Re-assessing monetary policy shocks in China*

Preliminary and not to be quoted

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May 15, 2017

Abstract

In this paper we investigate the effects of monetary policy shocks on economic activity in China by using a variety of Bayesian VAR techniques. We show that monetary policy shocks appear to have a significant effect on economic activity under standard BVAR specifications. These findings are robust across different model specifications and different interest rate measures. However, this result changes when we consider a specification which takes into account the non-stationarity of the data. In particular, we consider an underlying economic model for the long-run with either a linear trend for GDP or with a common time-varying equilibrium on the steady-state jointly with foreign demand. In the latter case we find that the common structural explanation for the economic downturn crowds out the role of interest rates.

Keywords: Monetary policy, China, Bayesian VAR.
JEL classification: C11, E32, E52

*We would like to thank Romain Legrand for helping us to set-up the BVAR models using the BEAR toolbox. In addition, we would also like to thank Michel Soudan, David Lodge, Feng Zhu and participants of the ECB China Export Network (CEN) workshop for very helpful comments and discussions. The views expressed in this paper are those of the authors and do not necessarily reflect those of the ECB or the IMF.

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1 Introduction

China has undergone periods of expansionary monetary policy notably between 1998 and 2003 and during the global financial crisis as well as periods of monetary tightening such as prior to the global financial crisis. The cuts in benchmark policy rates (deposit and lending rates) and the Reserve Requirement Ratio (RRR) in 2015 raise the question to what extent changes in interest rates or RRR will help to support the economy in comparison with more direct credit policies. Both in academia and among policy makers, the effects of China's monetary policy on growth are debated. This debate partly reflects that the People's Bank of China (PBoC) had various targets for monetary policy including controlling inflation, exchange rates and supporting growth. In addition, the PBoC has used variety of instruments in addition to interest rates including annual targets for broad money growth and adjusting Reserve Requirement Ratios (RRR). There are quite a few studies that have estimated monetary policy reaction functions of the Taylor rule or McCallum rule type to capture quantity and price. Fan et al. (2011), Mehrotra and Sanchez Fung (2010) and Liu and Zhang (2010) find the reactions tend to be fairly small, particularly for interest rates and even found it pro-cyclical for inflation. However, a more recent paper by Nuutilainen (2015) which estimated a variety of monetary policy reaction functions for China found that since 2008, interest rates were more responsive to the output gap, whereas money supply only responded to price changes. This provides some evidence of the increasing importance of interest rates. In terms of the effects of monetary policy on the Chinese economy, the traditional view has been that interest rates have only a limited effect on Chinese economic activity. Past studies suggested that changes in interest rates have been relatively less important in China in comparison with advanced economies. For instance, Fan et al. (2011) show that "official interest rates do not have any effect on future inflation rates and real output either". Mehrotra and Sanchez Fung (2010) estimated monetary policy models using a VAR until 2008 and found that an interest rates based rule is not significant and "does not provide an adequate description of monetary policy behaviour in China." Looking more broadly at the bank lending and property prices channels, Liang and H. (2007) found only a weak connection with interest rates and concluded that a policy rate is not an effective instrument to control them. More recently, He et al. (2013) confirm these finding by claiming that "the

Chinese economy is affected primarily by the growth rate of total loan and M2. Market-based policy instruments, such as repo and benchmark lending rates, are only mildly effective [...]." Overall, these findings gave reasons to believe that the Chinese economy behaves differently to other more market-based economies Fred Bergsten (2008), which could reflect the tight control maintained over some interest rates He and Wang (2012). However, many of these studies likely do not capture subsequent changes in the monetary transmission mechanism in China.

Recent analysis has found that interest rates and reserve requirements are more important for economic activity than direct quantity measures of lending. Fernald et al. (2014) find that "that changes in Chinese interest rates also have substantial impacts on economic activity and inflation, while other measures of changes in credit conditions, such as shocks to M2 or lending levels, do not once other policy variables are taken into account." Similarly Sun (2013) estimate that "using these shocks and various robustness tests indicate that monetary policy has large and persistent impact on output in China." They find similar effects for decreases in money growth, although these effects are much smaller. Zhang (2009) also found that interest rates are likely to be more effective than controlling money supply in managing the economy both for inflation and output. Pang and Siklos (2015) used a factor VAR model to look at the role of monetary policy in China once spillover effects between US and China are taken into account. They found that Chinese monetary policy helped mitigate the global financial crisis but that US financial factors also matter. Given changes in interest rates need to be approved by the PBoC and the State Council, the PBoC has increasingly relied since the mid-2000s on the Reserve Requirement Ratio (the share of deposits banks are required to hold in central bank reserves) as a policy instrument. Zuzana Fungacova and Weill (2015) investigated the role of both the RRR and interest rates in China by considering on bank loans using a large dataset of 170 Chinese banks between 2004 to 2013. They found both a tightening of RRR or an increase in interest rates leads to a decline in the growth rates of loans.[1]

Overall, these papers suggest the transmission mechanism in China is not too dissimilar from advanced economies. Our aim is to investigate to what extent monetary policy is generally effective for business cycle dynamics in China and if so, which monetary policy instruments are the most effective. We use the

[1] Although RRR appear to not affect bank lending directly.

Bayesian VAR methodology and check for robustness with alternative specifications and approaches. We show that under the standard Bayesian VAR approach, interest rates matter (more than money) in driving the business cycle and that higher financing costs have been a significant driver for the growth slowdown over the past few years. We find this result is robust to alternative Bayesian VAR specifications including steady-state priors approach, Villani (2009). However, the long-run value of a VAR model depends on the deterministic coefficients which may result in long term forecast at odds with the prior opinion of the researcher. To overcome this issue we use a generalisation of Villani (2009) where we allow for time-varying equilibrium on the steady-state, Akkaya et al. (2017) and Del Negro and Tambalotti. This approach applies to non-stationary data with time-vary steady-states where we specify an underlying economic model for the long-run. We show in this case that the role of monetary policy is much less prevalent.

2 The role of monetary policy shocks with a standard BVAR

2.1 The model setup

Time series analysis for countries with a short data sample are usually a challenging task. Given that data for China is only available for a very limited time period, we have to choose a model framework which appropriately approaches this caveat. One framework which is often used to mitigate over-fitting in traditional VAR models is Bayesian inference. In fact, Bayesian methods for vector autoregressions specifically allow to treat shorter time periods.

For our analysis on monetary policy shocks, we use a simple structural VAR, which is estimated using Bayesian methods. In particular, our model has the following form:

$$D_0 y_t = D_1 y_{t-1} + D_2 y_{t-2} + ... + D_p y_{t-p} + F x_t + \eta_t \tag{1}$$

with $\eta_t \sim \mathcal{N}(0, \Gamma)$ a vector of structural innovations with variance-covariance matrix Γ.

The Bayesian VAR model provides a sound framework to quantify the nexus

between China's monetary policy (and financing costs) and key macroeconomic variables. Given the significant structural changes China's economy has been undergoing in past decades, we limit our analysis to the past 15 years (2000Q4 to 2015Q3 using quarterly data on a year-on-year basis), which covers the lead-up to the global financial crisis, as well as the rebound and subsequent slowdown. In terms of monetary policy stance, we focus on the money supply (M2) and the 7-day interbank rate.
Although China could have been considered in many respects a closed economy in the 1990s, with the admission to the WTO, and the growth of trade and services in particular has played a very important role China's growth dynamics, and it has benefitted from current account surpluses. Ignoring the role of foreign variables in China's growth leads would lead to mis-specification errors. Furthermore, financial factors which tend to be volatile, and are also of increasing importance for China, Rey (2013). Therefore, in addition to China's real GDP growth (year-on-year) and the CPI inflation rate, we include the VIX as a measure of global financial uncertainty and China's foreign demand (weighted average of other countries' imports) to account for the role of external variables.

Although, there have been questions raised about the quality of Chinese data, there is no consensus on a better alternative measure. Some papers use Industrial Production to capture economic developments, however, whilst this might have been a good indicator in the past, it just focuses on the manufacturing sector, and therefore does not capture the increasing role of the service sector. Other papers used factor models to capture the underlying economy (Fernald et al. (2014), Pang and Siklos (2015), Liu and Zhang (2010), and He et al. (2013)). But some research over the past few years have suggested there is no systematic statistical discrepancy or indeed robust evidence of falsification Wu (2011), Mehrotra and Pakkonen (2011). Therefore, we use the published measure of real GDP growth.

Our modelling approach is a 6 variable Bayesian VAR model with four lags to allow for the often significant delays in monetary transmission to the real sector. For the baseline model, we use an Independent Normal-Wishart prior (with univariate AR). This approach has the advantage that Γ is treated as unknown, and allows for block exogeneity. As hyper-parameters we assume the autoregressive coefficient is 0.8; with an overall tightness of 0.1 and a cross-variable weighting parameter of 0.5. The VIX and foreign demand are assumed to be block exogeneous i.e. there are no second-round macroeconomic effects of China on rest of the world and back again to China.[2] We identify the VAR with a recursive Choleski identification) ordering, that is we assume that interest rates and money react contemporaneously to changes in GDP and inflation, while GDP growth and inflation only react to policy variables with a delay.

2.2 Quantifying the effects of interest rates on growth

Impulse responses suggest that increases in the interest rate lead to a persistent and significant decline in GDP growth (Figure 1). Similar effects are also found for shocks to money growth although the effect of a fall in money growth on activity is smaller and less significant than interest rates. It is also worth noting that increases in interest rates also reduce money growth. Shocks to foreign demand appear to affect growth (and inflation) positively, although the transmission of foreign demand shocks seems to be rather short-lived and international financial conditions (proxied by the VIX) have rather small effects as they are offset rather quickly by a lowering of interest rates and increasing money supply (see section 6). Inflation, whilst initially increasing (the price puzzle), subsequently falls after a few quarters.

2.2.1 Alternative measures for monetary policy instruments

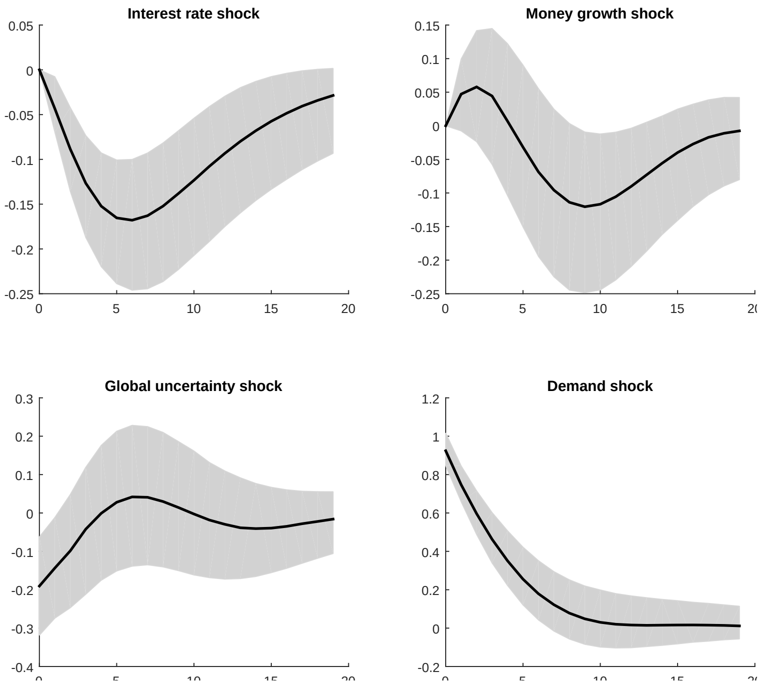
The finding that interest rate increases leads to a significant drop in GDP growth is in line with some analysis from the literature, e.g. Fernald et al. (2014) and Sun (2013), who find that monetary policy has a large and persistent impact on output in China.[3] This result is robust to the inclusion alternative measures of monetary policy: shocks to the RRR, prime lending and deposit rate (or an average of the two) affect real GDP growth in a similar way (Figure 2). However, the strongest and most persistent impact on growth is from the 7-day interbank rate, which is the one used in the baseline model. Nonetheless, the extent that this rate is influenced by the PBoC rather than reflecting market forces is uncertain.

The PBoC has also used quantity-based tools (e.g. short-term liquidity operations, lending facility instruments etc.) to stimulate the economy in addition

[2] Given the size of China it could be that they are significantly affected, however, relaxing this assumption does not change the results significantly.

[3] Sun (2013) find similar effects for decreases in money growth although these effects are smaller.

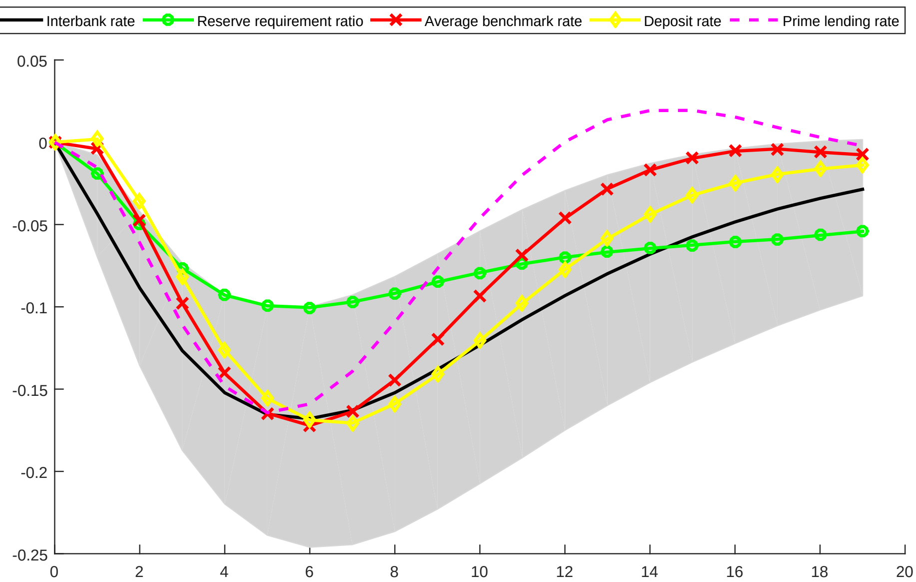
Figure 1: *Impulse responses of China GDP growth*



NOTES: Percentage point deviation from year-on-year growth. Size of the shock reflects 1 standard deviation shock. In the case of the interbank rate shock this is a 50 basis points increase. Shaded areas represent 68 percent posterior error bands. SOURCES: CEIC and own computations.

to its key refinancing rates to influence the financing costs in the economy. This allowed the PBoC to control the composition of credit in order to dampen the expansion of the shadow banking sector and growth in loans with short-term maturities. As a result of these measures, loan growth in the economy slowed, with total social financing growth moderating in 2014Q3 to the lowest level since 2005. When alternative measures to M2, such as total social financing are included the results also do not change significantly. Furthermore, the response of GDP to interest rates is also robust across alternative model specifications (such as inclusion of exchange rates) and across different sample periods.

Figure 2: *Impulse responses of GDP growth to alternative measures for monetary policy instruments*



Note: Shaded area represents 68 percent posterior error bands.

2.3 Alternative prior specifications

In order to see how much the results depend on our choice for the prior distribution, we compare our baseline model of an Independent Normal-Wishart prior with alternative prior assumptions.

Assuming that β follows a multivariate normal distribution, with mean β_0 and covariance matrix Ω_0:

$$\pi(\beta) \sim \mathcal{N}(\beta_0, \Omega_0) \tag{2}$$

We consider 4 different prior distributions:
(i) Minnesota (or Litterman (1986)) prior,
It is assumed that endogenous variables include a unit root in its first own lags and coefficients equal for zero for further lags and cross-variables lag coefficients. In addition it is assumed that the VAR residual variance-covariance matrix Σ is known and given for own lags by:

$$\sigma^2_{a_{ii}} = \left(\frac{\lambda_1}{l^{\lambda_3}}\right)^2 \tag{3}$$

and for cross-variable coefficients by:

$$\sigma^2_{a_{ij}} = \left(\frac{\sigma^2_i}{\sigma^2_j}\right)\left(\frac{\lambda_1\lambda_2}{l^{\lambda_3}}\right)^2 \tag{4}$$

where $lambda_2$ represents a cross-variable specific variance parameter.
For exogenous variables (including constant terms), the variance is given by:

$$\sigma^2_{c_i} = \sigma^2_i(\lambda_1\lambda_4)^2 \tag{5}$$

where λ_4 is a large (potentially infinite) variance parameter.

(ii) Normal-Wishart prior,
It is assumed that both β and Σ are unknown. For β, one thus assumes a multivariate normal distribution for the prior:

$$\beta \sim \mathcal{N}(\beta_0, \Sigma \otimes \Phi_0) \tag{6}$$

Similarly to the Minnesota prior, β_0 is an $q \times 1$ vector. Φ_0 is a $k \times k$ diagonal matrix, and Σ is the usual VAR residual variance-covariance matrix, which implies that $\Sigma \otimes \Phi_0$ is a $nk \times nk$ or $q \times q$ covariance matrix.

For lag terms (both own and cross-lags), define the variance as:

$$\sigma^2_{a_{ij}} = \left(\frac{1}{\sigma^2_j}\right)\left(\frac{\lambda_1}{l^{\lambda_3}}\right)^2 \tag{7}$$

where σ^2_j is the unknown residual variance for variable j in the BVAR model, approximated by individual AR regressions. For exogenous variables, define the variance as:

$$\sigma^2_c = (\lambda_1\lambda_4)^2 \tag{8}$$

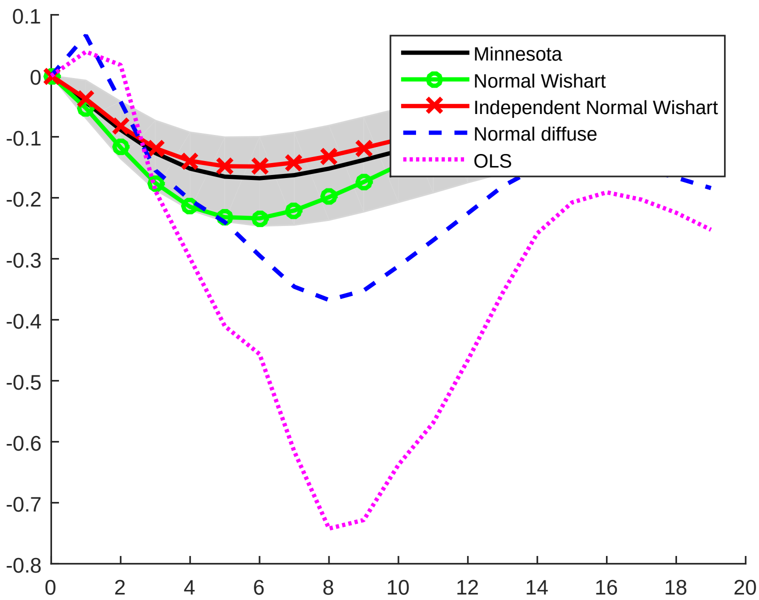
(iii) Independent Normal Wishart,
The normal-Wishart prior whilst being more flexible than the Minnesota prior in the sense that Σ is not assumed to be known, it nonetheless imposes a Kronecker structure on the prior distribution for β, constraining its covariance matrix to be equal to $\Sigma \otimes \Phi_0$. We therefore depart from the normal-Wishart assumption by assuming that β follows a multivariate normal distribution with mean β_0 and covariance matrix Ω_0, but with Ω_0 now specified as an arbitrary $q \times q$ matrix, i.e. not necessarily adopting the Kronecker structure described by 6.

(iv) Normal diffuse prior
Another alternative to prior is the so-called normal-diffuse prior distribution where the prior distribution for Σ, is now defined as the so-called Jeffrey's or diffuse prior:

$$\pi(\Sigma) \propto |\Sigma|^{-(n+1)/2} \tag{9}$$

Note that with the normal diffuse block exogeneity is not feasible.
The negative persistent response of real GDP to a shock in the interbank rate is robust across different prior specifications. Note however that the effect is even more pronounced when selecting an uninformative prior such as the Normal Diffuse Prior. In this case, real GDP drops by nearly 0.4 percent after a standard deviation shock in the interbank rate. The normal diffuse prior and the OLS estimate imply the strongest effects. The fact that the normal diffuse is closer to the OLS estimate is not surprising as it is a non-informative prior.

Figure 3: *Impulse responses of GDP growth to alternative prior specifications*

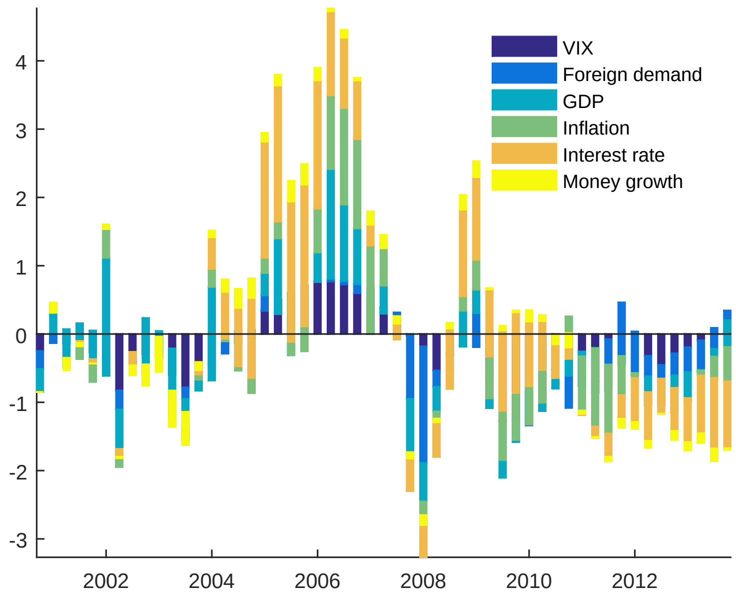


Note: Shaded area represents 68 percent posterior error bands.

2.4 Monetary policy as a driver of the business cycle

The BVAR results, which allow to disentangle the role of monetary policy and other factors in China's economic growth, suggests that interest rates and money developments played a significant role for China's business cycle over this period. The historical decomposition,using the baseline specification, finds that money growth (yellow bars in Figure 4) played a role prior to 2005 but much less so subsequently, whereas the importance of the interbank rates steadily increased, boosting GDP growth by up to 2 pp prior to the crisis (orange bars). At the height of the financial crisis, China's GDP continued to be supported by low interest rates, while the downturn in activity was particularly related to the collapse in foreign demand (blue bar) and the rise in global uncertainty as evidenced by the negative contribution from the VIX (dark blue bar). Thereafter, the fiscal stimulus (which is reflected by the contribution of GDP) and the recovery in world trade instigated a rebound of the Chinese economy in 2009 along with an increase in interest rates. Subsequently, growth in China has been rather subdued by historical standards. The historical decomposition suggests that the relatively high cost of financing held back Chinese growth. The drag continuously increased over the past years and at the end of 2014, more than half of the downward deviation from average growth can be attributed to high interest rates.[4] Historical decompositions can depend on the structural identification, however, in this case the contribution of interest rates is robust to alternative orderings in the BVAR.

Figure 4: *Historical shock decomposition*



Sources: Shock contributions are expressed in the deviation from the unconditional model forecast.

Overall, this suggests that China's economy increasingly behaves like other economies in that interest rates have become an important driver of growth. Such an increased role of the interest rate in the monetary transmission process also seems plausible given monetary policy liberalisation and increased marketisation of interest rates in recent years. The variance decomposition suggests that changes in the interbank rate contributed to about 20 percent of the variation in GDP growth, whereas changes in money supply contributed less than 10 percent.

[4]Part of this may reflect lags in the monetary transmission but could also reflect high financing costs.

3 The potential impact of monetary loosening - mean adjusted BVAR

We now we aim to quantify what effects interest cuts have for the outlook for China. Therefore, we implement a conditional forecast exercise, where we condition on lower interest rates while we leave the rest of the variables unrestricted and will compare it with a mean-adjusted BVAR following Villani (2009). To implement the conditions, we follow Waggoner and Zha (1999) who derive a Gibbs sampling algorithm to construct the posterior predictive distribution of the conditional forecast.[5] We focus on three potential monetary policy measure, i.e. the 7-day repo-rate, the average of the prime lending and the deposit rate, and the reserve requirement ratio. We start by considering the standard BVAR specification before switching to a mean-adjusted BVAR.

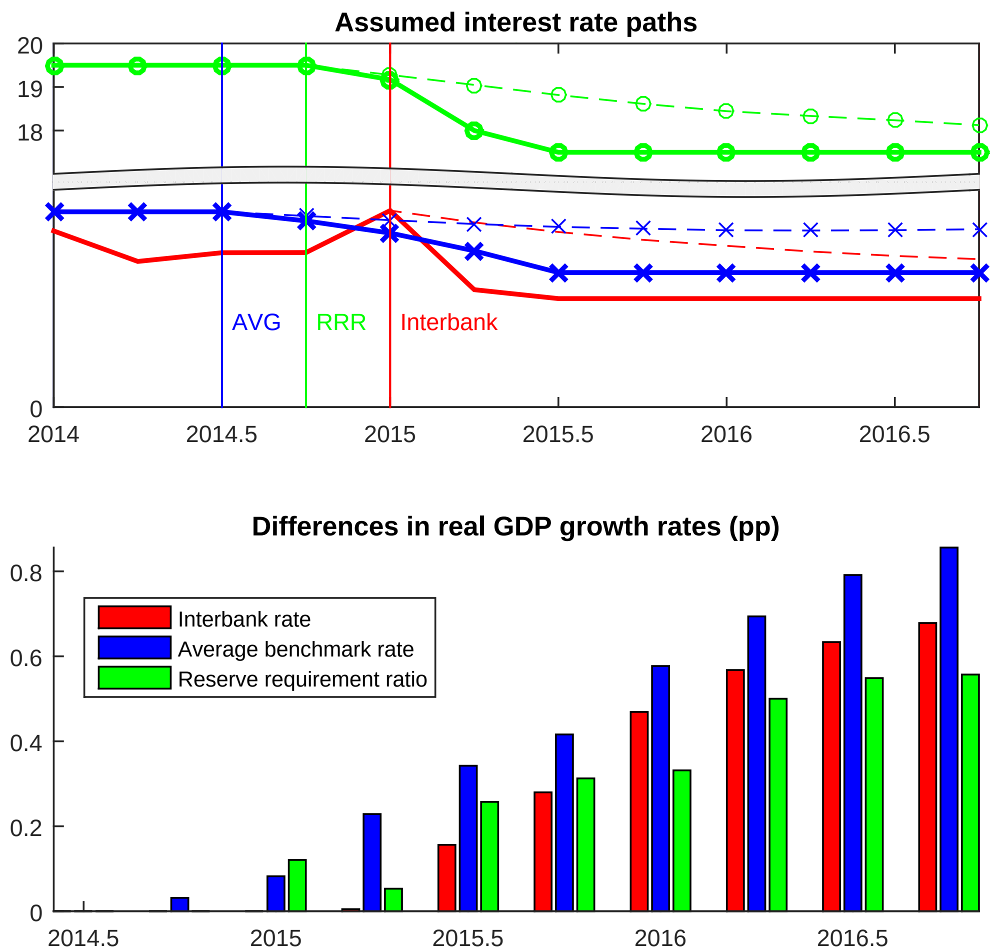
3.1 The effects of monetary loosening for the outlook with a standard BVAR

The starting points for the exercise vary across interest rate measures. While the average benchmark rate was already reduced in 2014Q4, the reserve requirement ratio was set lower one quarter later (2015Q1). At the same time, the 7-day interbank rate still increased in 2015Q1 and only dropped substantially in 2015Q2. We therefore start the conditional forecasts at each individual local peak of interest rates (Figure 5). The conditional path for the average benchmark rate starts with a decline from 4.5 percent (2014Q3) to 4.3 percent (2014Q4), 3.6 percent (2015Q1) and 3.1 percent until the end of 2016. The conditional path for the reserve requirement ratio starts with a decline from 19.5 percent (2014Q4) to 19.2 percent (2015Q1), 18 percent (2015Q2) and 17.5 percent until the end of 2016. The conditional path for the 7-day interbank rate starts with a decline from 4.5 percent (2015Q1) to 2.7 percent (2015Q2) and 2.5 percent until the end of 2016. At the end of the forecasting horizon, the average benchmark rate is 100 basis points, the reserve requirement ratio 70 basis points, and the interbank rate 140 basis points lower than in the baseline scenario.

The impact of monetary loosening is sizeable in all three scenarios. In all

[5] For an extensive overview on this technique refer to the technical guide of Dieppe et al. (2016).

Figure 5: *Conditional forecasts on monetary loosening*



Notes upper panel: Solid lines represent the imposed conditions while dashed lines represent the unconditional forecasts of the interest rates. The shock size is the difference between the unconditional and the conditional forecast. The conditional forecast starts for each interest rate at the beginning of monetary loosening. Conditional forecasting dates are indicated by the vertical coloured lines. Notes lower panel: The bars represent the GDP growth percentage point deviations from the baseline forecast, i.e. the difference between the conditional and the unconditional forecast.

three scenarios, real GDP growth is higher than under the baseline model (the unconditional forecast of the model). However, monetary transmission only works with a certain time lag, i.e. the effects get significantly stronger after a few quarters. As the monetary loosening is of a permanent nature, the effects get steadily stronger over the forecasting horizon.[6]

3.2 The effects of monetary loosening for the outlook with a mean-adjusted BVAR

The forecasts presented above are all relative to the baseline forecasts, i.e. the time series converge back to the unconditional posterior mean of the model. However, there are reasons to believe that the steady-state has changed over time. In particular, there is a widespread belief that potential GDP has declined in China in the past years. Therefore the assumption that real GDP growth will converge back to the posterior mean does not seem very plausible. Hence in the next step, we investigate imposing prior information on the steady-state of the model, i.e. we use a mean-adjusted Bayesian VAR in the spirit of Villani (2009). In particular, we can write the VAR in the following representation:

$$A(L)(y_t - Fx_t) = \varepsilon_t \tag{10}$$

In this representation, $A(L)$ is a lag polynomial, the p matrices $A_1, A_2, \ldots, A_p$ are of dimension $n \times n$. In addition, F is a $n \times m$ matrix of coefficients with respect to the m exogenous variables. This structure implies that each equation comprises $k_1 = np$ coefficients to estimate with respect to y_t, and m coefficients with respect to x_t, leaving a total of $q_2 = nk_1 = n^2p$ coefficients to estimate for the full model with respect to y_t, and $q_2 = nm$ coefficients with respect to x_t.

One challenging task is to come up with a prior distribution for the steady-state values of the model. In this exercise, we focus on GDP growth such that we are relatively agnostic about the prior distribution on the other variables, i.e. we impose a relatively flat distribution. The prior mean and the 68 percent posterior credibility bands are depicted in table 1.

[6]Note that the conditions are assumed to hold until the end of the forecasting horizon. After that the forecasts converge to the posterior mean of the model.

Table 1: *Prior and posterior distributions of the BVAR models*

		Prior		Posterior	
		Mean	95 % interval	Mean	68 % interval
Standard BVAR					
VIX	VIX			20.30	[29.7; 11.5]
Foreign demand	FD			4.8	[-1.5; 11.2]
Real GDP China	ΔGDP_t^{CH}			9.9	[7.6;12.0]
Inflation rate	π_t^{CH}			2.5	[0.3;4.7]
Interbank rate	i_t^{CH}			2.8	[1.8;3.7]
Money growth rate	ΔM_t^{CH}			17.0	[13.2;20.1]
Mean-adjusted BVAR					
VIX	VIX	20	[0.0; 40.0]	19.10	[1.8; 36.3]
Foreign demand	FD	4.5	[0.0; 9.0]	4.5	[0.5; 8.8]
Real GDP China	ΔGDP_t^{CH}	1.5	[1.0; 2.0]	1.5	[1.0;2.0]
Inflation rate	π_t^{CH}	3.5	[1.0; 6.0]	2.8	[0.8;5.2]
Interbank rate	i_t^{CH}	3.5	[1.0; 6.0]	3.7	[1.7;5.6]
Money growth rate	ΔM_t^{CH}	20.0	[10.0; 30.0]	16.37	[9.4;25.2]

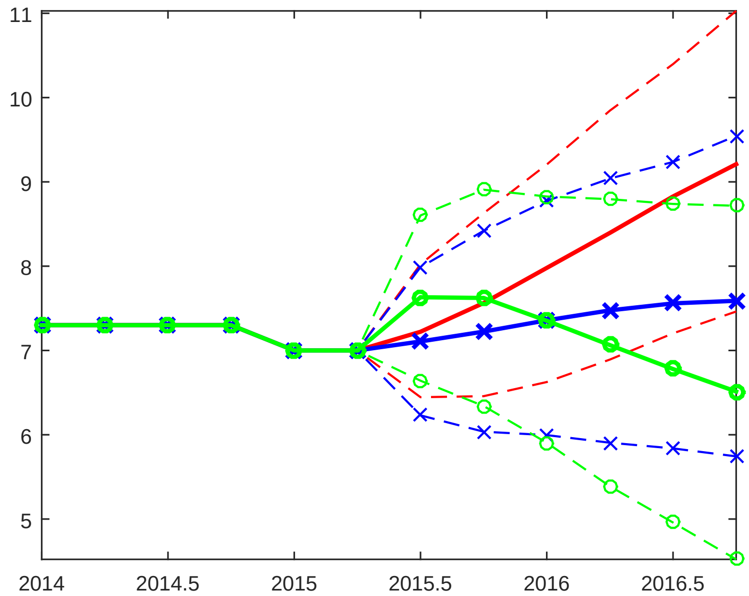
Source: Authors' calculations.

Note that we have imposed a very tight prior distribution on the GDP steady-state of the model with a very low mean for real GDP growth. This is necessary to force the model tight prior on the steady-state of the model forces the model to forecast a lower path for GDP growth for the forecasting horizon.[7] Still, the model indicates that an additional shock is necessary to expect a further decline in GDP growth. As a potential shock candidate we simulate tighter monetary conditions, i.e. higher interbank rates than in the unrestricted model. In particular, we use a conditional path of a 5 percent interbank rate. We then use soft conditional forecasts to allow for some flexibility and uncertainty of the conditional path.

The results indicate that tighter monetary conditions would be determining factor for lower GDP growth in China in the forecast horizon. While the unrestricted standard BVAR and the mean-adjusted BVAR suggest 9.1 percent and 7.6 percent growth respectively in the last quarter of 2016, whereas the scenario with tight monetary conditions suggests 6.5 percent growth (see Figure 6).

[7] We also tested for even tighter distributions and with a lower mean. Note however that lower values give even more implausible results for potential growth in China.

Figure 6: *Median forecast of Real GDP growth*



Notes: Solid lines represent the the median forecasts of real GDP growth while dashed lines are the 95 percent credibility bands. The red line is the unconditional forecast from the standard BVAR model, the blue line is the unconditional forecast from the mean-adjusted BVAR model, and the green line is the conditional forecast of the mean-adjusted model conditional on tight monetary conditions (interbank rate 5 percent over the horizon).

4 Equilibrium VAR

The main advantage of Bayesian modelling consists in integrating prior information into the model, allowing the final estimates to reflect (partly) the belief of the researcher about which values the parameters should take. Yet, if Bayesian VAR models traditionally integrate prior information about the dynamic coefficients (see the work of Litterman (1986) and section 2), they remain most of the time uninformative on long-run components. This approach presents two disadvantages, which both result from the fact that the long-run, or steady-state value of a VAR model depends on the deterministic coefficients. The first drawback is that if the researcher actually has some knowledge about the long run values of the model, not integrating these values into the model generates a loss of relevant prior information. The second disadvantage of not integrating this information into the model is that the deterministic coefficients and, hence, the steady-state will be entirely determined by the data. This may result in long term forecast grossly at odds with the prior opinion of the researcher. To overcome this issue, there are several alternative ways to address this. In what follows we use a generalisation of Villani (2009) where we allow for time-varying equilibrium on the steady-state Akkaya et al. (2017) and in Del Negro and Tambalotti. This approach applies to non-stationary data with time-vary steady-states where we specify an underlying economic model for the long-run. This approach uses a simulation smoother for latent processes and requires specific specification for the long-run properties of the model.

We start from the conventional VAR model 1:

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + C x_t + \varepsilon_t \ , \text{ where } t = 1, 2, ..., T \tag{11}$$

his model may rewrite as:

$$y_t = A(L)^{-1} C x_t + \Psi_0 \varepsilon_t + \Psi_1 \varepsilon_{t-1} + \Psi_2 \varepsilon_{t-2} ... \tag{12}$$

with $A(L) = I - A_1 L - A_2 L^2 \ldots A_p L^p$ the matrix lag polynomial representation of 11. This is the usual VAR model, or VAR model on standard form. Villani (2009) proposes an alternative representation:

$$A(L)(y_t - Fx_t) = \varepsilon_t \tag{13}$$

This representation is known as a VAR model on mean-adjusted form. In this representation, $A(L)$ is a lag polynomial similar to that in model 12. The p matrices $A_1, A_2, \ldots, A_p$ are of dimension $n \times n$. In addition, F is a $n \times m$ matrix of coefficients with respect to the m exogenous variables. This structure implies that each equation comprises $k_1 = np$ coefficients to estimate with respect to y_t, and m coefficients with respect to x_t, leaving a total of $q_2 = nk_1 = n^2p$ coefficients to estimate for the full model with respect to y_t, and $q_2 = nm$ coefficients with respect to x_t.
We now use a reformulation of the classical Bayesian VAR model with stochastic time-varying steady-state values. This is a generalisation of Villani (2009) following **?** with a potentially time varying F matrix:

$$A(L)(y_t - F_t x_t) = \varepsilon_t \tag{14}$$

The equilibrium values are written in the term $F_t x_t$, where F_t is a matrix $(n \times m)$:

$$F_t = \left[\begin{array}{cccc} \underset{(n\times1)}{F_t^0} & \underset{(n\times1)}{F_t^1} & \cdots & \underset{(n\times1)}{F_t^m} \end{array} \right]$$

where each F_t^i is a vector with the steady states. Consider a generic F_t^i, it contains the equilibrium values of all the variables at time t, in regime i. These equilibrium values are described by a model that can be written in a way very similar to a state space representation: F_t^i depends linearly on an unobserved vector of latent processes θ_t:

$$\underset{(n\times1)}{F_t^i} = \underset{(n\times h)}{H_i}\underset{(h\times1)}{\theta_t} \qquad \forall i = 1, ..., m\ . \tag{15}$$

Note that all the F_t^i's depend on the same θ_t, but with different linear combinations specified in the matrices H_i's.

Finally, the latent vector θ_t is assumed to be described by a linear Gaussian model, as a standard state equation in linear state space models::

$$\underset{(n\times h)}{\theta_t} = \underset{(h\times h)}{G}\underset{(h\times1)}{\theta_{t-1}} + \underset{(h\times j)}{P}\underset{(j\times1)}{\eta_t} \tag{16}$$

where η_t is a vector of uncorrelated shocks Normally distributed: $\eta \sim N(\mathbf{0}, \Omega)$

with Ω diagonal. We suppose the matrices H_i's and the matrix P are known, while it is possible to estimate unknown parameters in the matrix G. This requirement is not very restrictive since it is usually possible to write the model as in equations (15) and (16), with just an unknown G.

The way the model for F_t is written is quite general, and can be used to estimate deterministic trends as well as stochastic trends. We will now apply this to China where we start by writing down a long-run model.

4.1 Linear trend: model and estimates

We start first from the linear trends formulation of the model which is similar to the mean adjusted VAR in the previous section, with the difference that now long run restrictions on real variables are imposed by construction. This approach uses a simulation smoother for latent processes and requires specific specification for the long-run properties of the model. In our specification, VIX has a constant equilibrium. Foreign demand and Chinese potential output have constant growth rate, g^f and α respectively and inflation, interest rate and money supply have constant steady states:

$$Vix_t = Vix \tag{17}$$

$$Fdem_t = Fdem_{t-1} + g^f_{t-1} \tag{18}$$

$$g^f_t = g^f \tag{19}$$

$$y_t = y_{t-1} + \alpha \tag{20}$$

$$\pi_t = \pi \tag{21}$$

$$i_t = i \tag{22}$$

$$m_t = m \tag{23}$$

$$\alpha_t = \alpha \tag{24}$$

The steady states defined as : $\begin{bmatrix} VIX_t \\ Fdem_t \\ GDP_t \\ \pi_t \\ i_t \\ m_t \end{bmatrix}$ and the vector of states: $\begin{bmatrix} \overline{VIX} \\ Fdem_t \\ g_t^f \\ \eta_t^f \\ GDP_t \\ g_t^l \\ \eta_t^l \\ \overline{\pi} \\ i_t \\ \overline{m} \end{bmatrix}$

In matrix form:

$$\begin{bmatrix} \overline{Vix_t} \\ \overline{Fdem_t} \\ \bar{y}_t \\ \bar{\pi}_t \\ \bar{\imath}_t \\ \bar{m}_t \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} Vix \\ Fdem_t \\ g^f \\ y_t \\ \pi \\ i \\ m \\ \alpha \end{bmatrix}$$

$$\begin{bmatrix} Vix \\ Fdem_t \\ g^f \\ y_t \\ \pi \\ i \\ m \\ \alpha \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} Vix \\ Fdem_{t-1} \\ g^f \\ y_t \\ \pi \\ i \\ m \\ \alpha \end{bmatrix}$$

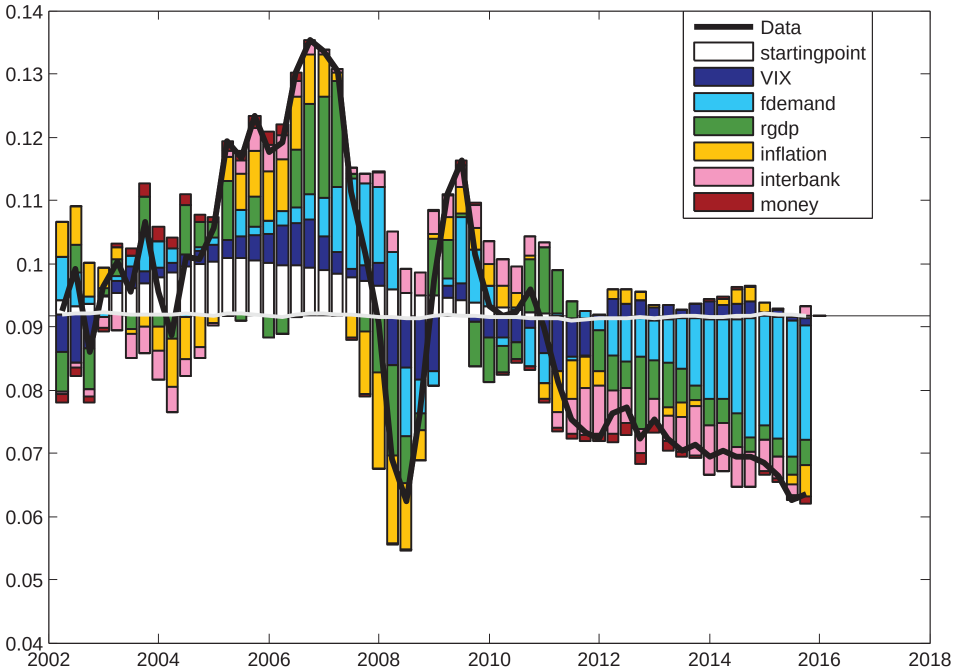
This linear trends case is comparable with the results above, because if you differentiate a variable in levels with a linear trend it will have a constant as steady state. In this case long run neutrality holds by construction. The table below reports the prior and posterior distributions for all the parameters and the full set of impulse response functions are reported in the Appendix. They are similar to the baseline VAR estimated in deviation from steady states. However, there are two main differences. The first is that the integral of IRFs of foreign demand and real GDP (that are in growth terms to directly compare with the baseline IRFs) are zero because these shocks have zero effects in the long run. The second difference is the IRF for money supply shocks where in contrast to the previous specification, the interbank rate goes down and real GDP increases. The historical decomposition of the GDP growth is reported below. In this case there is a significant role of a slowdown in foreign demand driving weaker growth since 2012 and in contrast to the previous findings, the role of interest rates in the slowdown is still significant but substantially reduced.

Prior and Posterior Distributions

Parameter	Prior Density	Prior Mean	Prior Variance	Posterior
Vix	Normal	20	6.08ˆ2	19.52 [18.59 20.20]
g^f	Normal	0.01	0.003ˆ2	0.0107 [0.0101 0.0114]
π	Normal	3.5	0.91ˆ2	2.70 [2.49 3.06]
i	Normal	2.5	0.61ˆ2	2.65 [2.35 2.84]
m	Normal	15	3.04ˆ2	16.36 [15.59 17.05]
α	Normal	0.025	0.006ˆ2	0.023 [0.022 0.024]

90% probability interval in brackets

Figure 7: *Historical shock decomposition linear trend*



linear trend.pdf

Sources: Shock contributions are expressed in the deviation from the unconditional model forecast.

4.2 Common trend

Suppose instead that we want to treat Chinese potential output growth as time varying, and we want to capture its downward sloping pattern. One possible explanation is that a similar pattern can be recognized in the foreign demand, and the two are related. This hypothesis is very much inspired by the previous findings: the big role of foreign demand in explaining the GDP growth in the historical decomposition. The following model aims at capturing this common pattern:

$$Vix_t = Vix \tag{25}$$

$$Fdem_t = Fdem_{t-1} + g^f_{t-1} \tag{26}$$

$$g_t^f = \left(1 - \rho^f\right) \mu^f + \rho \tag{27}$$

$$^f g_{t-1}^f + \varepsilon_t^f \tag{28}$$

$$y_t = y_{t-1} + \alpha + \beta g_{t-1}^f + \varepsilon_t^y \tag{29}$$

$$\pi_t = \pi \tag{30}$$

$$i_t = i \tag{31}$$

$$m_t = m \tag{32}$$

In this specification, VIX would have a constant equilibrium. Foreign demand has a growth rate, g_t^f, that is described by an AR process around a mean μ^f. Chinese potential output has a growth rate that is the sum of two components: a Chinese specific component α, and a term that depends on Foreign demand. Inflation ,interest rate and money supply have constant steady states.

$$\begin{bmatrix} \overline{Vix_t} \\ \overline{Fdem_t} \\ \bar{y}_t \\ \bar{\pi}_t \\ \bar{\imath}_t \\ \bar{m}_t \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} Vix \\ Fdem_t \\ g_t^f \\ y_t \\ \pi \\ i \\ m \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} Vix \\ Fdem_t \\ g_t^f \\ y_t \\ \pi \\ i \\ m \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \rho^f & 0 & 0 & 0 & 0 & \left(1-\rho^f\right)\mu^f \\ 0 & 0 & \beta & 1 & 0 & 0 & 0 & \alpha \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} Vix \\ Fdem_{t-1} \\ g_{t-1}^f \\ y_{t-1} \\ \pi \\ i \\ m \\ 1 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \varepsilon_t^f \\ \varepsilon_t^y \end{bmatrix}$$

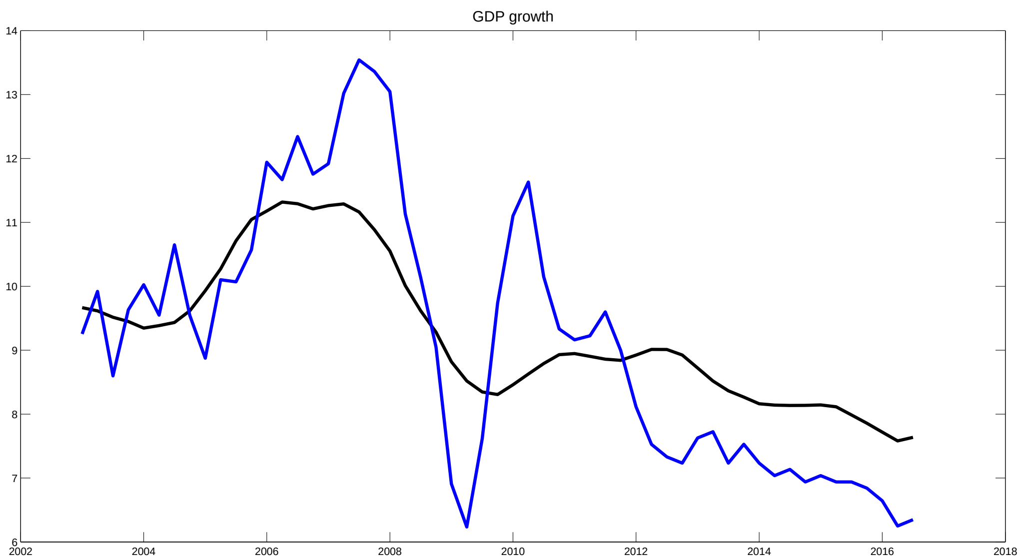
The parameters α, β, μ^f and ρ^f are estimated using a standard prior on the coefficients of the matrix in the state equation. To get a conjugate posterior we specify a prior on the coefficient $\left(1-\rho^f\right)\mu^f$ and then we back out the value implied for μ^f The table reports the prior and the posterior distributions for all the parameters:

Prior and Posterior Distributions

Parameter	Prior Density	Prior Mean	Prior Variance	Posterior
Vix	Normal	20	6.08ˆ2	19.74 [18.60 20.57]
π	Normal	3.5	0.91ˆ2	2.88 [2.64 3.29]
i	Normal	2.5	0.61ˆ2	2.61 [2.36 2.79]
m	Normal	15	3.04ˆ2	16.74 [16.16 17.35]
α	Normal	0.02	0.005ˆ2	0.019 [0.017 0.021]
β	Normal	0.3	0.1ˆ2	0.48 [0.25 0.65]
ρ^f	Normal	0.8	0.1ˆ2	0.85 [0.71 0.96]
$\left(1-\rho^f\right)\mu^f$	Normal	0.003	0.0015ˆ2	0.0013 [0.0001 0.0028]

90% probability interval in brackets

Figure 8: *GDP growth*

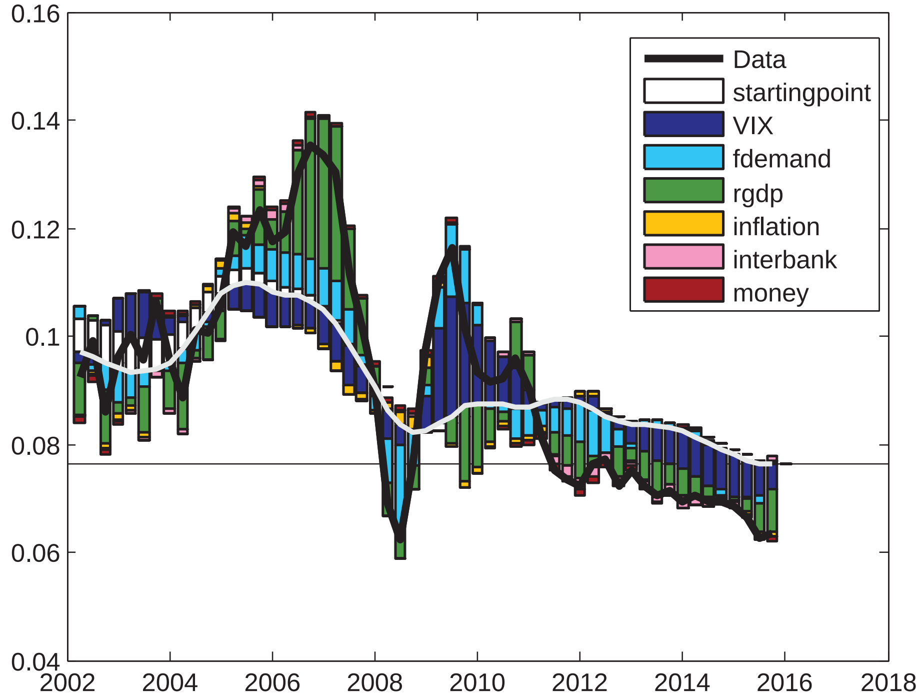


Sources: Black line is equilibrium value for China GDP growth

The last row implies a median estimate of 3.47 for μ^f

The equilibrium value for the Chinese GDP growth is estimated as in Figure 9, and reflects a similar downward trend in the potential foreign demand. If we suppose that the downward trend in the potential GDP growth is due to structural factors, the historical decomposition (Figure 10) shows this crowds out both interest rates shocks and foreign demand shocks. The interbank still plays a role, but it is very little, while the foreign demand shocks disappear because the common drop in these variables is now captured by the trend.

Figure 9: *Historical shock decomposition common trend*



common trend.pdf

Sources: Shock contributions are expressed in the deviation from the unconditional model forecast.

5 Conclusion

In line with previous literature, we find that under standard Bayeisan VAR specifications, monetary policy shocks in China have a significant effect on major macroeconomic variables. This finding is robust to different selections of interest rates, i.e. interbank rate, reserve requirement ratio, deposit rate, prime lending rate, and the average benchmark rate. In addition, it is robust to different prior specifications and suggest high interest rates have substantially contributed to the growth slowdown since 2012.

However, this result changes when we consider a specification which takes into account the non-stationarity of the data. In particular we considered an underlying economic model for the long-run with either a linear trends for GDP or common time-varying equilibrium on the steady-state jointly with foreign demand. With inclusion of a linear trend we find similar impulse responses and we also find that the interbank rate is important in explaining the low GDP growth over the recent period, in line with the previous analysis. Moreover we find that foreign demand contributes substantially to the slowdown of Chinese GDP. This suggests that a similar slowdown has occurred in foreign demand and the decomposition show that the model interpret this as a common phenomenon.

This raises the question about the nature of this phenomenon: in the linear trend case we imposed that this is a only a temporary event that affects only the cyclical component of GDP. On the other hand it could represent a permanent shock to the level of both foreign demand and Chinese GDP. This lead us to the second specification in which the Chinese slowdown is treated as a common pattern with foreign demand. The model we estimated has both the growth in foreign demand and in domestic GDP to be time varying and related. We find that the common structural explanation for the economic downturn crowds out the role of interest rates (and also crowds out foreign demand shocks, as expected).

One caveat to note is that monetary and fiscal policy are strongly interacted in China. For future analysis we intend to also integrate this interaction into the model. Furthermore, commodity prices could also play an important role in China's business cycle.

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6 Appendix

Figure 10: *Data used in estimation and in-sample model fit*

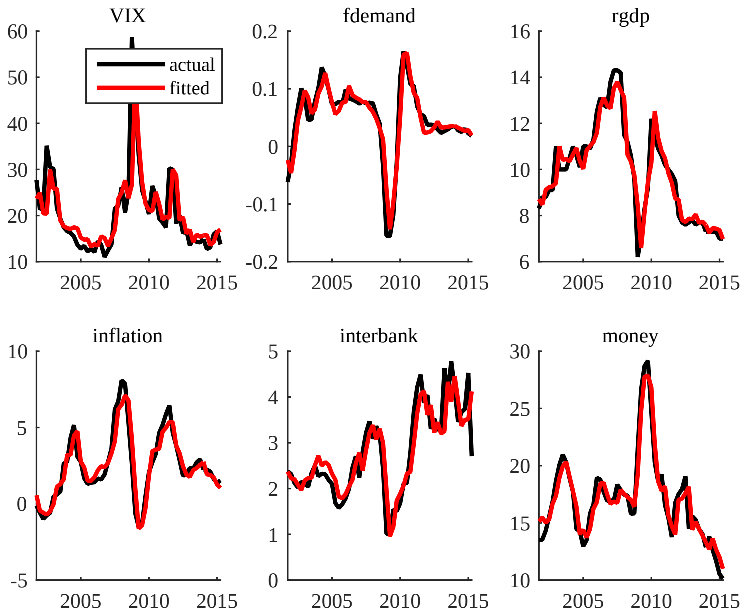


Figure 11: *Reduced form residuals*

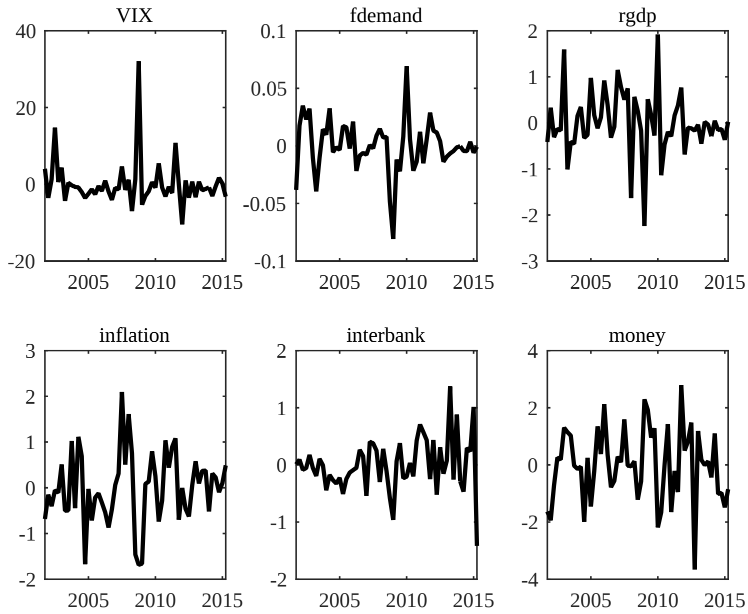


Figure 12: *Unconditional model forecast*

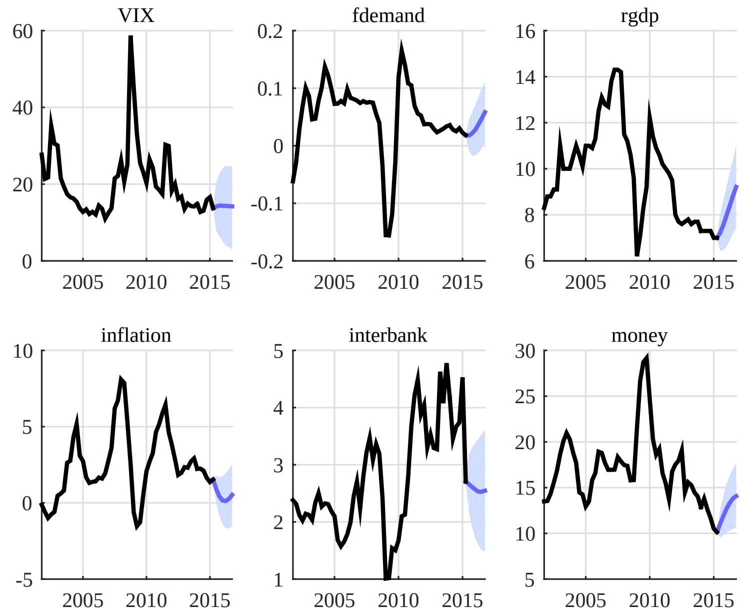
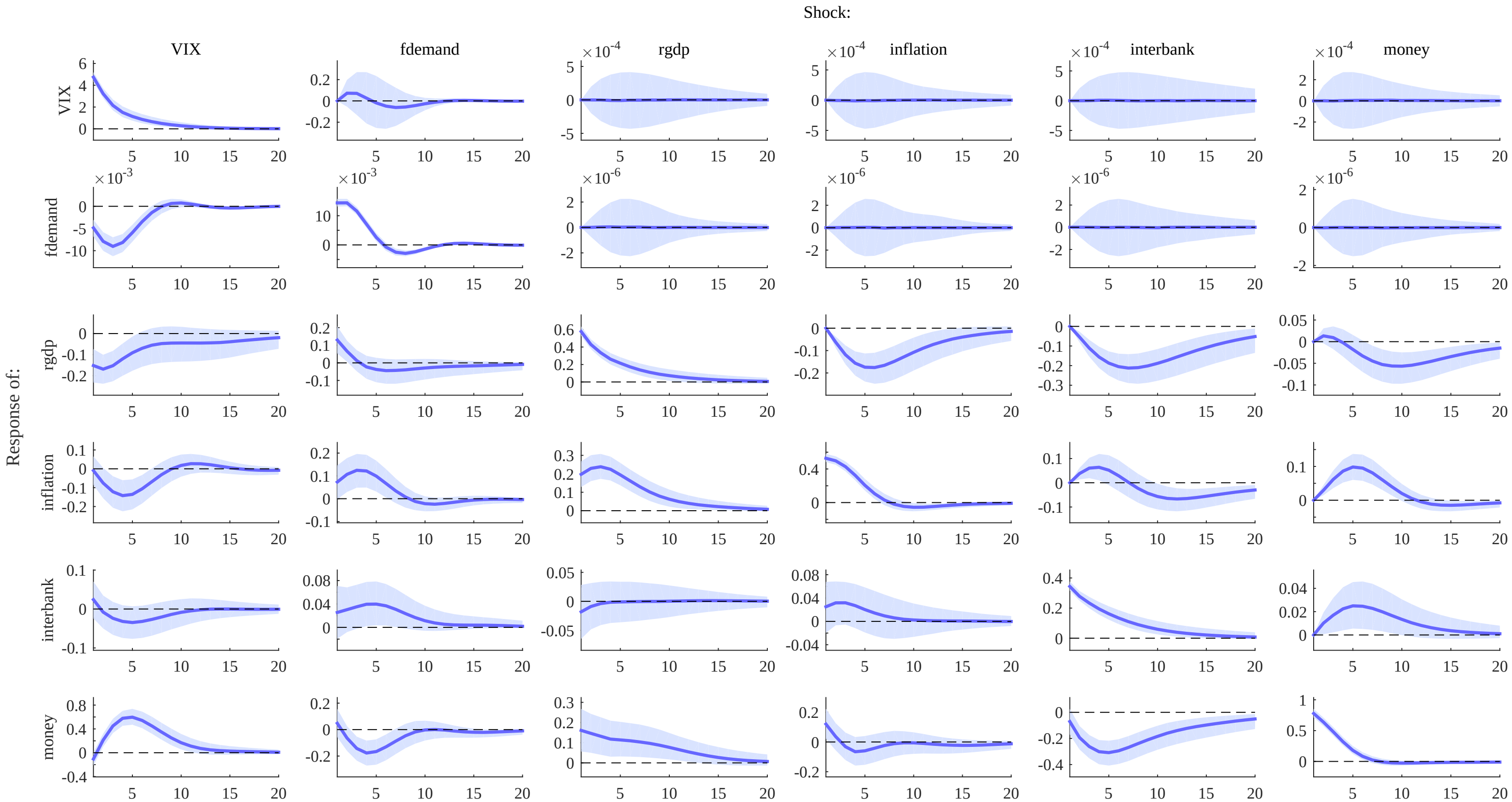
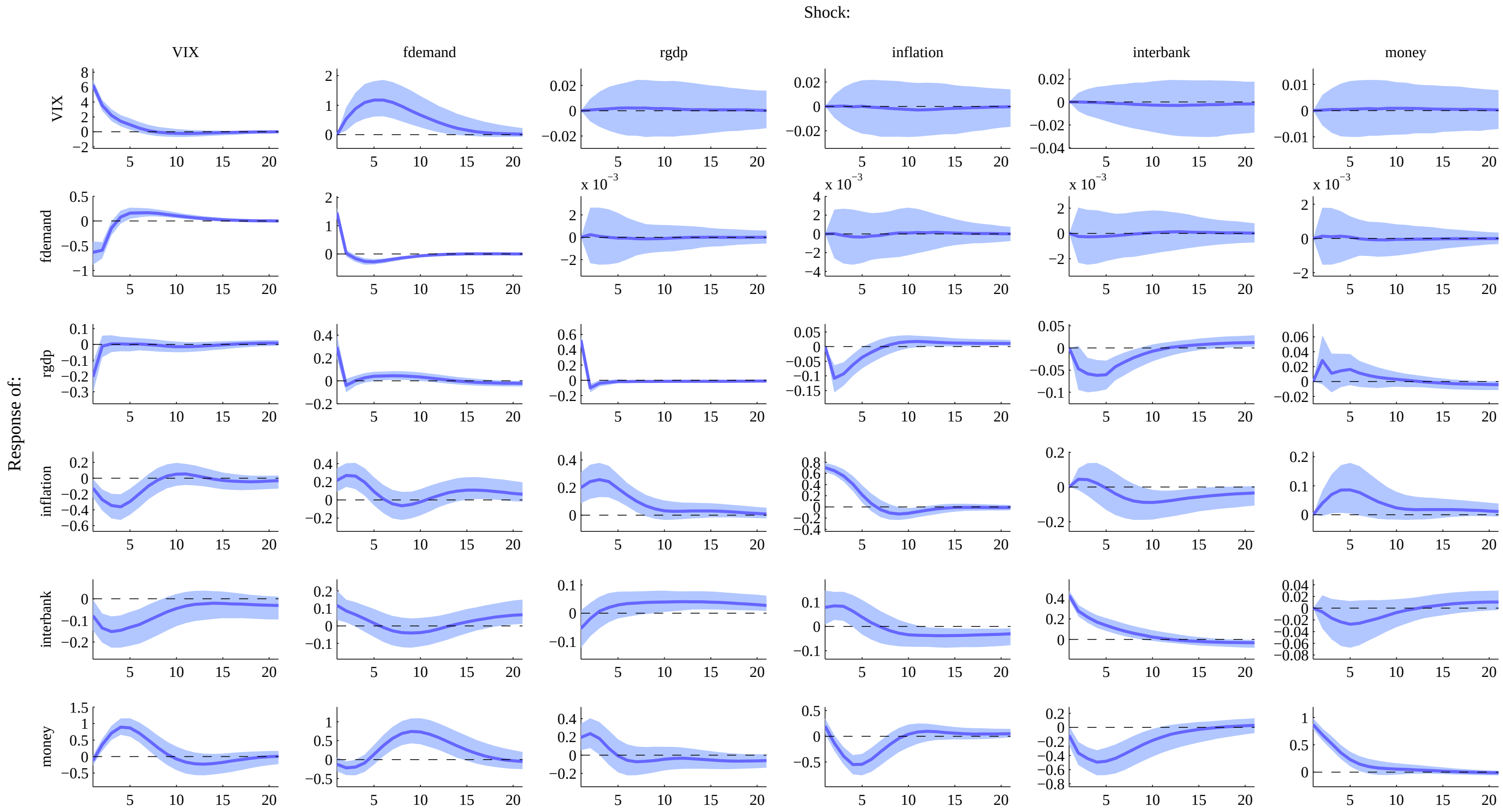


Figure 13: *Full set of Impulse Response Functions baseline*



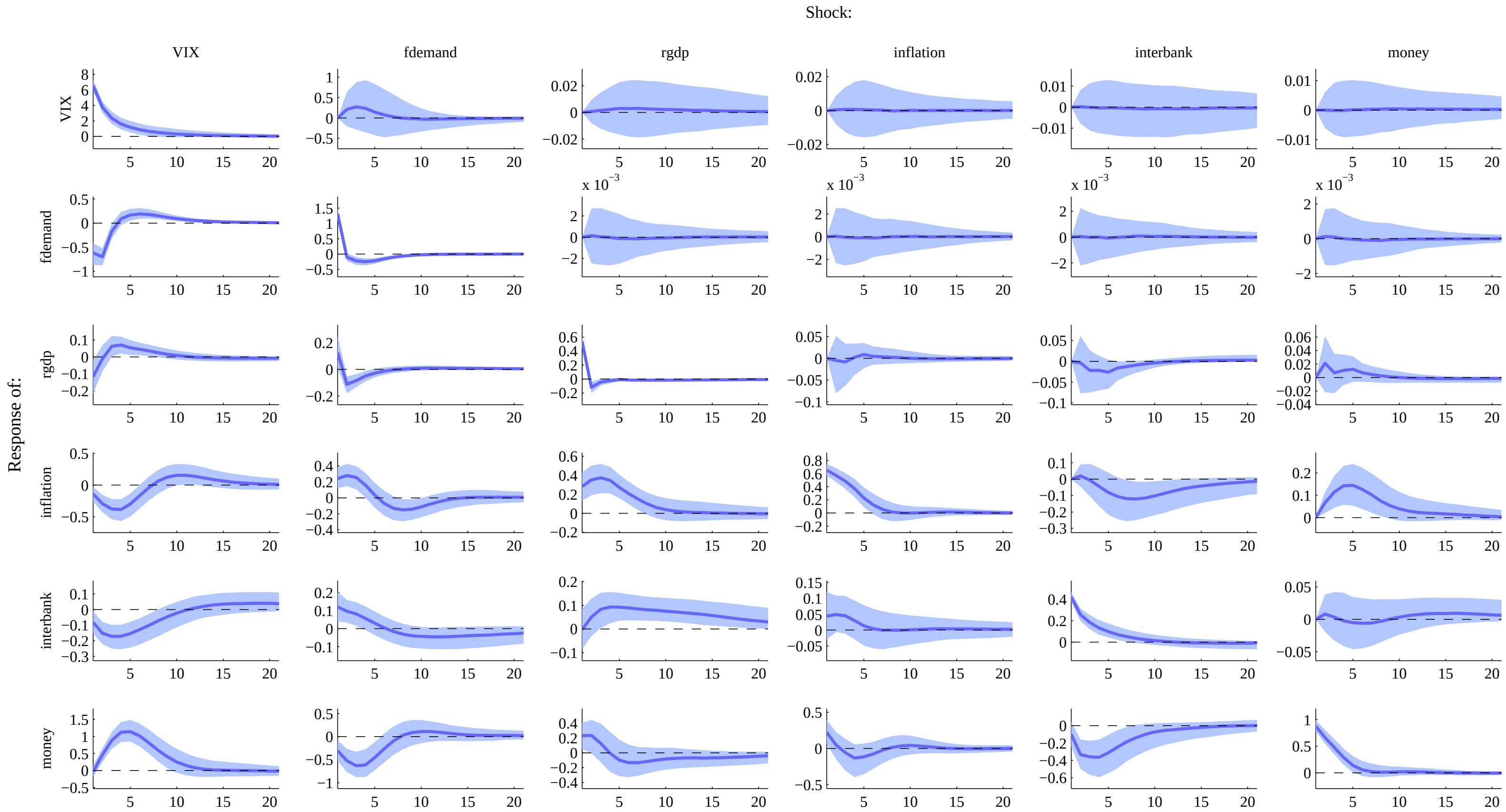
NOTE: Shaded area represents 68 percent posterior error bands.

Figure 14: *Full set of Impulse Response Functions linear trends*



NOTE: Shaded area represents 68 percent posterior error bands.

Figure 15: *Full set of Impulse Response Functions common trends*



NOTE: Shaded area represents 68 percent posterior error bands.