# The Impact of Monetary Policy on Agricultural Price in China: A Factor-Augmented Vector Autoregressive (FAVAR) Approach

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**Abstract**

We use recently available Chinese data from 2005m1 to 2016m2 to examine the impact of monetary policy on agricultural price using a factor-augmented vector autoregressive (FAVAR) model proposed by Bernanke et al. (2005). Results show the superiority of a FAVAR model with three variables and three factors over other specifications. Impulse response functions show that both money supply and interest rate have no impact on agricultural price in the long-run (beyond 50 months). However, results indicate the considerable short-run impact of monetary policy on agricultural price. According to forecasting error variance decompositions, the interest rate could account more for the fluctuations in agricultural price than the money supply.



**Keywords:** Agricultural Price, FAVAR, Interest Rate, Money Supply

**JEL codes:** Q11, E69

# The Impact of Monetary Policy on Agricultural Price in China: A Factor-Augmented Vector Autoregressive (FAVAR) Approach

## 1 Introduction

Since the economic reform and opening up of China in 1978, the country has achieved a remarkable economic growth averaging about 9% per year (He et al., 2013). The agricultural sector in the country has also been growing at a high rate (Yu and Zhao, 2009). As shown in Figure 1, even though China has maintained a sustained growth in money supply, the agricultural price is not growing rapidly. Regarding a year-on-year growth rate, the monthly rate of money supply (M2) is greater than the rate of agricultural price (AP) in most periods since 2005. Moreover, the stock of M2 is growing substantially from 25.8 trillion RMB in January 2005 to 142.5 trillion RMB in February 2016. We shed light on how China's monetary policy affects agricultural price using alternative vector autoregressive (VAR) model specifications.

Since Schuh (1974), a growing number of studies have paid attentions to the impact of macroeconomic policies on agriculture, which is called "macro-agricultural nexus" (Kwon and Koo, 2009). Previous studies have paid attentions to the impact of monetary policy on agricultural price (e.g., Tweeten, 1980; Chambers and Just, 1982; Orden, 1986; Dorfman and Lastrapes, 1996； Sahaian et al., 2002; Awokuse, 2005; Kwon and Koo, 2009). Some of these studies have indicated that the U.S. agriculture sector benefitted from expansionary monetary shocks while others indicated that agricultural price decreased in response to positive monetary shocks. Given the inconclusiveness of the impact, this study reinvestigates the effects of monetary policy on agricultural price in the Chinese context.

Most of the recent studies focus on the magnitude and directions of the impact of monetary policy on agricultural price. Kwon and Koo (2009) show that the overshooting hypothesis, which argues that the monetary policy has real impacts on agricultural price in short run, offers a better way to understand the macro-agricultural nexus and to identify underlying sources of agricultural instability than the monetarist view. As Kwon and Koo (2009) summarize, there are two kinds of transmission channels by which macroeconomic policies impact agricultural sectors. These are domestic channels (e.g., Sahaian et al., 2002; Dorfman and Lastrapes, 1996) and international channels (e.g., Orden, 2002). The issues associated with the agricultural sector, such as food security, are paramount to the Chinese government, so the domestic markets are highly regulated (Yang et al., 2008). For instance, due to the food security concerns, Chinese government attempts to keep high self-sufficiency in the main cereals (Yu, 2014). Thus, the effects from international markets on these commodities are very limited in China (Yang et al., 2008; Yu, 2014). In this paper, our focus is on domestic channels. Specifically, we measure the magnitude and directions of the effects of domestic monetary shocks on agricultural price.

The frequently used methods in the existing literature related to macro-agricultural nexus are standard vector autoregressive (VAR) models and its variants such as vector error correction (VEC) and structural VAR models. However, Bernanke et al. (2005) point out that the information which could be captured by these models are usually small and sparse thereby resulting in three critical problems. First, it is likely that the measurement of policy innovations is contaminated since we do not consider enough information in the standard VAR analyses. Second, we have to take a stand on specific observable measure corresponding precisely to some theoretical constructs. However, it is very hard to do so because of the sparse information set in standard VAR analyses. Third, we can only calculate the impulse response functions for included variables, which usually limits our ability to do more generalized analyses. Therefore, Bernanke et al. (2005) propose a new model which combines dynamic factor model with standard VAR model to solve the problems caused by sparse information in the standard VAR model. This new model is known as the factor-augmented vector autoregressive (FAVAR) model.

The naïve way to overcome the problems caused by sparse information is to add more variables into the standard VAR model. For example, Dorfman and Lastrapes (1996) estimate an eight-variable VAR model to examine the dynamics of agricultural price. However, adding too many variables would lead to loss of degrees-of-freedom and over-parameterization concerns. Fortunately, following Bernanke et al. (2005), we can conduct VAR analyses of the impact of monetary policy on agricultural price by conditioning on richer information sets and without losing the statistical advantages. Alternatively, we could restrict the VAR analysis to a shorter period. We take advantages of the FAVAR model to control estimation bias due to the sparseness of information in the standard VAR analyses.

As Fernald et al. (2014) pointed out, there are two reasons why we should use the

FAVAR model to explore Chinese data. The first reason is the well-known skepticism about the quality of Chinese data. The famous example is Keqiang Index (Anderlini, 2014). In 2007, the Secretary of Chinese Communist Party of Liaoning province, Keqiang Li (current Premier of People's Republic of China) told a US ambassador that instead of GDP figures in Liaoning which are to some extent unreliable, he preferred to rely on three other indicators: electricity consumption, the volume of rail cargo, and amounts of loan disbursed. Thus, relying on limited variables as done in a traditional VAR model may not be sufficient to understand the Chinese economy. Additionally, the Chinese economy is growing rapidly, and there are several institutional and structural changes along the way. For instance, China abandoned the fixed exchange rate regime in June 2005 and then turned to a more flexible one, resulting in dramatic changes in Chinese macroeconomic conditions. To the extent that data quality is poor and the institutional changes are frequently happening in China, using the FAVAR model can overcome many concerns outlined above.

We organize the rest of this paper as follows. In section 2, we provide details related to the econometric model, i.e., FAVAR model. Section 3 introduces Chinese data used in the paper. In section 4, we present our empirical results. Section 5 concludes.

## 2 Econometric Model

We follow the econometric notations of Bernanke et al. (2005). Let $Y_t$ be a $M \times 1$ vector of observable economic variables, which drives the dynamics of the Chinese economy. Generally, $Y_t$ could contain the policy variables as well as other observable variables which reflect the real activities and prices. In our baseline setting, we assume that the variables of interest which include monetary policy instruments and agricultural price are observable. That is, we let $Y_t = (M2_t, IR_t, AP_t)'$, where $M2_t$ is money supply, $IR_t$ is interest rate, and $AP_t$ is agricultural price. This ordering is consistent with most of the previous studies which are based on the active money hypothesis that states that agricultural price has no contemporaneous effect on monetary policy in the VAR system (e.g. Awokuse, 2005; Orden and Fackler, 1989). However, Bernanke et al. (2005) argue that $Y_t$ does not fully capture the economic information. Therefore, we would assume that a $K \times 1$ vector of unobservable common factors $F_t$ could summarize the additional information of the Chinese economy, where $K$ is small. Therefore, the factor-augmented vector autoregressive model (FAVAR) could be given by the following transition equation:

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + v_t, \tag{1}$$

where $\Phi(L)$ is a lag operator of finite order, the error term $v_t$ is IID with mean zero and covariance matrix $\Omega$.

Because the factors $F_t$ are unobservable, we cannot directly estimate equation (1). To overcome this constraint, we first employ a large-dimensional dynamic factor model to extract the latent factors $F_t$ from a large and informational time series dataset $X_t$ which includes various aspects of the Chinese economy. The dynamic factor model can be presented as:

$$X_t = \Lambda^f F_t + \Lambda^y Y_t + e_t, \tag{2}$$

where $X_t$ is a $N \times 1$ vector, $\Lambda^f$ is a $N \times K$ matrix of factor loadings and $\Lambda^y$ is

$N \times M$, and $e_t$ is a $N \times 1$ vector of error terms that is assumed to have a zero mean. Note that $N$ is large here, which means it is much greater than the number of factors and observed variables in the FAVAR system (i.e., $N \gg K + M$).

Bernanke et al. (2005) propose two approaches to estimate the FAVAR model. One is a two-step principal components approach and another is a single-step Bayesian likelihood approach. Based on Bernanke et al. (2005)'s justification, we utilize the two-step approach because it is simple to compute and easy to implement. We first extract the common factors $F_t$ from the dataset $X_t$ using equation (2), the estimated factors are denoted as $\breve{F}_t$. Bai and Ng (2002) propose a method to estimate factors under the framework of large cross sections (*N*) and large time dimensions (*T*), that does not impose restrictions on the relation between *N* and *T*, and that could estimate consistent factors. Since $Y_t$ is not assumed as a common component in this step, we follow the approach suggested by Bernanke et al. (2005) to remove the direct dependence of $\breve{F}_t$ on $Y_t$ to get $\hat{F}_t$ which does not involve the observable economic variables. We estimate a standard VAR model by replacing $F_t$ with $\hat{F}_t$ in equation (1) with a recursive structure, which orders the variables of interest at last.

Another concern related to the FAVAR model is to determine the number of factors to be included in the estimation process. One approach is to directly estimate the number of factors based on different methods provided by several authors (Ahn and Horenstein, 2013; Alessi et al., 2010; Bai and Ng, 2002; Bai, 2004; Kneip et al., 2012; and Onatski, 2010). However, Bernanke et al. (2005) argue that we should determine the number of factors by exploring the sensitivity of the results rather than using the estimated number of factors directly available from using methods developed by previous studies. Thus, we use the estimated number of factors from the range using different methods, and then we examine the sensitivity of impulse response functions. If the impulse response functions are not stable, the analyses will not be conducted using that number of factors in the model.

## 3 Data

We use data collected from Wind Info database (http://www.wind.com.cn/en/) between January 2005 and February 2016. Our starting data period is January 2005 as the wholesale price index of agricultural products is available only from this time forward in China. Moreover, it is appropriate to focus on the recent period so that we can capture the rapid pace of institutional and structural change in China (Fernald et al., 2014). Following Bernanke et al. (2005) and He et al. (2013), we use informational time series dataset $X_t$ with 117 variables[2]. We divide the dataset into 12 groups, which includes industrial production, price indices, investment, real estate, government revenue and expenditure, retail sales, international trade, exchange rate, interest rate, money and credit, stock market, and prosperity indices.

We suspect seasonality in the data series. For example, the Chinese New Year results in significant seasonal effects on monthly economic activities (Fernald et al., 2014). We choose monthly growth rate series on a year-on-year basis, which is a simple way to adjust the seasonality. To check stationarity of variables in the model, we use

[2] The list of these variables are available from the corresponding author upon request.

the augmented Dickey-Fuller test. If the data series are non-stationary, we took the first difference to make them stationary.

We use both money supply and interest rate as monetary policy instruments. Money supply is indicated by the broad definition, M2. Several authors (Dai and Liang, 2006; Peng and Lu, 2010; and Wan et al., 2015) argue that interbank bond repo rate is the highest marketized benchmark short-term interest rate of the financial market in China. We use a seven-day interbank weighted bond repo rate as an indicator of the interest rate. We could have used Shanghai Interbank Offered Rate (Shibor) as a proxy for the interest rate as its function in China is similar to the function of the Federal Fund Rate in the U.S. However, we did not use Shibor mainly because of marketization concern, and also because it got officially started in January 2007 which is later than the starting point of our data period.

It is not possible to directly use sale price of individual agricultural products as we have to include many variables of individual price in the VAR model to fully examine the categories of agricultural products. It would also cause loss of degrees-of-freedom and over-parameterization concerns as we have mentioned before. Kwon and Koo (2009) use the index of price received by farmers as the indicator of agricultural price. Similar to them, we use the wholesale price index of agricultural products to denote agricultural price. For the comparison purpose, we also include industrial value-added output and consumer price index in FAVAR and VAR models.

## 4 Empirical Results

We evaluate the number of factors based on different criteria before estimating the FAVAR and VAR models. Table 1 shows estimated number of factors obtained using various criteria. The number of factors ranges from 1 to 11. Considering the sensitivity of impulse response function as suggested by Bernanke et al. (2005), we first estimate VAR model with three variables and three factors. In this FAVAR specification, we only assume the variables of interest are observable. Second, we estimate a model with the FAVAR specification, where $Y_t$ contains five variables but there is only one factor in the whole setting. The five variables are: $IVA_t, CPI_t, M2_t, IR_t, AP_t$ ; where all other variables except industry value added ($IVA_t$) and consumer price index ($CPI_t$) have been defined before. Here, these two variables ($IVA_t$ and $CPI_t$) are observable variables used to model the Chinese economy. Third, we estimate a standard five-variable VAR model without factors. Obviously, the third model is nested in the second model.

Following Bernanke et al. (2005), we begin our empirical analysis by comparing three models – FAVAR with three variables and three factors, FAVAR with five variables and one factor, and VAR with five variables. We use Schwarz information criterion (SIC) to select the lags. We also use Akaike information criterion (AIC) and Hannan-Quinn (HQ) information criterion to select lags which provided similar results. We change the ordering of the variables in $Y_t$ in all three models which produce very similar results proving the robustness of the estimated models. For sensitivity analysis, we expand the FAVAR model to five factors with different orderings of variables in $Y_t$. If the FAVAR model with three factors provide similar impulse response functions then it indicates that a five factor model is unnecessary.

### *4.1 Impulse Response Functions (IRFs)*

To explore the dynamic relationship among the variables in the VAR system, we estimate the impulse response functions which is the response of one variable due to a shock in another variable. Figure 2 displays the results of impulse response functions of agricultural price to money supply (M2) based on FAVAR with three variables and three factors, FAVAR with five variables and one factor, and VAR with five variables. Generally, the positive shock of the unanticipated money supply will increase the agricultural price at first and then decrease it. In the FAVAR with three variables and three factors, the situation changes and the impact disappears after 47 months. Its impulse response of agricultural price is the lowest among the three models estimated. In the FAVAR with five variables and one factor, the impulse response function of agricultural price at the beginning would be lower than the standard VAR model, approaches to zero around 38 months and becomes negative afterward. In the case of standard VAR specification, the impulse response of agricultural price is the highest at the beginning among the three models, and then it approaches to zero around 40 months and continues to become negative afterward. To some extent, these latter two models are not consistent with long-run money neutrality, since they have persistent impulse response functions.

The impulse response functions of agricultural price to interest rate shock are presented in Figure 3. All the three models produce a small price puzzle at the early period, which show a rise in the agricultural price level in response to contractionary monetary policy (Sims, 1992). Here adding factors does not remove the prize puzzle effect, which is consistent with the results obtained by Bernanke et al. (2005). In the latter period, the contractionary interest rate shock is negatively related to agricultural price. It is also important to note that the FAVAR model with three variables and three factors produces an impulse response function of agricultural price that returns towards zero but the two other models do not.

Bernanke et al. (2005) argue that adding factors do not impact the unbiasedness of estimates in the VAR model but it would render the estimation less precise if the additional information is irrelevant. The estimated impulse response functions should not change considerably from one model to another. Our results do not change dramatically, allowing us to compare the performance of the three models based on the economic theory such as the long-run neutrality of money. The results of impulse response functions indicate that both money supply and interest rate have no long-run impacts on agricultural price. These results imply that the FAVAR specification with three variables and three factors would be more appropriate from the long-run money neutrality perspective. Therefore, we argue that this model would properly capture the information such as real activities and price.

Two concerns can cause our model to be less robust. First, the results might be sensitive to the ordering of the variables in $Y_t$. Figures 4 and 5 show the results of the models with different orderings. Since the ordering affects the contemporaneous relationship among the variables, the path of impulse response functions at the beginning period is different from the results presented in Figures 2 and 3. However, the remaining path is very similar.

Second, we suspect we might have omitted some critical dimensions in the Chinese economy by considering only three factors. We show the results of the model which is augmented with five factors in Figures 6 and 7. In this case, there exists a persistent effect of the impulse response at the end even though it is small. This persistent effect might have been caused by the inclusion of additional irrelevant information into the model causing the estimation to be less precise.

This comparison suggests that the FAVAR model with three variables and three factors performs well when we attempt to model the Chinese economy by extracting common factors from a large dataset of macroeconomic indicators. To sum up, our results not only tend to support the monetarist view of the long-run money neutrality but also confirms the overshooting hypothesis that monetary changes could have real short-run effects on agricultural price. This result is consistent with the previous studies (e.g. Kwon and Koo, 2009; Saghaian et al., 2002).

### *4.2 Forecasting Error Variance Decompositions (FEVDs)*

The estimated impulse response functions indicate that there are remarkable effects of monetary policy on agricultural price in the short-run. In what follows, we use the forecasting error variance decompositions (FEVDs) to illustrate that the instrument of monetary policy is the main force that affects the agricultural price. The FEVD provides the relative contribution of each source of shock to the variance of forecasting error. In this subsection, we focus on comparing the results from the three models since either changing the ordering or expanding to more than three factors does not make the performance (impulse response function) of the models better. The results are presented in Table 2.

We draw attention to the estimates at the 60 months ahead forecasting error variance. In the upper panel of Table 2, the FAVAR model with three variables and three factors shows that the interest rate could account for 8.36 percent of the variation in agricultural price in the long-run. The money supply, however, explains only 5.42 percent of the variations in agriculture price which is relatively smaller than the impact from the interest rate. The middle panel of Table 2 shows FEVDs of FAVAR model with five variables and one factor. The results show that 13.22 percent of the variability in agricultural price is explained by money supply in the long run and 10.30 percent of the variability in agricultural price is explained by the interest rate. The lower panel of Table 2 shows FEVDs of VAR model with five variables. The difference in variability caused by money supply and interest rate is much larger. Here, 21.05 percent of variations comes from money supply whereas interest rate determines only 9.92 percent of variations in agricultural price. Results from these latter two models show that money supply contributes more variability in agricultural price than the interest rate, which is not consistent with previous studies (Kwon and Koo, 2009; Saghaian et al., 2002).

To compare the results of the three models, we subtract the contribution of interest rate from the contribution of money supply $(M_2 - IR)$ and then analyze the difference. The results are presented in Figure 8. In the FAVAR model with three variables and three factors, the difference between these two components is negative except in the first period, which means interest rate is the main force that affects agricultural price. The results from FAVAR model with five variables and one factor change the result dramatically, showing that money supply dominates the volatility of agricultural price. The results of the standard VAR model show that money supply dominates the volatility of agricultural price. The difference of contributions to forecasting error variance decompositions of agricultural price between money supply and interest rate is larger than the results from FAVAR model with five variables and one factor.

Previous studies support that the unexpected movement of interest rate is the main monetary shock causing fluctuations in agricultural price (e.g. Kwon and Koo, 2009; Saghaian et al., 2002). However, only the results from the FAVAR model with three variables and three factors are consistent with this argument.

In the standard five-variable VAR model, we are modeling the whole Chinese economy only by the observable variables which might omit some important information. Although money supply would be able to explain some fluctuations in agricultural price, it is not able to capture all the economic information to make results more consistent with previous studies. After conditioning on enough information through the FAVAR model with three variables and three factors, results obtained using Chinese data are consistent with other studies.

## 5 Conclusions

We employed a factor-augmented vector autoregressive (FAVAR) approach proposed by Bernanke et al. (2005) to examine the impact of monetary policy on agricultural price in China. Results obtained from FAVAR models were reasonable and consistent with previous studies.

Results of impulse response functions from the FAVAR model with three variables and three factors were consistent with the overshooting hypothesis. Results indicated that economic shocks from both money supply and interest rate would have considerable effects on agricultural price in the short-run. However, they have no impact on agricultural price in the long-run, which is consistent with the long-run money neutrality theory. Additionally, results show that interest rate could contribute more to the volatility in agricultural price based on the forecasting error variance decompositions.

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Table 1. Estimated Number of Factors under Different Panel Criteria

| Criteria | Kneip, Sickles, and Song (2012) | Bai and Ng (2002) | | | | | | | Ahn and Horenstein (2013) | | Bai (2004) | | | Onatski (2010) | Alessi, Barigozzi, and Capasso (2010) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | KSS.C | PC1 | PC2 | PC3 | BIC3 | IC1 | IC2 | IC3 | ER | GR | IPC1 | IPC2 | IPC3 | ED | ABC.IC1 | ABC.IC2 |
| Number of Factors | 5 | 11 | 11 | 11 | 10 | 11 | 11 | 11 | 10 | 9 | 1 | 1 | 1 | 1 | 6 | 6 |

**Notes:** (1) KSS.C stands for the criterion proposed by Kneip, Sickles, and Song (2012). (2) PC stands for panel criterion, BIC stands for Bayesian information criterion, IC stands for information criterion; these criteria are proposed by Bai and Ng (2002). Subscripts in PC and IC indicate factor selection based on a different penalty term. (3) ER stands for eigenvalue ratio, GR stands for growth ratio; these criteria are proposed by Ahn and Horenstein (2013). (4) IPC stands for integrated panel criterion proposed by Bai (2004); the subscripts indicate factor selection using a different panel term. (5) ED stands for eigenvalue difference proposed by Onatski (2010). (6) ABC.IC stands for information criterion proposed by Alessi, Barigozzi, and Capasso (2010).

Table 2. Forecasting Error Variance Decompositions of Agricultural Price

| FAVAR with three variables & three factors (Y= M2,IR,AP; K=3) | | | | | | |
|---|---|---|---|---|---|---|
| step | f1 | f2 | f3 | M2 | IR | AP |
| 1 | 2.18 | 0.14 | 0.48 | 1.00 | 0.37 | 95.83 |
| 10 | 25.52 | 1.14 | 0.77 | 1.90 | 5.45 | 65.22 |
| 20 | 25.27 | 1.68 | 0.76 | 4.85 | 6.82 | 60.62 |
| 30 | 24.98 | 1.64 | 0.85 | 5.42 | 8.17 | 58.95 |
| 40 | 25.03 | 1.65 | 0.87 | 5.43 | 8.36 | 58.67 |
| 50 | 25.03 | 1.65 | 0.87 | 5.42 | 8.36 | 58.65 |
| 60 | 25.03 | 1.65 | 0.87 | 5.42 | 8.36 | 58.65 |
| FAVAR with five variables & one factor (Y=IVA,CPI, M2,IR,AP; K=1) | | | | | | |
| step | f1 | IVA | CPI | M2 | IR | AP |
| 1 | 4.40 | 2.80 | 52.03 | 1.50 | 0.27 | 38.99 |
| 10 | 32.08 | 1.46 | 40.19 | 4.60 | 3.29 | 18.38 |
| 20 | 32.27 | 1.27 | 33.64 | 11.60 | 5.38 | 15.84 |
| 30 | 29.98 | 1.51 | 31.08 | 13.44 | 9.37 | 14.62 |
| 40 | 30.46 | 1.62 | 30.54 | 13.07 | 10.27 | 14.05 |
| 50 | 30.77 | 1.61 | 30.38 | 13.10 | 10.21 | 13.93 |
| 60 | 30.69 | 1.61 | 30.27 | 13.22 | 10.30 | 13.90 |
| VAR with five variables (Y=IVA,CPI,M2,IR,AP; K=0) | | | | | | |
| step | | IVA | CPI | M2 | IR | AP |
| 1 | | 0.09 | 58.50 | 1.87 | 0.29 | 39.26 |
| 10 | | 10.10 | 57.82 | 8.86 | 2.81 | 20.40 |
| 20 | | 9.78 | 50.48 | 18.72 | 4.21 | 16.81 |
| 30 | | 8.95 | 46.11 | 21.38 | 8.11 | 15.45 |
| 40 | | 8.76 | 45.70 | 20.86 | 9.86 | 14.83 |
| 50 | | 8.82 | 45.92 | 20.76 | 9.93 | 14.58 |
| 60 | | 8.82 | 45.73 | 21.05 | 9.92 | 14.48 |

Note: f1, f2, and f3 are factors. M2 is money supply, IR is interest rate, AP is agricultural price, CPI is consumer price index, and IVA is industry value added. K is number of factors.

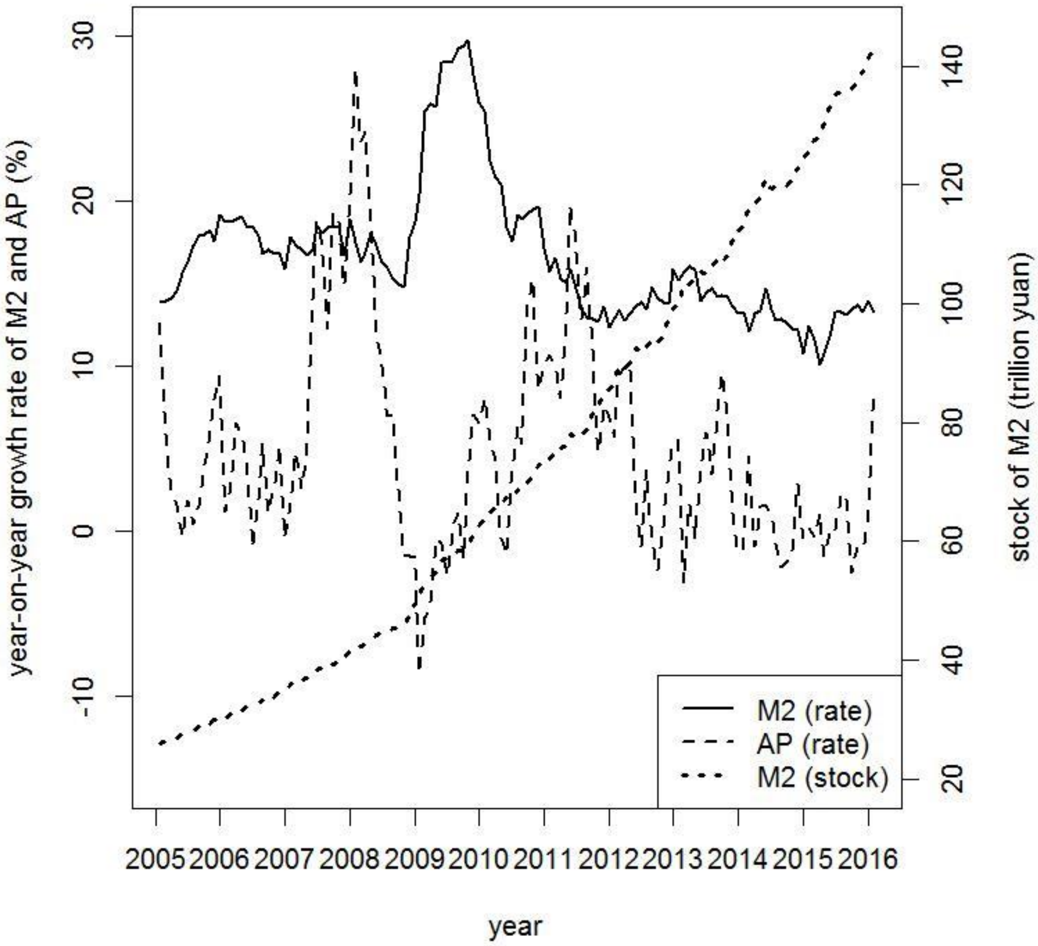


Figure 1. Money Supply and Agricultural Price in China

[Note: M2 is money supply and AP is agricultural price.]

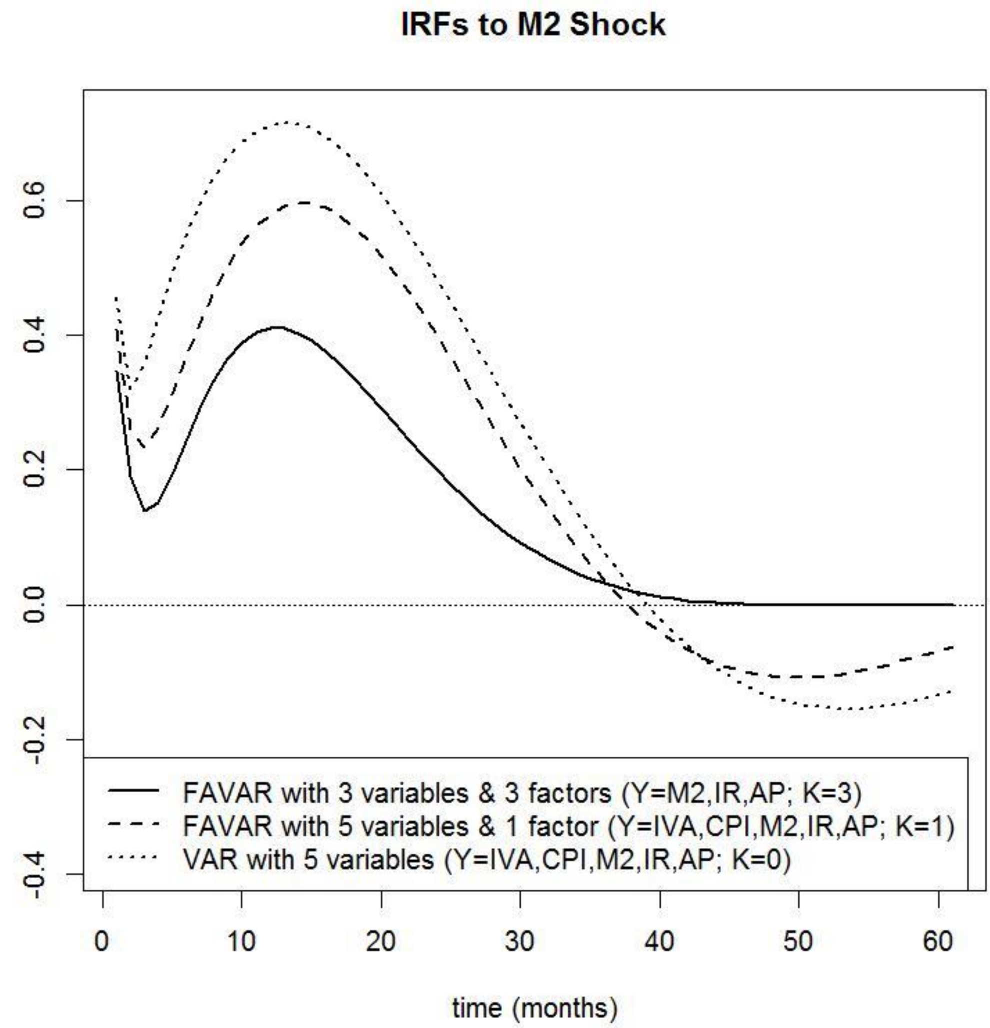


Figure 2. Impulse Response Functions of Agricultural Price to Money Supply Shock

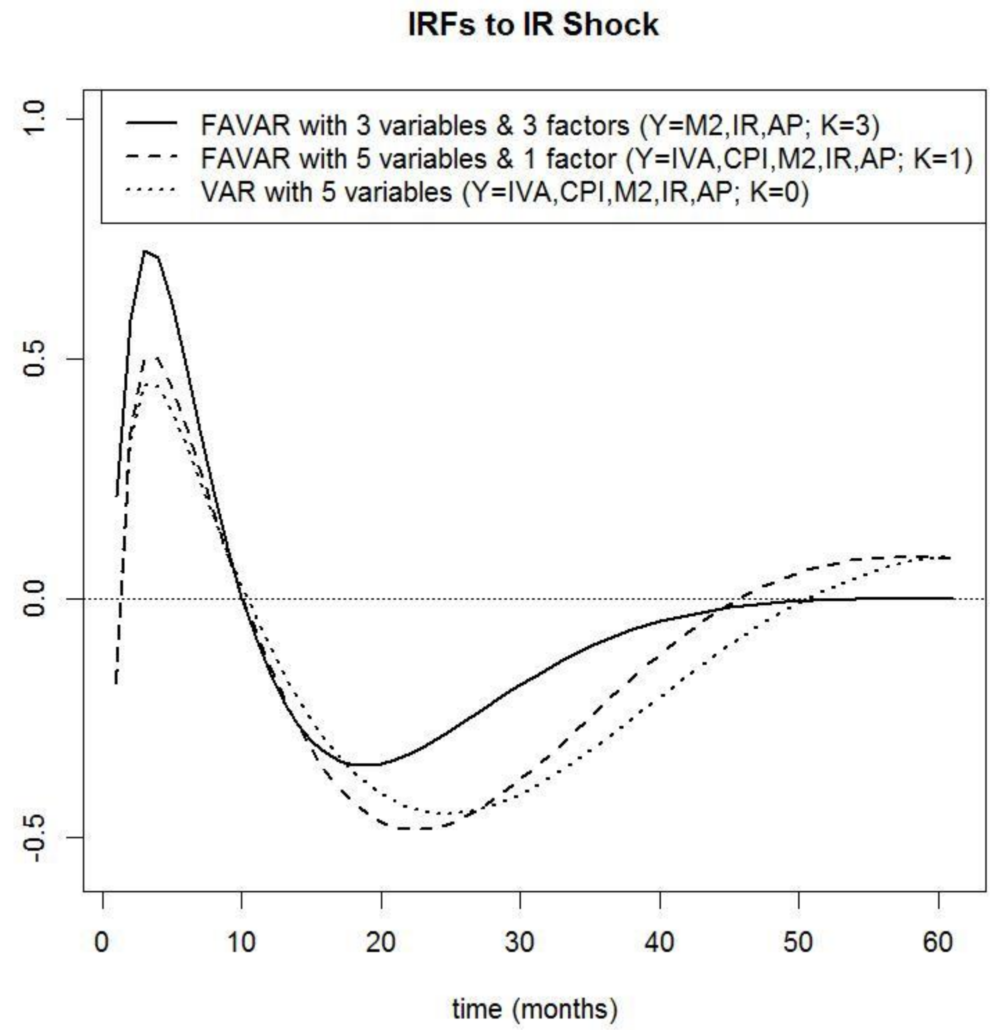


Figure 3. Impulse Response Functions of Agricultural Price to Interest Rate Shock

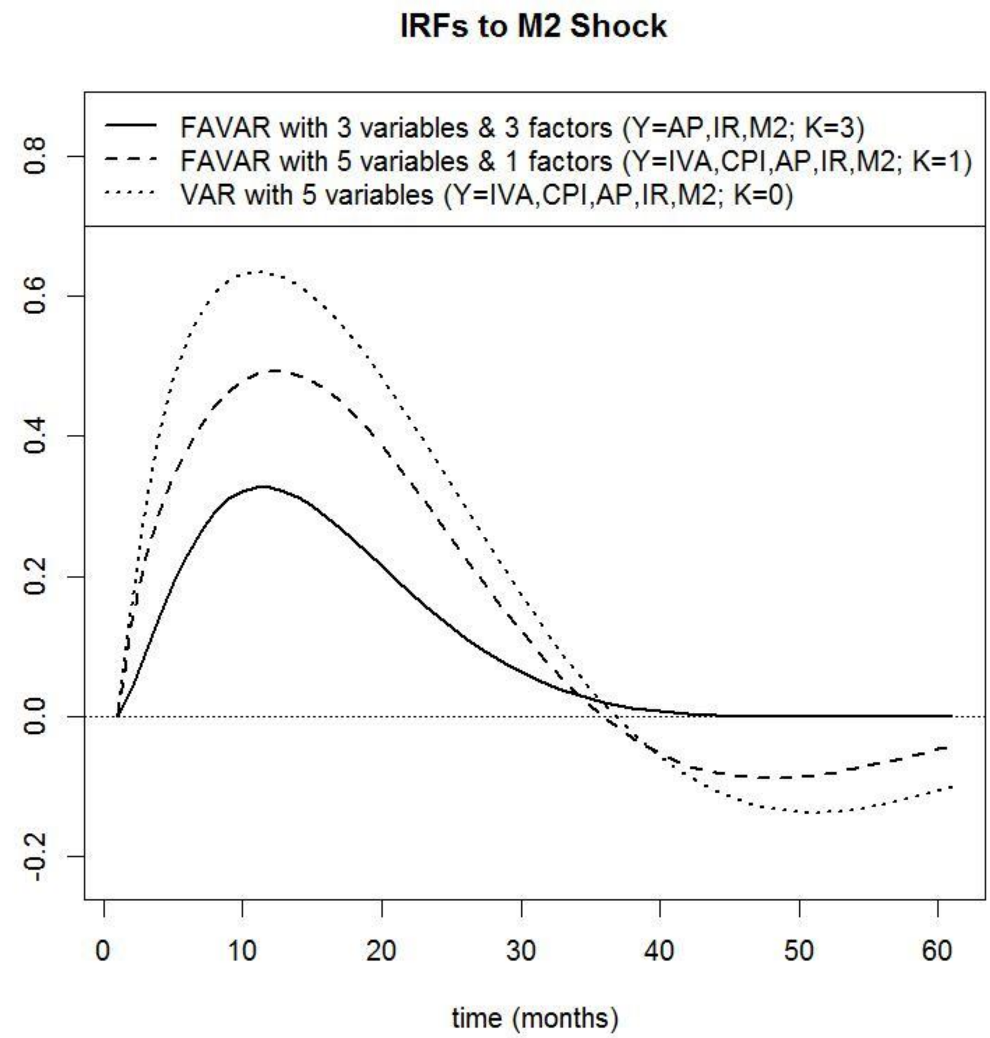


Figure 4. Impulse Response Functions of Agricultural Price to Interest Rate Shock

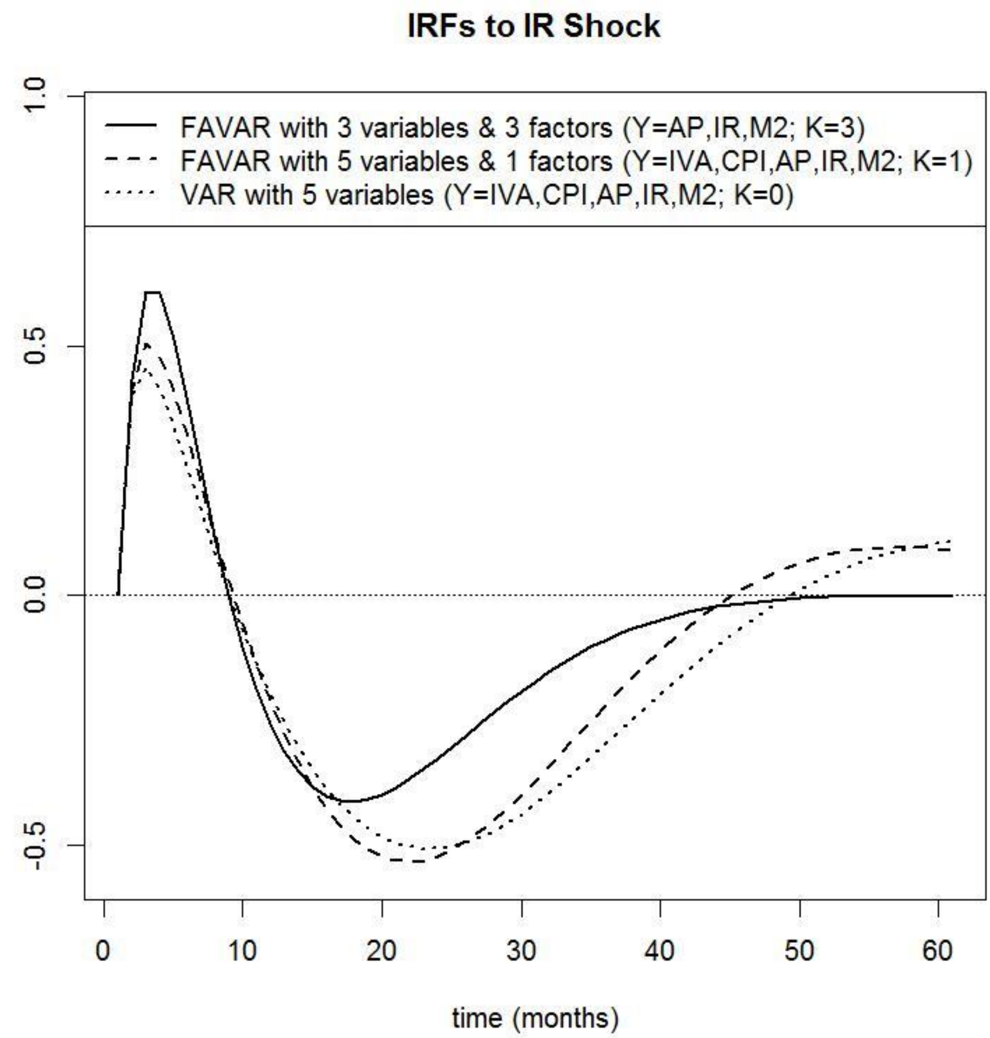


Figure 5. Impulse Response Functions of Agricultural Price to Interest Rate Shock

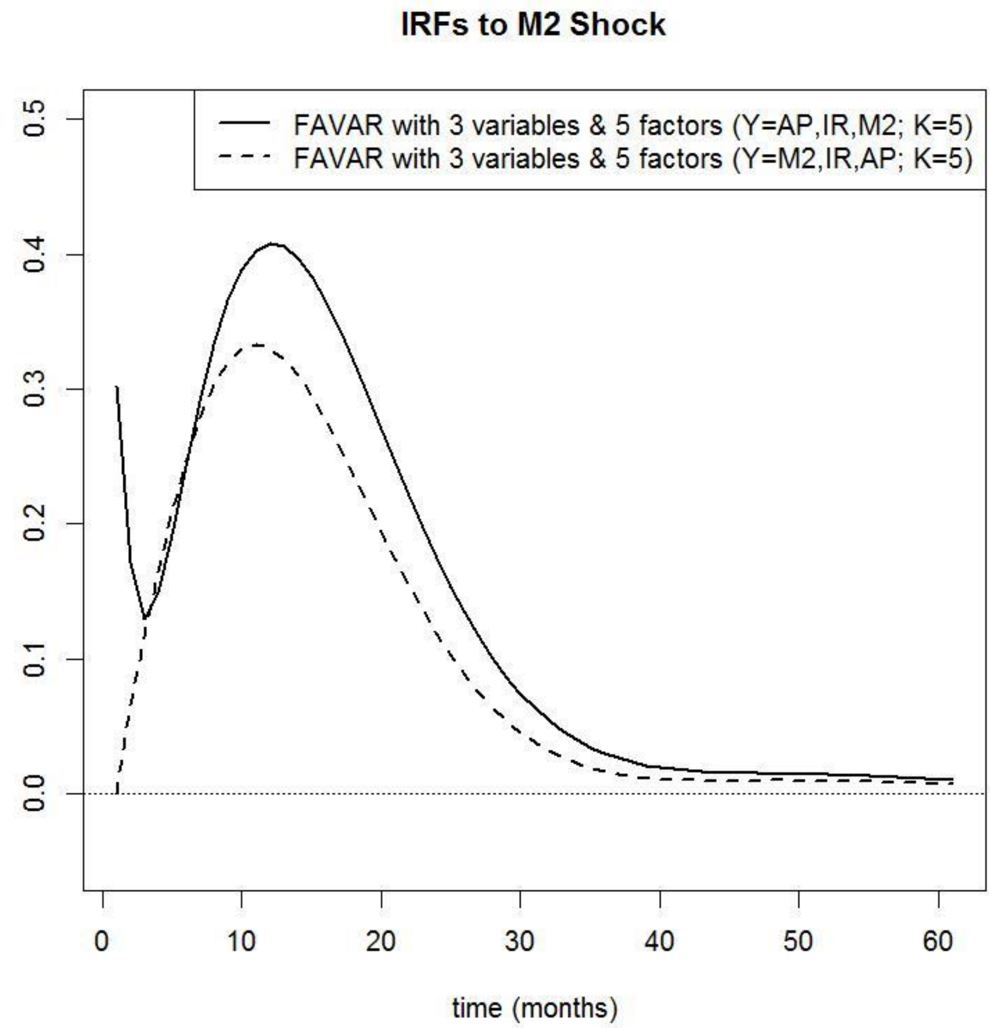


Figure 6. Impulse Response Functions of Agricultural Price to Money Supply Shock

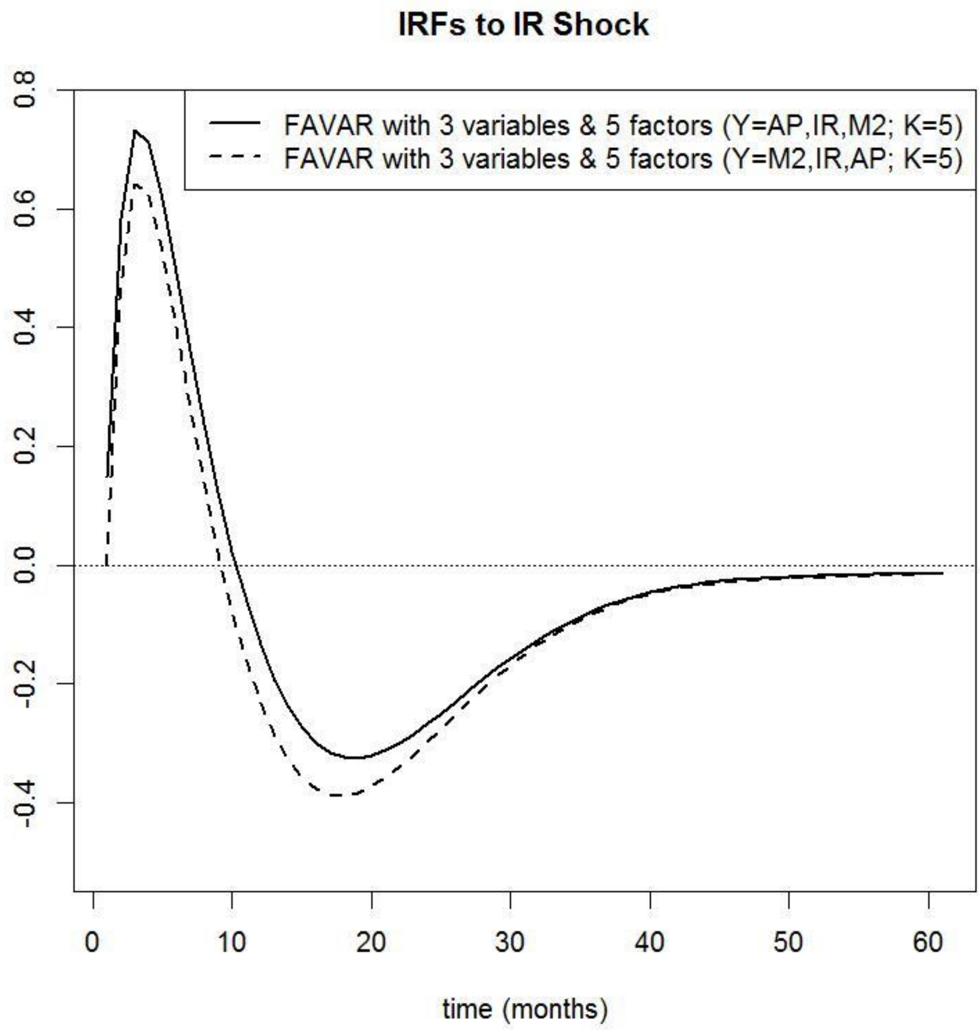


Figure 7. Impulse Response Functions of Agricultural Price to Interest Rate Shock

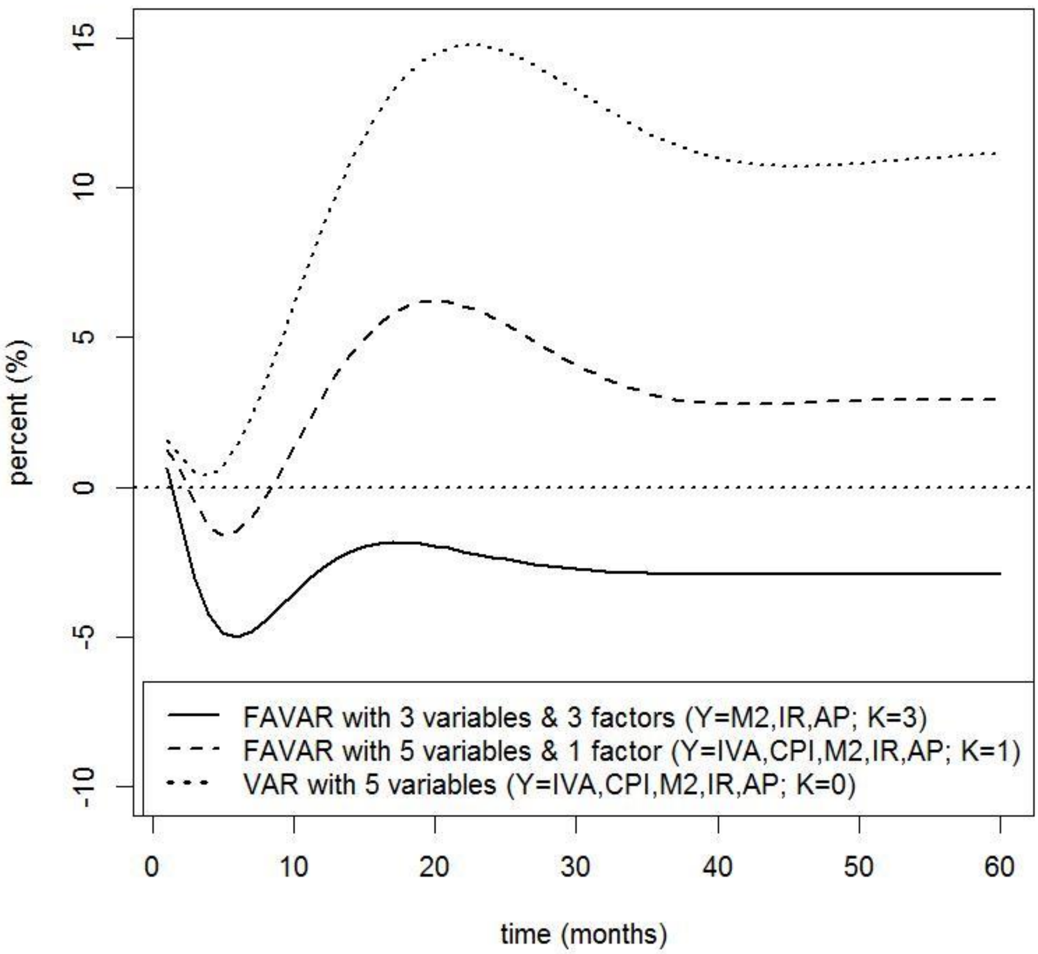


Figure 8. The Differences of Contributions to Forecasting Error Variance Decompositions of Agricultural Price between Money Supply and Interest Rate