion is done by imposing restrictions on how the variables would relate to one another contemporaneously and dynamically.

- Economic analysis relies on the analysis of the nonlinear impulse response functions (NIRF) which depict the time path of responses of variables to unpredicted shocks that hit the economy. These shocks could be structural shocks (e.g. demand shock or price shock) originated domestically or from overseas, or policy shocks like fiscal policy shocks considered in the case here.

- The deduced NIRFs can be cross-checked using economic theory to see if the results are meaningful.

- 2 examples provided – the impact of the 3-11earthquake, and the various alternative scenarios possibly identified in the financial tsunami.

- In the first case, the earthquake brings along a negative export shock that could wipe out around 0.7% point in Real GDP growth this year.

- In the second, the fiscal stimulus package in 2009-10, though somewhat difficult to quantify, have shortened the time (by about a year) the economy spent lying below its baseline (unperturbed) Real GDP path.

- The conversion exercise found that the output elasticity of fiscal reserves (approximately equivalent to the difference between the elasticity of fiscal revenues and elasticity of fiscal spending) is about 0.33, a figure comparable to those of other advanced countries.

CHAPTER 1: Forecasting

1. Introduction

Macroeconometric modeling has a long history in Hong Kong. Chou and Lin (1983) built one of the earliest forecasting models of HK back in the late ‘70s. It was in use in the Chinese University of Hong Kong for about three decades, and is part of the Project Link at the United Nations. In 2010, Prof. Chou left CUHK for CityU where the model is now based. The University of Hong Kong operates a high frequency model built in collaboration with Prof. Lawrence Klein, and has been delivering forecasting reports since 2000. HKUST has its own forecasting model that stems from the work of Chow (1998). Apart from the academia, publicly funded organization is the other major platform where forecasting models are designed and operated. Example includes Gerlach and Yiu (2004).

Another objective of macroeconometric modeling concerns the studying of macroeconomic dynamics. In particular, attention is paid to the response of the economy to economic or policy shocks. Genberg (2003) and Ha et al. (2002) belong to this strand of research.

This report discusses the building of a model that serves both purposes mentioned. Specifically, it is expected to deliver accurate forecasts and facilitate the analysis of the HK economic dynamics. The model is modified from Chow (1998) and features a threshold transition mechanism aimed at fine-tuning forecast figures. Section 2 describes the structure of the model and the data used. This is followed by a comparison of forecast performance across different models in Section 3.

2. The Model

2.1 The Basics of Vector Autoregression (VAR)

The Chow (1998) model is an 8-variable VAR model that incorporates the so-called Minnesota prior and has cross equation dependence explicitly modeled. The setup is Bayesian in nature and is estimated with Markov Chain Monte Carlo methods. These features are retained in the new model. The following paragraph recaps some basics information of VAR.

The n-variate VAR(k) model can be written as

$$Y_t = cD_t + \sum_{i=1}^{k} A'_i Y_{t-i} + \varepsilon_t, \qquad t = 1,2,\cdots,T \qquad (1)$$

where Y_t is a vector containing *n* endogenous variables of interest and D_t is the vector of *p* deterministic variables including the seasonal dummies. The error term is Normal, $\varepsilon_t \sim N(0, \Sigma)$. As far as forecasting is concerned, equation (1) is all we need and once the unknown coefficients c and A_s are estimated, the forecast figures – the unconditional mean of the RHS – can be easily obtained. Note that forecasts of longer horizon can be generated recursively, i.e. given forecast $\hat{Y}_{T+1}$, this can replace the not-yet-observed Y_{T+1} on the RHS to get $\hat{Y}_{T+2}$, etc..

If a subset of the endogenous variables in system (1) are co-trending[1], the expression (1) is an insufficient representation of the data process. Subtracting Y_{t-1} from both sides, and adding and subtracting $\sum_{i=1}^{k-1} \sum_{j=i}^{k} A'_j \, Y_{t-i}$ on the RHS gives the vector error correction (VECM) representation

$$\Delta Y_t = cD_t + \Pi' Y_{t-1} + \sum_{i=1}^{k-1} B'_i \, \Delta Y_{t-i} + \varepsilon_t \qquad (2)$$

where Δ is first-differences, $\Pi' = \sum_{j=1}^{k} A'_j - I_n$ and $B'_i = -\sum_{j=i+1}^{k} A'_j$. The term $\Pi' Y_{t-1}$ is the so-called error correction term which indicates the extent of adjustment needed for the system to move back to equilibrium values in the long run. We will not be dealing with VECM explicitly[2], but this will be used as one of the benchmarks for forecast comparison in Section 3.

2.2 The Minnesota Prior

Like Chow (1998), we impose the Minnesota prior on c and A_s which suggests that data generating process (1) can be described by *n* random walks. This is of course extreme, and we strike a balance between such a prior belief and what the data is telling us. This is done by controlling the "tightness" of the prior belief described below. Details of the implementation can be found in Doan et al. (1984).

The prior mean of c is a vector of zeros. The prior means of A_s are matrices of zeros, except for the coefficient that corresponds to its own first lag term. Write $A_m = [A_{ijl}], \quad i = 1, \cdots, n, \; j = 1, \cdots, n, \; l = 1, \cdots, k.$ The prior means of A_{ijl} are

$$\bar{A}_{ijl} = \begin{cases} 1 & \text{if } i = j \text{ and } l = 1 \\ 0 & \text{otherwise} \end{cases} \qquad (3)$$

[1] This is the issue of cointegration, see Engle and Granger (1987).

[2] We actually tried the specification of Kleibergen and Paap (2002), but the performance is highly sensitive to the priors adopted. The priors for the coefficients are relatively easy, but the prior for the error correction term does not seem to admit a wide range of choices. In fact, many researchers warned against conducting cointegration analysis for high dimensional system.

The prior covariance matrix of all these coefficients is Ψ which is a diagonal matrix. The diagonal elements of Ψ are $s_{i,j,l}^2$ which corresponds to the *l*-th lag term of the *j*-th variable in the *i*-th equation,

$$s_{i,j,l}^2 = \begin{cases} \left(\frac{\lambda}{l}\right)^2 & \text{if } i = j \\ \left(\frac{\gamma\theta\sigma_i}{l\sigma_j}\right)^2 & \text{if } i \neq j \\ \omega & \text{for exogenous terms} \end{cases} \qquad (4)$$

where λ, γ, θ and ω are hyperparameters, and σ_i is the *i*-th diagonal element of the OLS estimator of Σ. λ controls the overall tightness and as this gets closer to 0, the more weight we put on the prior belief of random walks. In the exercise, we use small values of λ and θ but a large ω as it is very likely that there are seasonal and other deterministic effects.

2.3 Threshold-BVAR Model

In Chow (1998) the model contains 8 equations, one for each endogenous variables under study. They are Real GDP (RGDP), Composite CPI (CCPI), Unemployment Rate (UR), M3, Total Exports (EXP), Total Floor Areas with Consent to Commence Work (FACCW), Trade-weighted Exchange Rate (TWER) and the Hang Seng Index (HSI). **In this work, a major extension is that we add another variable – Fiscal Reserves (RES) – which might prove useful when we do analysis concerning fiscal policy**. The new model to be introduced, referred to as the Threshold-BVAR model for convenience, thus incorporates 9 equations and 9 endogenous variables.

Another aspect that distinguishes the Threshold-BVAR with the Chow model is the incorporation of a time varying adjustment term which scales down excessive fluctuations of the model variables and generates predictions that are more consistent with the underlying cycles of the economy. Specifically, we modify model (1) as follows:

$$Y_t = cD_t + \sum_{i=1}^{k} A'_i Y_{t-i} + G(RGDP, \alpha, \beta)\eta + \varepsilon_t, \qquad t = 1,2,\cdots,T \qquad (5)$$

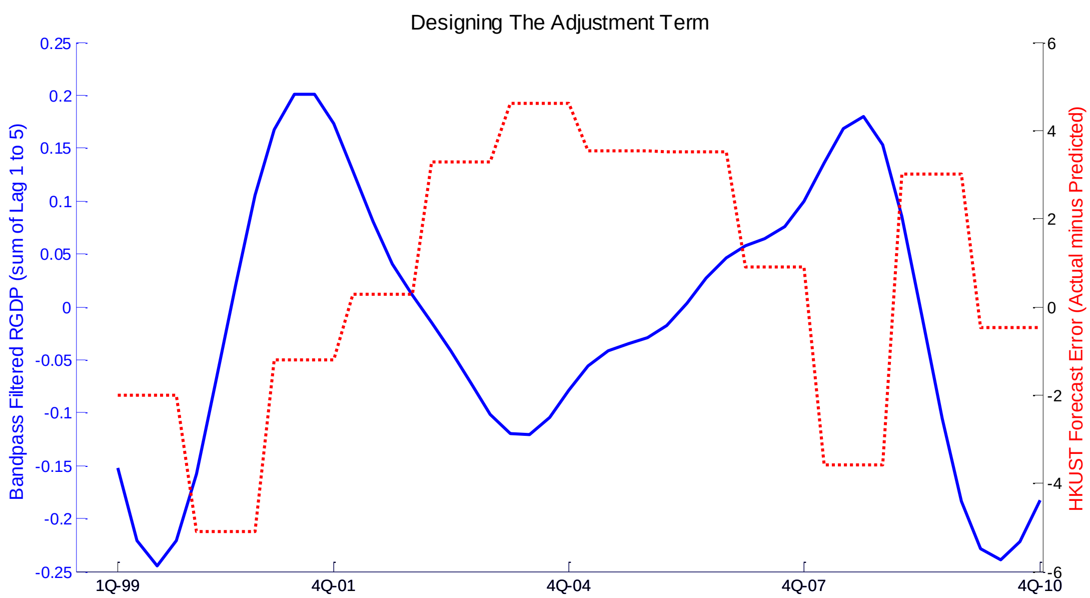
$$Y_t = [RGDP_t, CCPI_t, UR_t, M3_t, EXP_t, FACCW_t, TWER_t, HSI_t, RES_t\,]',$$

$$G(RGDP, \alpha, \beta) = \frac{1}{1 + exp\left(-\alpha\left(\left|\widetilde{RGDP}_{t-2}\right| - \beta\right)\right)}\left(-\widetilde{RGDP}_{t-2}\right), \qquad (6)$$

where $\widetilde{RGDP}$ is the sum of the past k values of the bandpass filtered series of $RGDP$, β is the threshold value that governs the transition, α is the parameter controlling the smoothness of the transition, and η determines the size of the adjustment terms for each equation in the system.

Equation (6) is the product of a logistic function and the negative of the cumulative sum of bandpass filtered values of Y up to lag k. Intuitively, the filtered values are cyclical deviations from long term trends, and the adjustment terms scale the predictions according to the size of excessive deviations in economic activity. The negative sign on the RHS of (6) ensures that the adjustment goes in opposite directions. The design can be understood by referring to Fig.1. In the diagram, The sum of lag 1 to 5 of the bandpass filtered RGDP is plotted together with the forecast errors of the Chow model, defined by actual annual RGDP growth rates minus the predicted values. **It can be seen that when the bandpass cycle overshoots (+ve values), the Chow model tends to over-predict RGDP (–ve forecast errors), and vice versa. Hence, equation (6) is imposed to hopefully reduce forecast errors committed**.

Figure 1: Intuition of the Design of the Adjustment Term



The full model is thus defined by equations (5) – (6), and supplemented by the Minnesota prior (3) – (4). To invoke the Markov Chain Monte Carlo (MCMC) simulation, two more things have to be sorted out. First, we need a prior for the error variance Σ which is assumed to be inverted Wishart. Second, the dimension of the adjustment terms has to be decided. In a way, how many of the nine equations should contain an adjustment term has to be confirmed. This can be done by fixing the dimension of η. In this exercise, we incorporate a non-zero element of η for each of the 9 equations[3]. Each of these non-zero elements is distributed uniformly over the interval $[-1,1]$ *a priori*.

2.4 Outline of the MCMC simulation

The MCMC is a recursive simulation algorithm with which one can sample parameters of interest from conditional probability distributions, see Chow (1998) for an introduction. We skip the technical details of derivation here and list out the major simulation steps.

The data we work with span 1Q:1984 to 4Q:2010. In evaluating forecast accuracy, we estimate the parameters using a subset of the sample and check how the predictions compare to the actual values in the rest of the series. We start with an in-sample of 1Q:1984 – 4Q:2000. Up to four quarters ahead predictions are made. Thus, we get forecasts for 1-4 Q of 2001 which we can contrast with the actual values and compute the forecast errors. We then move the window of the in-sample forward for one year[4] and do forecasts for 2002, and so on. Note doing this means that only information up to the point of forecast can be used.

The simulation proceeds as follows:

1. Set $\gamma = \theta = 0.1$, $\omega = 9999$, $\alpha = 50$ and $\beta = 0.15$.
2. Perform the Gibbs Sampler for the following:
   2.1 Sample $\{c, A_i\}$ from the matric-variate Normal conditional distribution.
   2.2 Sample Σ from the inverted Wishart conditional distribution.
3. Perform a Metropolis Hastings step for the vector η:
   3.1 Draw for non-zeros elements of η from a univariate Normal distribution.
   3.2 Evaluate the Metropolis Hastings acceptance ratio.
   3.3 Make a random draw u from Uniform $[0,1]$.
   3.4 If u is smaller than the acceptance ratio, accept the draw for η. Otherwise, keep the previous simulated value of η.
4. For in-sample with observations from 1 to T_0, make forecasts of $Y_{T_0+1}, Y_{T_0+2}, Y_{T_0+3}$, and Y_{T_0+4}.
5. Repeat step 1 to 4.
6. For simulation with $M = M_1 + M_2$ iterations, discard draws of the first M_1 iterations and process Monte Carlo integration of the remaining M_2 outputs.

3. Forecasting Results

Forecasting performance is assessed using Root Mean Square Error, defined as

[3] Various specifications tried, but to include a non-zero term for all nine equations gives better forecasts of RGDP.

[4] In many studies, recursive forecasts are done by moving forward one quarter a time.

$$RMSE_h = \sqrt{\frac{\sum_{t \in T(h)} \left(Y_{t+h} - \hat{Y}_{t+h}\right)^2}{\#T(h)}}$$

where $\hat{Y}_{t+h}$ is the h-step ahead forecast made at time t = all in-sample end points where forecast is made. $\#T(h)$ is the total number of time the h-step ahead forecast is made, or the number of recursive forecast made.

In the Table below, the RMSEs of the Threshold-BVAR model are stipulated with those obtained from other benchmark forecasting models, including (i) the BVAR model without the transition term, (ii) the Chow model, (iii) the VECM model of equation (2), and the (iv) ARIMA model of individual variables.

Table 3: RMSE of Various Forecasting Models

RMSE of	Threshold-BVAR	BVAR	VECM	Chow Model	ARIMA
RGDP					
1-Q	0.0232	0.0256	0.0263	0.0169	0.0232
2-Q	0.0275	0.0250	0.0560	0.0204	0.0289
3-Q	0.0272	0.0275	0.0707	0.0302	0.0256
4-Q	0.0321	0.0433	0.1274	0.0557	0.0423
Full Year	**0.0222**	**0.0254**	**0.0604**	**0.0276**	**0.0251**
CCPI					
1-Q	0.0145	0.0141	0.0066	0.0060	0.0037
2-Q	0.0162	0.0160	0.0108	0.0104	0.0064
3-Q	0.0150	0.0152	0.0157	0.0158	0.0115
4-Q	0.0184	0.0184	0.0223	0.0227	0.0132
Full Year	**1.4529**	**1.4447**	**1.2556**	**1.2728**	**0.6664**
Unemp. Rate					
1-Q	0.7833	0.8030	0.3989	0.3232	0.4571
2-Q	1.0408	1.0515	0.9509	0.7014	0.8684
3-Q	1.1124	1.1243	0.6509	0.7980	0.9465
4-Q	1.2600	1.3263	1.2394	0.9735	0.9979
Full Year	**0.9595**	**0.9914**	**0.5558**	**0.6041**	**0.7456**
Total Exports					
1-Q	0.0693	0.0732	0.0556	0.0410	0.0563
2-Q	0.0669	0.0634	0.1267	0.0440	0.0592
3-Q	0.0745	0.0747	0.2085	0.0720	0.0731
4-Q	0.0894	0.0881	0.2833	0.0922	0.0811
Full Year	**0.0657**	**0.0663**	**0.1623**	**0.0552**	**0.0608**
Remarks	(1) Red cells are the most accurate. (2) Blue cells are the second most accurate. (3) Quarterly RMSE are based on predicted levels of variables. (4) Annual RMSE are based on differences between actual and predicted annual growth rates.				

As can be witnessed, the Threshold-BVAR outperforms all benchmark models in GDP forecast. The performances on Export forecast are more or less the same across models. However, it yields less accurate inflation and unemployment forecasts. The weaker performance in inflation and unemployment forecasts could be attributed to the larger model dimension – 9 variables against 8 in the Chow model and the univariate (1 variable) ARIMAs. Bigger models have more covariance terms which can increase the variability of the estimation and forecast.

If the prime objective is to forecast RGDP, the Threshold-BVAR should be a right choice although the performance comes at the expense of less accurate inflation and unemployment forecasts. **If the reverse is true, an alternative is to first-difference the CCPI and UR before running the model (see Appendix 5.2). This produces much better inflation and unemployment forecasts, but the RGDP growth predictions become less accurate.** The Appendix shows other specifications tried in the working process.

Table 1 and 2 in the Executive Summary contain forecast comparison between the Threshold-BVAR and other models or sources. Note that the structure of the out-of-sample forecast is to ascertain all models to be compared on equal footing. In making prediction for a certain year (1stQ-4thQ), only data up to the 4thQ of the previous year will be used to estimate the model and run the forecast.

The Threshold-BVAR has the most red cells in Table 1, indicating the largest number of most accurate 1-quarter ahead forecasts. It also tops Table 2 with the most red cells which mark the best prediction of annual growth forecasts in each year. Table 4 shows the forecast performance of the model on exports, inflation and unemployment. Finally, a graphical illustration of actual and forecast values of the major variables can be found in Figure 2 – 5. The blue solid lines are the actual values and the black dotted lines are the forecast figures. The closer the dotted line sticks to the solid line, the better the forecast performance of a particular model on the variable concerned.

Table 4: Forecast comparison of various annual growth rates (%)

Year	Frequency	Threshold-BVAR	Chow Model	BVAR	VECM	Actual RGDP
CCPI						
2001	FY	-0.19	-0.30	-0.07	0.41	**-1.61**
2002	FY	-1.66	-4.59	-1.69	-4.99	**-3.04**
2003	FY	-1.85	-2.83	-2.24	-1.94	**-2.58**
2004	FY	-1.81	-0.71	-2.05	-1.88	**-0.37**
2005	FY	1.51	0.57	1.29	0.72	**0.91**
2006	FY	2.65	3.74	2.56	3.21	**2.02**
2007	FY	3.10	4.03	3.29	2.94	**2.02**
2008	FY	3.02	6.12	3.24	5.38	**4.30**
2009	FY	1.81	-0.63	2.04	-0.55	**0.52**
2010	FY	-0.67	2.78	-0.49	3.17	**2.40**
Unemp. Rate						
2001	FY	4.2	4.5	4.2	5.0	**5.1**
2002	FY	5.6	6.8	5.6	6.6	**7.3**
2003	FY	6.7	6.7	6.8	7.4	**7.9**
2004	FY	7.4	6.1	7.5	7.6	**6.8**
2005	FY	6.5	6.3	6.6	5.9	**5.6**
2006	FY	5.6	5.3	5.7	4.7	**4.8**
2007	FY	4.6	4.1	4.8	3.7	**4.0**
2008	FY	3.7	3.1	3.8	2.8	**3.5**
2009	FY	4.1	5.4	4.2	6.2	**5.3**
2010	FY	4.9	4.3	5.1	3.9	**4.3**
Total Exports						
2001	FY	6.87	2.03	7.71	19.04	**-1.67**
2002	FY	2.05	-1.81	1.97	-18.81	**9.04**
2003	FY	12.05	2.10	6.71	-2.57	**12.79**
2004	FY	15.45	12.06	11.39	-11.97	**15.42**
2005	FY	13.12	8.20	7.84	-1.60	**10.60**
2006	FY	11.17	10.40	6.85	-1.07	**9.44**
2007	FY	10.68	11.81	8.47	4.55	**8.34**
2008	FY	12.68	9.33	11.57	0.57	**2.58**
2009	FY	4.00	-8.43	2.25	-17.49	**-10.10**
2010	FY	13.99	12.57	11.62	4.64	**16.80**

Remarks (1) Red shaded cells are the most accurate full year forecasts of variables concerned.
(2) Blue shaded cells are the second most accurate forecasts.

Figure 2: RGDP Forecasts of Various Models

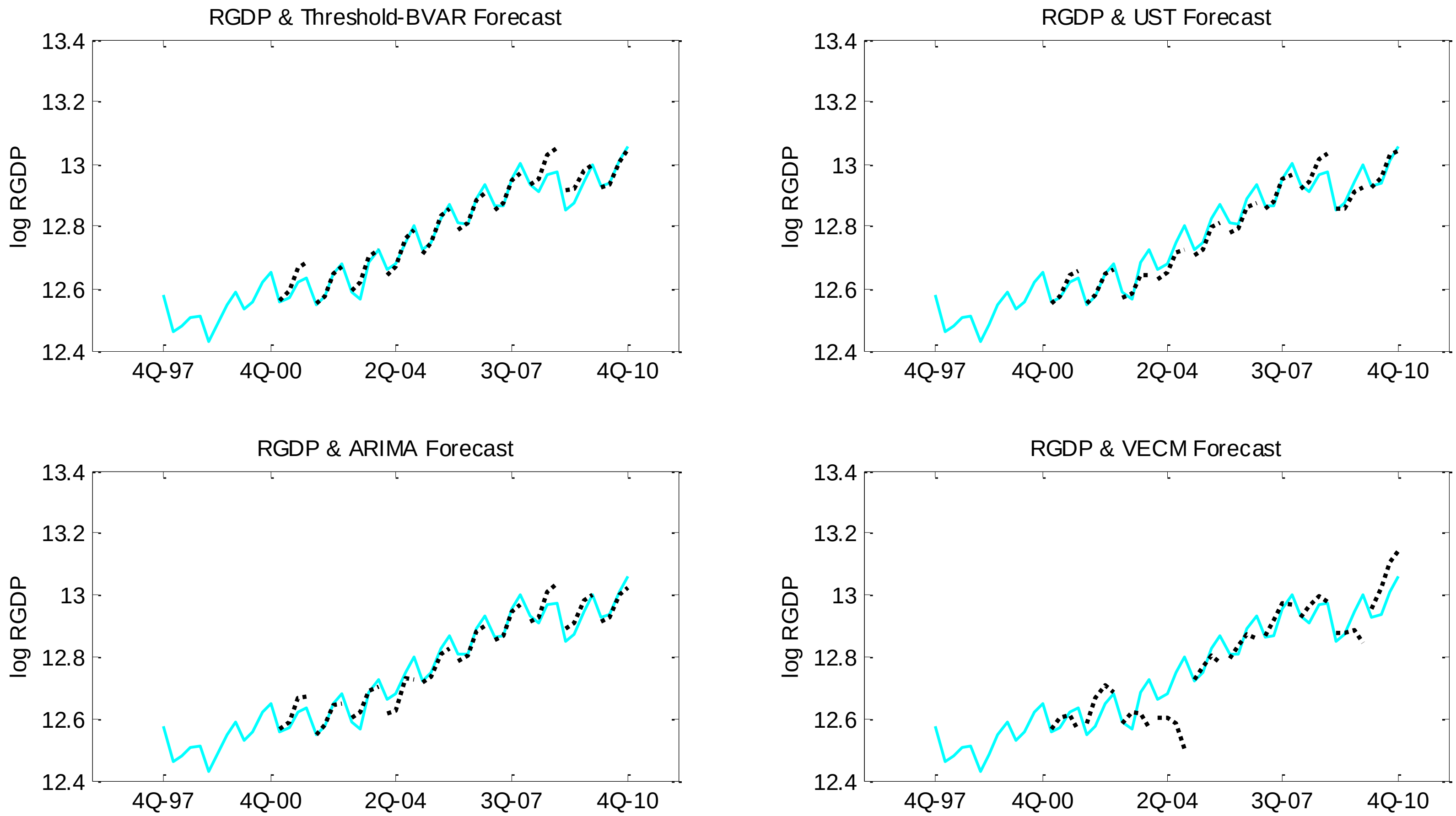


Figure 3: CCPI Forecasts of Various Models

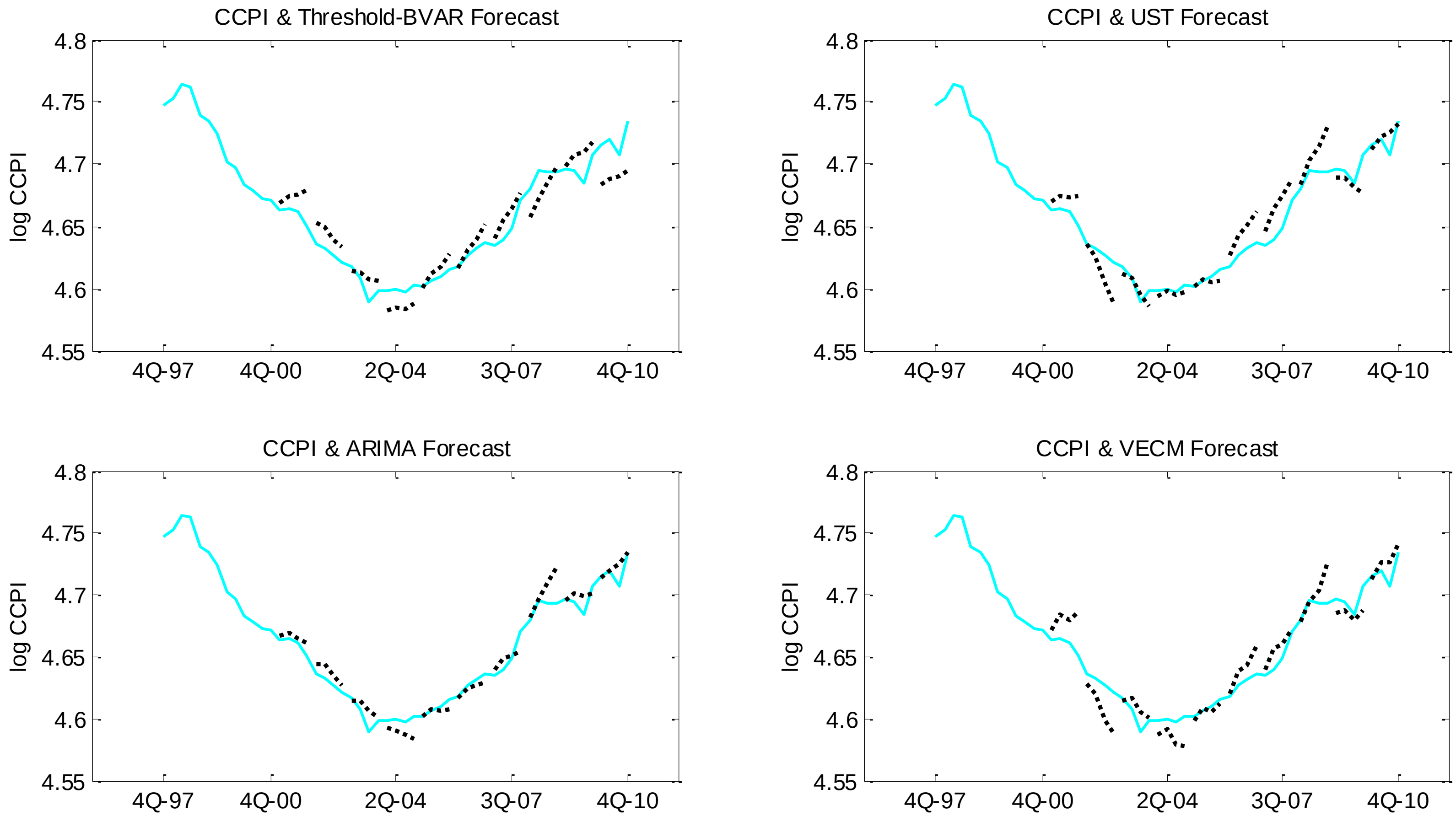


Figure 4: Unemployment Rate Forecasts of Various Models

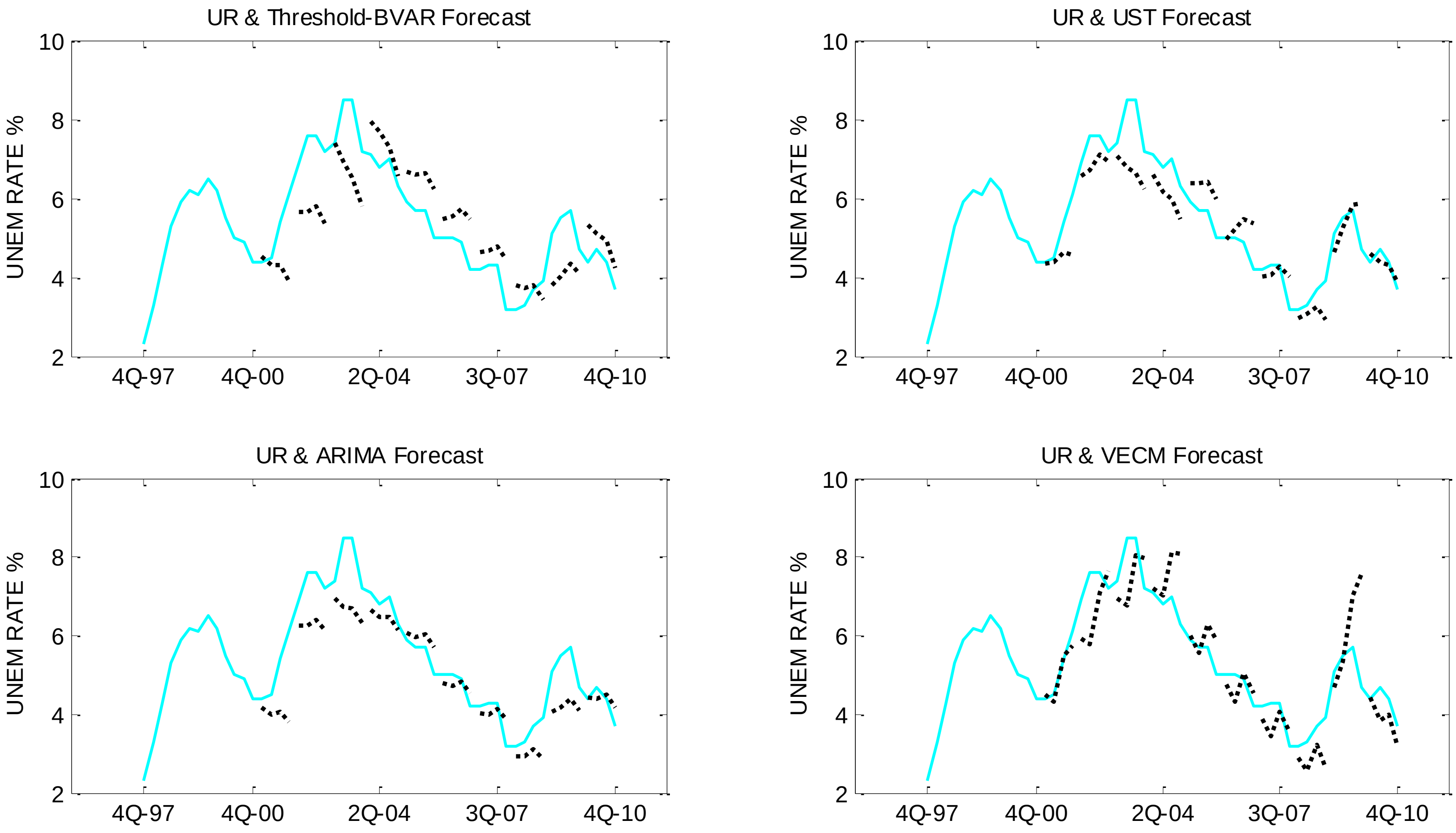
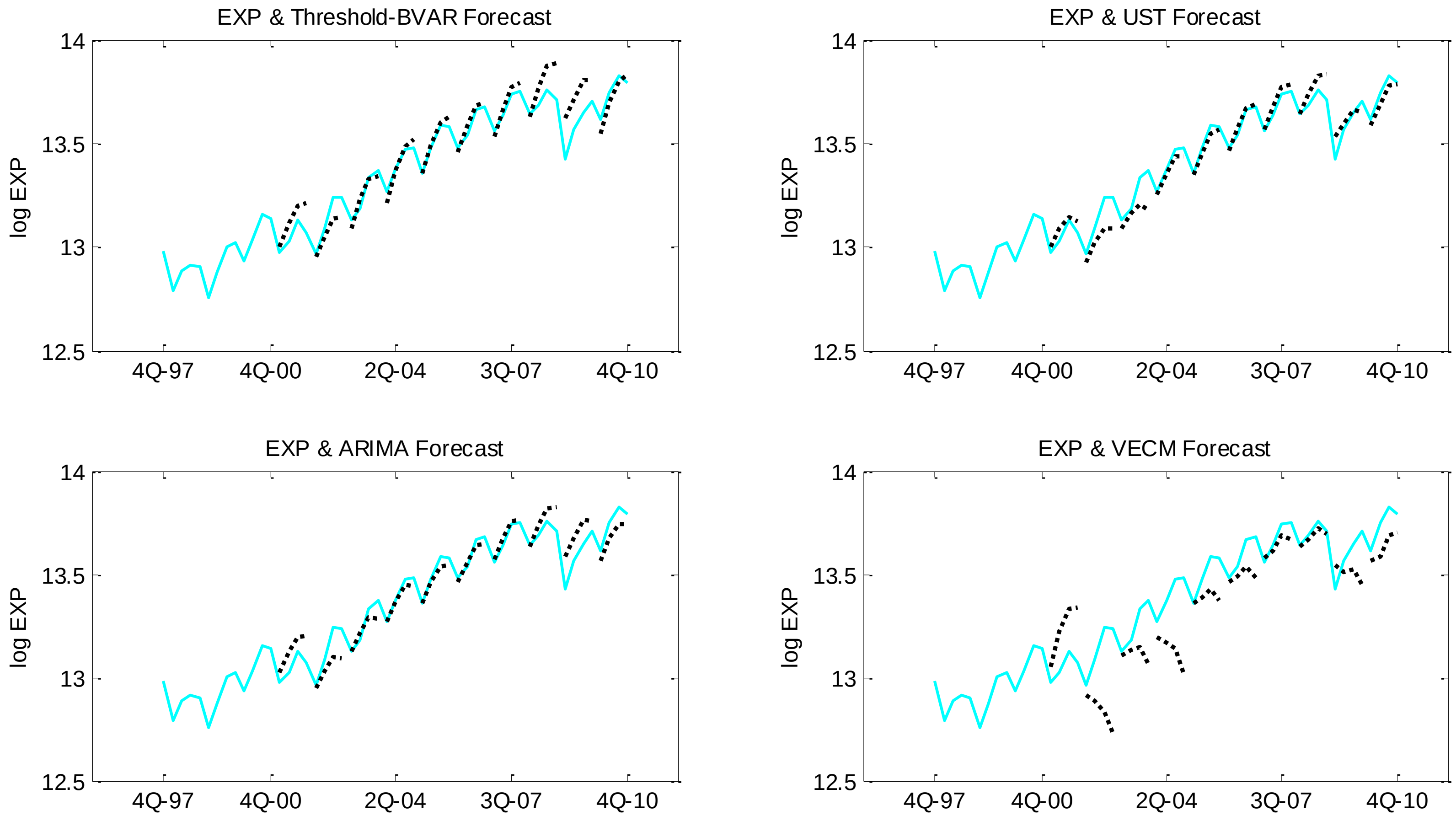


Figure 5: Export Forecasts of Various Models



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5. Appendix

5.1 The Threshold-BVAR model (5) – (6) is a restricted version of the more general class of Threshold models where the regime changes dictate what values the coefficients of the model would command. Specifically, (5) will become something like

$$Y_t = G(RGDP, \alpha, \beta)\left[c_0 D_t + \sum_{i=1}^{k} A'_{0i}\, Y_{t-i}\right] + \left(1 - G(RGDP, \alpha, \beta)\right)\left[c_1 D_t + \sum_{i=1}^{k} A'_{1i}\, Y_{t-i}\right] + \varepsilon_t$$

and instead of a single correction term in each equation, all coefficients will become regime dependent. The switching between regimes however remains smooth. While more general and richer in dynamics, the forecast accuracy is less than the Threshold-BVAR.

5.2 The same specification as (5) – (6), but with

$$Y_t = [RGDP_t, \Delta CCPI_t, \Delta UR_t, M3_t, EXP_t, FACCW_t, TWER_t, HSI_t, RES_t\ ]'.$$

As mentioned in the main text, this produces much better inflation and unemployment forecasts, but unfortunately there is the tradeoff of less accuracy in GDP forecasts.

5.3 Instead of (6), other forms of transition function have been tried:

$$G(RGDP, \alpha, \beta) = \frac{1}{1 + exp\left(-\alpha\left(\widetilde{RGDP}_{t-2} - \beta_1\right)\left(\widetilde{RGDP}_{t-2} - \beta_2\right)\right)}\left(-\widetilde{RGDP}_{t-2}\right),$$

$$G(RGDP, \alpha, \beta) = \frac{1}{1 + exp\left(-\alpha\left(\left|\widetilde{RGDP}_{t-2}\right| - \beta\right)\right)}\left(-\widetilde{RGDP}_{t-2}\right)DUR_{t-2}^2,$$

$$G(RGDP, \alpha, \beta) = \frac{1}{1 + exp\left(-\alpha\left(\left|\widetilde{RGDP}_{t-2}\right| - \beta\right)\right)}\left(-\widetilde{RGDP}_{t-2}\right)log(DUR_{t-2}),$$

$$G(RGDP, \alpha, \beta) = \frac{1}{1 + exp\left(-\alpha\left(\left|\widetilde{RGDP}_{t-2}\right| - \beta\right)\right)}sgn\left(\widetilde{RGDP}_{t-2}\right)log(DUR_{t-2}),$$

where DUR_t is the duration of the above trend or below trend episode at time *t* (i.e., the number of consecutive observations of $\widetilde{RGDP}$having the same sign as the latest measurement) and *sgn* being the sign of the bracket argument. Again, the accuracy of GDP forecasts are all lower than the chosen model.

CHAPTER 2: Structural Analysis

1. Economic Analysis with Threshold-BVAR

1.1 Reduced Form and Structural Form

To recap, the 9-variable Threshold-BVAR takes the form:

$$Y_t = cD_t + \sum_{i=1}^{k} A'_i \, Y_{t-i} + G(RGDP, \alpha, \beta)\eta + \varepsilon_t, \qquad t = 1,2,\cdots,T \qquad (1)$$

$$Y_t = [RGDP_t, CCPI_t, UR_t, M3_t, EXP_t, FACCW_t, TWER_t, HSI_t, RES_t\,]',$$

$$G(RGDP, \alpha, \beta) = \frac{1}{1 + exp\left(-\alpha\left(\left|\widetilde{RGDP}_{t-2}\right| - \beta\right)\right)}\left(-\widetilde{RGDP}_{t-2}\right), \qquad (2)$$

where $\widetilde{RGDP}$ is the sum of the past *k* values of the bandpass filtered series of *RGDP*. So, it is just the standard VAR augmented with a threshold adjustment term for each of the nine equations in the system. As long as the deviations of RGDP from its trend remain small, the transition term *G* will not be large and the behavior of the endogenous variables will be determined principally by the autoregressive structure. When the overshootings and undershootings increase in size, the logistic term in *G* approaches 1 and the adjustment term sets in. The magnitude of the adjustment will go in opposite direction of the deviation (hence, sort of mean reverting), and it will be proportional to the size of the deviation.

Note that (1) – (2) is a reduced form system which implies that the parameters, say A_i, do not have an economic meaning in themselves. If the model is to be used for conducting economic analysis, it would have to be converted into structural form first. To proceed, let us simply notation by rewriting (1) as

$$Y_t = \Gamma_0 + \sum_{i=1}^{k} A'_i \, Y_{t-i} + \varepsilon_t, \qquad (1.1)$$

$$E(\varepsilon_t \varepsilon_t') = \Sigma, \qquad \Gamma_0 = cD_t + G(RGDP, \alpha, \beta)\eta.$$

Consider a typical structural model

$$B_0 Y_t = \Upsilon_0 + \sum_{i=1}^{k} B'_i \, Y_{t-i} + \xi_t, \qquad (1.2)$$

$$E(\xi_t \xi_t') = \Omega$$

where B_0 is the matrix of contemporaneous coefficients of the endogenous variables (which shows how variables affect one another contemporarily), ξ_t is the vector of structural shocks as opposed to the reduced form shocks ε_t and Ω is a diagonal matrix. If there is a mapping between (1.1) and (1.2), then, based on the estimated parameters of the reduced form model, we will be able to retrieve the structural form counterparts and perform economic analysis. This is the core of structural VAR (SVAR) methodology.

There are various ways to identify (1.2) from (1.1), see for instance the discussion of Lütkepohl (2005), Uhlig (2005) and Gottschalk (2001). The method of short run restrictions is a common choice. It stipulates explicitly how one variable is related to another in the short run via relating structural and reduced form shocks. Suppose we have the decompositions $\Sigma = PP'$ and $\Omega = HH'$. Then we can write

$$W = PH^{-1}, \qquad (3)$$

$$\varepsilon_t = W\xi_t \;\; \Rightarrow \;\; \Sigma = W\Omega W'. \qquad (4)$$

Pre-multiplying (1.1) by W^{-1} on both sides, we can retrieve (1.2) where

$$B_0 = W^{-1}, \quad B'_i = W^{-1}A'_i, \quad \Upsilon_0 = \mathrm{W}^{-1}\Gamma_0. \qquad (5)$$

1.2 Identifying the Structural Form of Threshold-BVAR

To pin down the values of *W*, researchers resort to economic theories to formulate the relationship between structural and reduced form shocks with policy shocks being an integral part of the consideration. While monetary policy variables take the center stage in most SVARs, the peculiar economic environment of HK means that such a focal point will be largely irrelevant. Instead, we consider mainly the role of fiscal policy in this paper.

Most SVAR works on fiscal policy, e.g. De Arcangelis and Lamartina (2003), follow the footprint of Blanchard and Perotti (2002) and identify their models with restrictions on *W*. This is a viable approach given that it distinguishes between unexpected policy shocks and the impact of automatic stabilizers (a feedback to the policy variables). There is, however, an element that differentiates other models from ours. The Threshold-BVAR has only one policy variable – fiscal reserves – in contrast to other models where typically both government revenues and spending are separately included. Our model is constructed with the prime objective of delivering forecast while being as parsimonious as possible[5]. Others, on the hand, value more the congruence of the model setup with

[5] The identification of a structural model for VAR becomes more and more trickier as the model dimension increases.

standard macro theories. This fact implies that, in our context, the impact of, say, RGDP on a tax cut is equivalent to a government spending increase.

Recall that $\varepsilon_t = W\xi_t = PH^{-1}\xi_t = P\upsilon_t$. The Blanchard and Perotti approach specifies a particular form for P:

$$\Lambda\varepsilon_t = \Xi\upsilon_t \quad \Rightarrow \quad \varepsilon_t = (\Lambda^{-1}\Xi)\upsilon_t = P\upsilon_t. \qquad (6)$$

This essentially spells out how structural shocks are related to reduced form ones contemporaneously. Consider for now a bivariate model with $Y_t = [RGDP_t,\ RES_t]'$. Then if we write

$$\varepsilon_t^{RES} = \alpha_2\varepsilon_t^{RGDP} + \beta_2\upsilon_t^{RES}$$

the second row of $\Lambda = [-\alpha_2 \quad 1]$ and the second row of $\Xi = [0 \quad \beta_2]$. Moreover, the first element of the RHS gives the impact of the automatic stabilizer[6], while the second term indicates the direct, first round impact of the policy shock. Note that the structural shock υ_t^{RGDP} is the normalized form of ξ_t^{RGDP}. That is, υ_t^{RGDP} has mean 0 and variance 1. Also, it does not enter into the equation as information lags and the decision-making process prevent the government from reacting instantaneously (within the quarter) to the output shock.

There are altogether $2n^2$ elements in the matrices Λ and Ξ. The equation $vech(\Sigma) = vech(\Lambda^{-1}\Xi\Xi'\Lambda^{-1\prime})$ puts in $\frac{n(n+1)}{2}$ restrictions. This leaves a further $2n^2 - \frac{n(n+1)}{2} = 117$ restrictions to be imposed to just-identify the model. The identification scheme adopted is represented by:

$$\varepsilon_t^{RGDP} = \alpha_{11}\varepsilon_t^{EXP} + \alpha_{12}\varepsilon_t^{HSI} + \alpha_{13}\varepsilon_t^{RES} + \beta_1\upsilon_t^{RGDP}$$

$$\varepsilon_t^{CCPI} = \alpha_{21}\varepsilon_t^{RGDP} + \alpha_{22}\varepsilon_t^{TWER} + \alpha_{23}\varepsilon_t^{RES} + \beta_2\upsilon_t^{CCPI}$$

$$\varepsilon_t^{UR} = \alpha_{31}\varepsilon_t^{RGDP} + \alpha_{32}\varepsilon_t^{FACCW} + \alpha_{33}\varepsilon_t^{RES} + \beta_3\upsilon_t^{UR}$$

$$\varepsilon_t^{M3} = \alpha_{41}\varepsilon_t^{RGDP} + \alpha_{42}\varepsilon_t^{CCPI} + \alpha_{43}\varepsilon_t^{FACCW} + \alpha_{44}\varepsilon_t^{TWER} + \alpha_{45}\varepsilon_t^{HSI} + \alpha_{46}\varepsilon_t^{RES} + \beta_4\upsilon_t^{M3}$$

$$\varepsilon_t^{EXP} = \alpha_{51}\varepsilon_t^{RGDP} + \alpha_{52}\varepsilon_t^{TWER} + \beta_5\upsilon_t^{EXP}$$

$$\varepsilon_t^{FACCW} = \alpha_{61}\varepsilon_t^{RGDP} + \alpha_{62}\varepsilon_t^{M3} + \beta_6\upsilon_t^{FACCW}$$

[6] For instance, a downturn in the economy will have an impact on tax revenues, and other things being the same, reduce the fiscal reserves of the economy. This is reminiscent of a easier fiscal policy and help alleviate the impact of the negative demand shock.

$$\varepsilon_t^{TWER} = \alpha_{71}\varepsilon_t^{RGDP} + \alpha_{72}\varepsilon_t^{EXP} + \alpha_{73}\varepsilon_t^{RES} + \beta_7 \upsilon_t^{TWER}$$

$$\varepsilon_t^{HSI} = \alpha_{81}\varepsilon_t^{RGDP} + \alpha_{82}\varepsilon_t^{CCPI} + \alpha_{83}\varepsilon_t^{M3} + \beta_{81}\upsilon_t^{RGDP} + \beta_{82}\upsilon_t^{CCPI} + \beta_{83}\upsilon_t^{UR} + \beta_{84}\upsilon_t^{M3} + \beta_{85}\upsilon_t^{EXP} + \beta_{86}\upsilon_t^{FACCW} + \beta_{87}\upsilon_t^{TWER} + \beta_{88}\upsilon_t^{HSI} + \beta_{89}\upsilon_t^{RES}$$

$$\varepsilon_t^{RES} = \alpha_{91}\varepsilon_t^{RGDP} + \alpha_{92}\varepsilon_t^{CCPI} + \alpha_{93}\varepsilon_t^{UR} + \beta_9 \upsilon_t^{RES}$$

Or, we can write in matrix form

$$\Lambda\varepsilon_t = \begin{bmatrix} 1 & 0 & 0 & 0 & -\alpha_{11} & 0 & 0 & -\alpha_{12} & -\alpha_{13} \\ -\alpha_{21} & 1 & 0 & 0 & 0 & 0 & -\alpha_{22} & 0 & -\alpha_{23} \\ -\alpha_{31} & 0 & 1 & 0 & 0 & -\alpha_{32} & 0 & 0 & -\alpha_{33} \\ -\alpha_{41} & -\alpha_{42} & 0 & 1 & 0 & -\alpha_{43} & -\alpha_{44} & -\alpha_{45} & -\alpha_{46} \\ -\alpha_{51} & 0 & 0 & 0 & 1 & 0 & -\alpha_{52} & 0 & 0 \\ -\alpha_{61} & 0 & 0 & -\alpha_{62} & 0 & 1 & 0 & 0 & 0 \\ -\alpha_{71} & 0 & 0 & 0 & -\alpha_{72} & 0 & 1 & 0 & -\alpha_{73} \\ -\alpha_{81} & -\alpha_{82} & 0 & -\alpha_{83} & 0 & 0 & 0 & 1 & 0 \\ -\alpha_{91} & -\alpha_{92} & -\alpha_{93} & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_t^{RGDP} \\ \varepsilon_t^{CCPI} \\ \varepsilon_t^{UR} \\ \varepsilon_t^{M3} \\ \varepsilon_t^{EXP} \\ \varepsilon_t^{FACCW} \\ \varepsilon_t^{TWER} \\ \varepsilon_t^{HSI} \\ \varepsilon_t^{RES} \end{bmatrix}$$

$$= \Xi\upsilon_t = \begin{bmatrix} \beta_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \beta_2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \beta_3 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \beta_4 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \beta_5 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \beta_6 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \beta_7 & 0 & 0 \\ \beta_{81} & \beta_{82} & \beta_{83} & \beta_{84} & \beta_{85} & \beta_{86} & \beta_{87} & \beta_{88} & \beta_{89} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \beta_9 \end{bmatrix} \begin{bmatrix} \upsilon_t^{RGDP} \\ \upsilon_t^{CCPI} \\ \upsilon_t^{UR} \\ \upsilon_t^{M3} \\ \upsilon_t^{EXP} \\ \upsilon_t^{FACCW} \\ \upsilon_t^{TWER} \\ \upsilon_t^{HSI} \\ \upsilon_t^{RES} \end{bmatrix}. \qquad (7)$$

The α_s and β_s can be identified by solving the equation $\Lambda^{-1}\Xi\Xi'^{\Lambda^{-1}} = \Sigma$ once the RHS term is obtained from the MCMC estimation of the reduced form Threshold-BVAR.

1.3 Impulse Response Analysis

The core of economic analysis with SVARs is the evaluation of how the economy/system responds to various economic/structural shocks over time. This is the so-called Impulse Response Analysis. Impulse Response Function (IRF) assumes a pivotal role in multiplier analysis. An IRF maps out the time path of the response of an endogenous variable *x* from time *t* onwards to a shock in another variable occurred at time *t*.

Derivation of the IRFs for a *linear* SVAR requires inverting the system to obtain the coefficients of the Moving Average Representations. Details of this can be found in Lütkepohl (2005) and would not be pursued here. Unfortunately, the exploration of IRFs for a *nonlinear* SVAR, like ours, is not as straightforward. While the IRF for linear models are independent of the sign (hence, symmetric) and size of the shocks, this is not the case for nonlinear models. In our context, the shocks could alter the weights of the regimes embedded in the adjustment term. Thus, the responses will both be size and sign dependent. Following Koop et al. (1996), the Nonlinear IRF (or the Generalized IRF), NIRF, is used instead for the analysis.

The NIRF is the difference in the forecast paths of the variables subject to a shock and those without experiencing a shock. Specifically,

$$NIRF(h, \upsilon_t^0, \Theta_{t-1}) = E(Y_{t+h}|\upsilon_t^0, \Theta_{t-1}) - E(Y_{t+h}|\Theta_{t-1}) \qquad (8)$$

where h is the time horizon, υ_t^0 is a particular realization of normalized structural shocks at time t, Θ_{t-1} is the information set available before the time of shock, and $E(\quad)$ being the conditional expectation of the argument inside the bracket. To assess the expected values, we have to simulate realizations of the 2 terms on the RHS and take averages of them. Koop et al. (1996) contains the following algorithm for estimating the NIRFs:

1. Pick a history Θ_{t-1} which is the actual values of the lagged endogenous variables at a particular date.
2. Sample a sequence of n-dimensional $\upsilon_{t+h},\ h = 0,1,\cdots,40$ from the estimated structural form[7] of the model (1.2).
3. Simulate the evolution of Y_{t+h}, for $h = 0,1,\cdots,40$ given Θ_{t-1} and υ_{t+h}. This is the baseline path $Y_{t+h}(\Theta_{t-1})$.
4. Repeat step 3 but with the *i-th* element (the structural shock of interest) of υ_{t+h} set to +/- 1 and +/- 2 standard error at $h = 0$. This is the perturbed path $Y_{t+h}(\upsilon_t^0, \Theta_{t-1})$.
5. Repeat steps 2 – 4 for M_0 times to get M_0 baseline and perturbed paths. Take the average of the differences of the two paths.
6. Repeat steps 1 – 5 for all histories for $\Theta_{t-1},\ t = 1,\cdots,T$. Compute the average of the mean IRFs from step 5. The last two steps here prompt for the evaluation of the following expression
$$NIRF(h, \upsilon_t^0, \Theta_{t-1}) = \frac{1}{T}\sum\nolimits_{\leq T}\left\{\frac{1}{M_0}\sum\nolimits_{\leq M_0}[Y_{t+h}(\upsilon_t^0, \Theta_{t-1}) - Y_{t+h}(\Theta_{t-1})]\right\}.$$

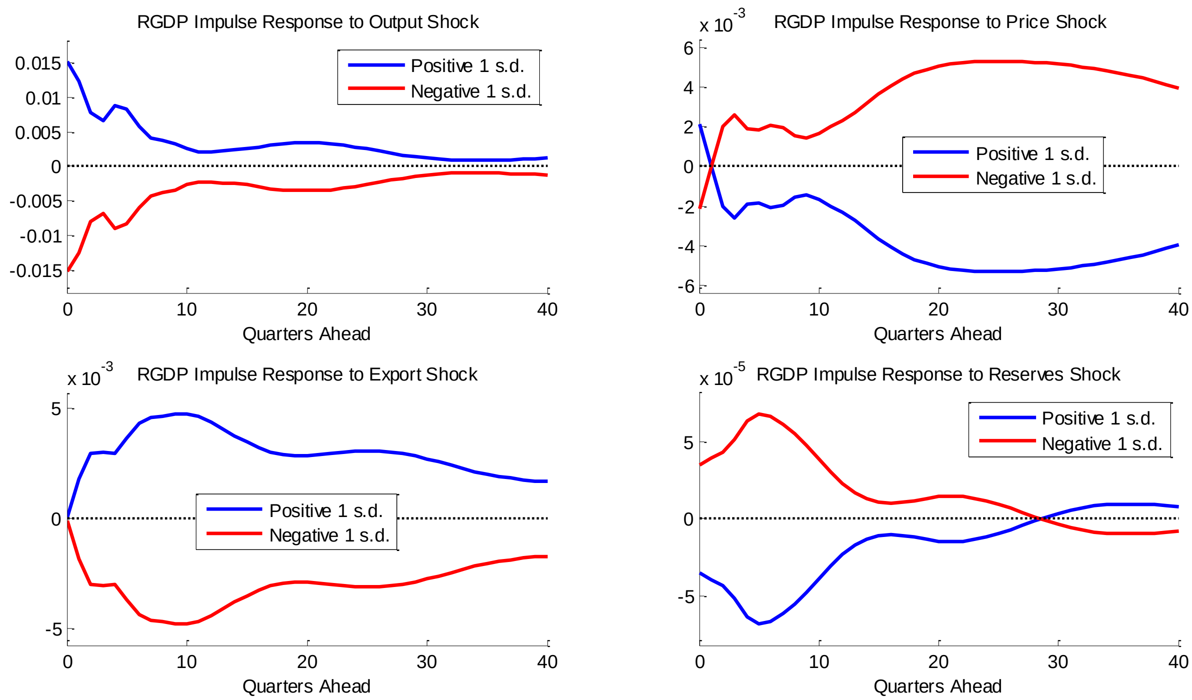
[7] To simulate from the reduced form model (1.1) corresponds to generating economy wide shocks on the endogenous variables, whereas draws from the structural version generate disturbances from specific structural sources.

2. Empirical Results

2.1 Nonlinear Impulse Responses

Based on the algorithm above, we set $M_0 = 500$ and work for all histories that have at least 21 data points[8]. This allows us to have a fair amount of data in each history to perform the bandpass filtering needed to evaluate the NIRFs. There is a total of 88 such sequences. The following figures highlight the impulse responses of major economic variable to shocks that are of interest to us. All shocks are simulated from the standard normal distribution to get a plus and a minus 1 standard deviation of the structural shocks. As a reminder, note that: (i) the NIRF diagrams show only a 1-to-1 impulse response relationship between two variables, with everything else held constant. That is, shocks of a "third" variable are non-existent. (ii) The NIRFs show the time paths of the response variable from the impact point onwards.

Figure 1: RGDP Responses to Shocks



[8] The shortest history contains data from 1984:1Q to 1989:1Q.

Figure 2: CCPI Responses to Shocks

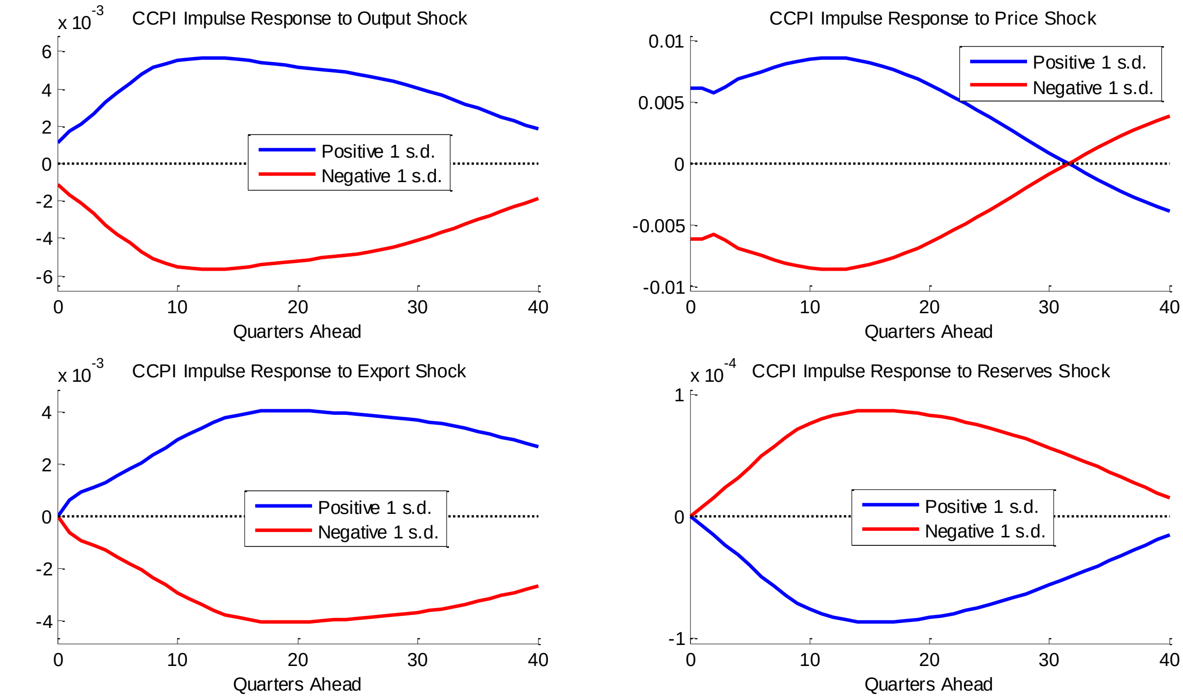


Figure 3: Unemployment Rate Responses to Shocks

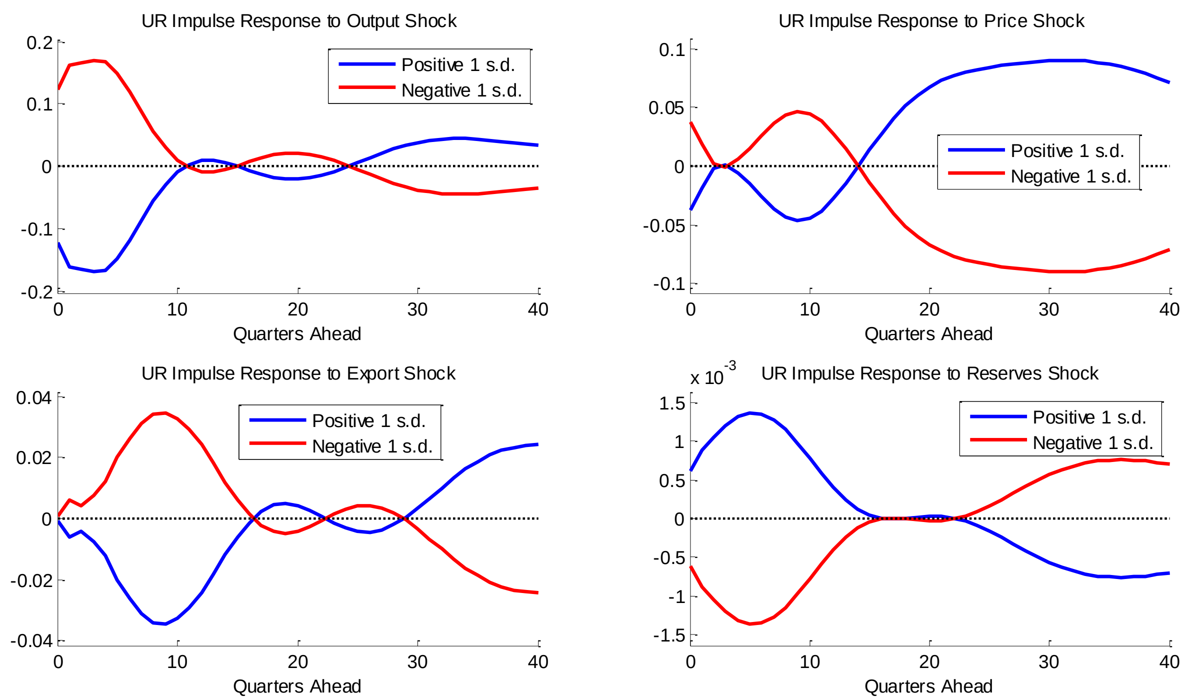


Figure 4: Exports Responses to Shocks

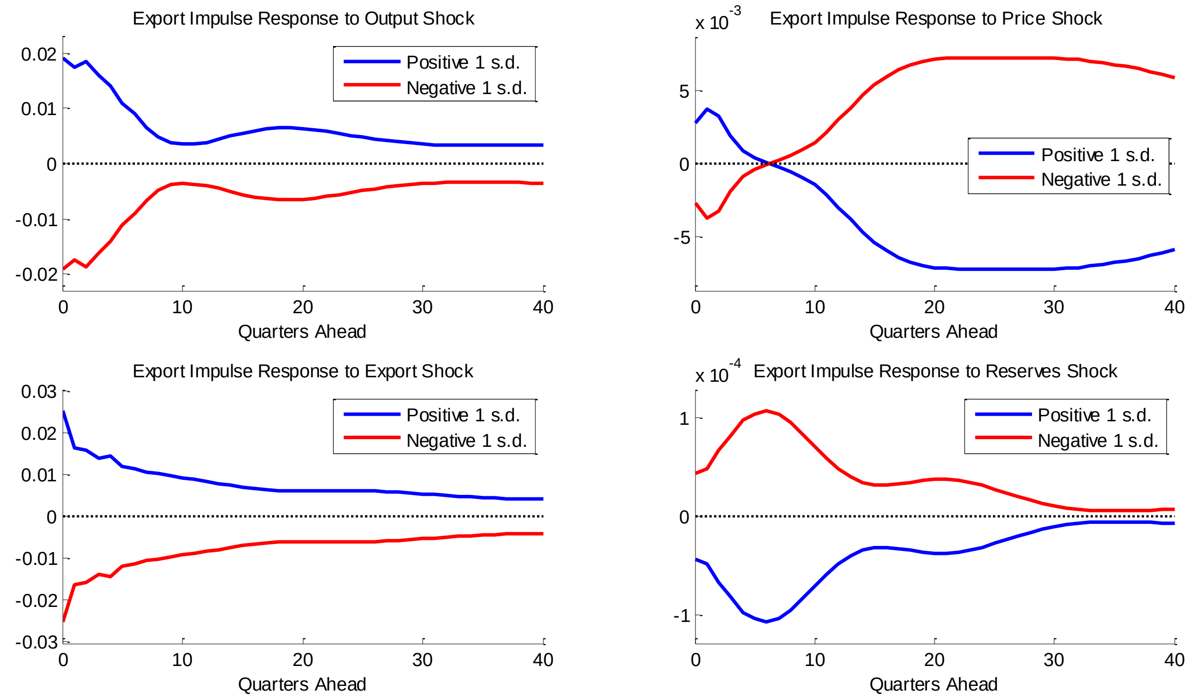


Figure 5: Fiscal Reserves Responses to Shocks

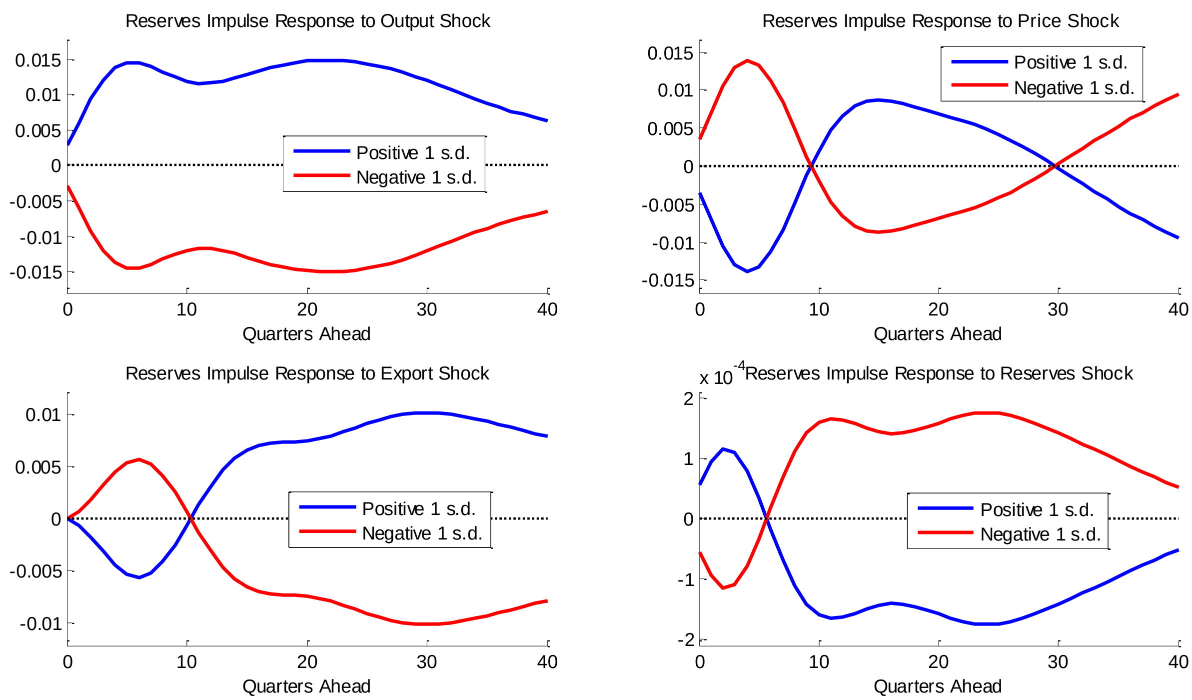


Fig. 1 shows that RGDP reacts positively to an output (e.g. domestic demand) shock but the effect will be more or less digested in 3 years. Its response to an export shock (e.g. foreign demand) is positive as well, but the adjustment back to the baseline level is much weaker and slower. An inflation shock is going to have a very mild and brief positive impact on RGDP before a lengthy negative effect sets in. As for a positive shock in fiscal reserves (this corresponds to a tightening fiscal stance in our context), it will inflict a negative impact on RGDP instantaneously with the situation keeps worsening in 1.5 years before improvement will surface. The majority of the negative impact from the tightening will dissipate after around 3 years[9].

Other diagrams can be interpreted in a similar way. For instance, the lower right hand corner of Fig. 2 shows that fiscal tightening would take some steam off CCPI with the sharpest drop felt after 3 to 4 years. In a similar fashion, Fig. 3 shows that a fiscal tightening would indeed prop up unemployment rate with the worst situation realizing in about 1.5 years but the impact will dissipate in 3 years. Yet, compared to other types of shocks, the impact of shock in fiscal reserves is relatively modest.

2.2 Output Elasticity of Fiscal Component

The last row of system (7) shows how the reduced form shock of fiscal reserves is related to shocks of other variables

$$\varepsilon_t^{RES} = \alpha_{91}\varepsilon_t^{RGDP} + \alpha_{92}\varepsilon_t^{CCPI} + \alpha_{93}\varepsilon_t^{UR} + \beta_9 v_t^{RES}.$$

As remarked earlier, $\alpha_{91}\varepsilon_t^{RGDP}$ gives the contribution of the automatic stabilizer to fiscal reserves, and α_{91} is the output elasticity of fiscal reserves which is expected to have a positive sign. The estimate of α_{91} from solving (7) is 0.3256. This is in the ballpark of elasticities of other advanced countries[10].

[9] Although the NIRFs are not symmetric over positive and negative shocks, the figures we obtained are close to symmetry. So, the opposite is true for an expansionary fiscal policy (shock).

[10] Figures are not directly comparable given the different model settings.

Table 1: Output Elasticities of Fiscal Components

Country	Of Revenues	Of Spending	Of Fiscal Reserves	Reference
HKG			**0.3256**	-
France	0.58	-0.11	0.47 #	Alfonso & Claeys (2007)
Germany	0.59	-0.18	0.41 #	ditto
Portugal	0.47	-0.05	0.42 #	ditto
Spain	0.49	-0.15	0.34 #	ditto
Finland	0.18			Pommier (2006)
France	0.49			ditto
U.K.	0.37			ditto
Ireland	0.34			ditto
Italy	0.26			ditto
Netherlands	1.13			ditto
Sweden	0.30			ditto
Germany	0.85			ditto
Remarks: # are approximate figures only and are based on the difference between the elasticity of revenues and elasticity of spending.				

3. Applications

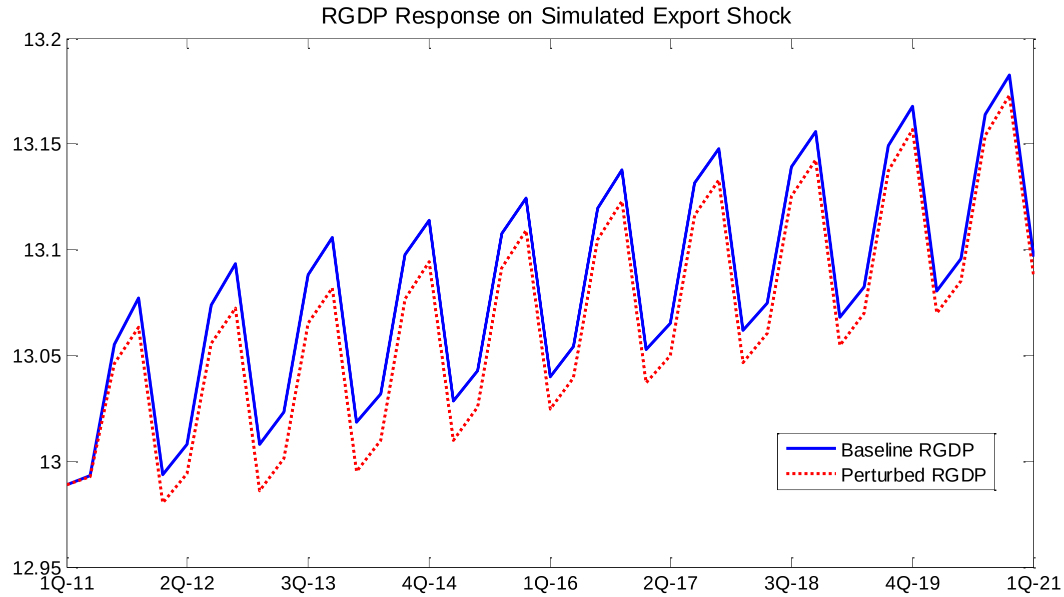
To further indicate how the NIRFs can aid economic analysis, two examples are illustrated below.

3.1 Simulating the Impact of the 3-11 Earthquake in Japan

The 3-11 earthquake and the nuclear crisis that followed rocked the production base of Japan and aroused concern of breaks in the global supply chain. We mimic the situation with a negative 5 s.d. structural shock on exports in 2011:2Q. This basically slows the total exports growth (y-o-y) of 2011:2Q from a baseline forecast of +10.5% to -2.6%. The corresponding impact on RGDP growth in 2011 (full year) is a slowdown from a baseline projection of around +5.02% to +4.38%, i.e. a reduction of 0.64 percentage point[11]. The following figure shows the trajectories of the baseline projection and the path perturbed by the negative export shock, assuming no other shocks of whatever kind will intervene with the system in the next 10 years.

[11] Note that the baseline forecast differs from the unconditional forecast stated in the Executive Summary. The former is based on simulating random shocks as observed historically, while the latter is an unconditional forecast where the expected values of shocks are equal to their zero means.

Figure 6: Simulated Paths of RGDP with and without Impact of 311 Earthquake



3.2 Simulating the Outcome of the Financial Tsunami

The second exercise replicates the Financial Tsunami of 2008-9. Recall that the actual economic system amasses various variables that are subject to shocks (concurrently) all the times. Our job is to disintegrate the sources of these shocks and see to what extent an economic variable is responding to a certain shock with all other shocks being controlled for. The exact date of this episode is difficult to gauge, and we use the two quarters with the sharpest decline in economic activities as the impact point. Likewise, the actual dates when the government's relief plan[12] took effect is also unclear, so we assume the easing occurred *after* the impact points mentioned above and last for 4 quarters. In sum,

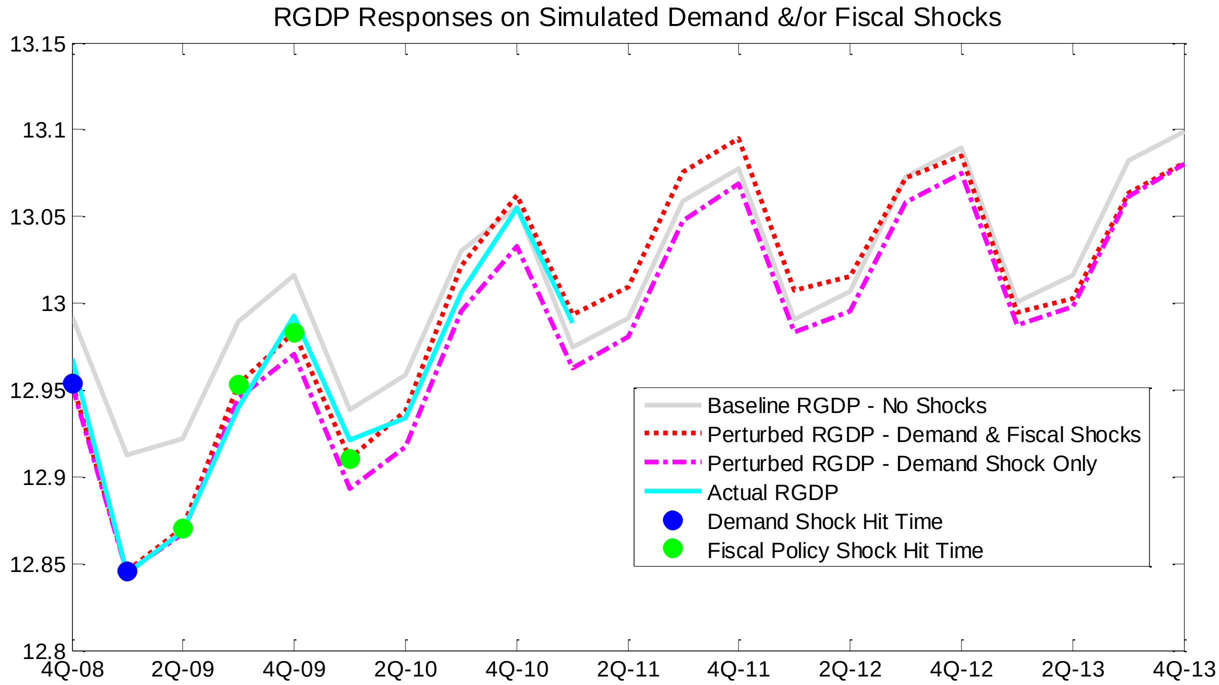
Type of Shocks	Impact Point	Magnitude
Demand Shock – adversary	2008:4Q – 2009:1Q	-10.3% in 2 quarters
Fiscal Shock – expansionary	2009:2Q – 2010:1Q	- HK$ 40 bn in reserves

As a result, the shocks hit the system in sequence – first the negative demand shock and then a negative shock (expansionary) in fiscal reserves. This is done by setting a level for

[12] The 2009-10 budget speech unveiled a relief package of size that equals HK$40 billion. However, the timing of the relief package is difficult, and the impact on fiscal reserves is marred by increase in tax income due to the recovery. The actual year end reserve level for 2009-10 fiscal year was HK$508 bn vs a projected value of HK$448 bn, the difference itself is more than the size of the relief package.

the structural shocks so that the resulting reduced form discrepancies are as we actually observed[13]. The situation is depicted by the next diagram.

Figure 7: Simulated Paths of RGDP amidst the Financial Tsunami



The light grey line is the baseline forecast of RGDP as at 2008:4Q and should represent what it would be like if there are no shocks to the economic system whatsoever. The pink line gives the trajectory if there is only the negative demand shock and no fiscal relief plan. The red line shows the RGDP path when both kinds of shocks exist. Finally, the blue line is the actual RGDP. Major observations are:

1. Comparing the grey and pink curves – if government did nothing to dilute the negative demand shock, it would take around 3 years (towards end of 2011) for the economy to revert to its baseline trajectory.

2. Comparing the grey and the red – with the additional fiscal shock, the economy moved back to the baseline much earlier (by end of 2010).

[13] The cumulative decline in fiscal reserves that signify the fiscal shock is -2.81%. As stated in footnote 7, the actual reserve level increased, but that could be due to some other shocks that took place but we have not taken into account.

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