Effects of Monetary Policy on Food Inequality in India*

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Abstract

Food insecurity and hunger are pressing issues in emerging market economies but have received less attention in the practice and conduct of monetary policy. This paper studies the impact of monetary policy on food inequality in India. Specifically, we examine the impact of monetary policy shocks on the relative food prices and the distribution of food consumption, focusing on subsistence food consumption of poor households. Food continues to be a significant component of standard poverty measures in emerging market economies. Using the most recent household survey data, we estimate the dynamic effects of monetary policy shocks on relative food prices and the distribution of food consumption in rural and urban India using a dynamic common factor model (Bernanke, Boivin, and Eliasz, 2005 and Stock and Watson, 2011), and identify monetary policy shocks using the sign restriction approach of Uhlig (2005). Our results show that expansionary monetary policy shocks increase the *relative* price of food, reduce the food consumption of poor households, and raise food consumption inequality across households. Increase in the relative price of food following a monetary expansion disproportionately hurts the poor relative to the non-poor. This is the first study to provide evidence of a *"food price channel"* in monetary policy transmission to understand food inequality. This study holds important policy implications for Indian central bankers and policymakers as well as for those in similar emerging market economies.

Keywords: Monetary Policy, FAVAR, Food, Prices, Consumption, Inequality, Poverty, Development

JEL Classification Numbers : C32, D63, E31, E52, I3, O11, O23, Q11

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1 Introduction

Food insecurity and hunger are a primary concern in developing countries with significant and adverse implications for long-term economic growth.[1] Food intake below the biological minimum leads to undernutrition, malnutrition, and mortality, which represent a direct loss to the human capital and productivity, reducing the pace and durability of economic growth (Dreze and Sen, 1989; Behrman et al., 2004; Deaton and Dreze, 2009; Dreze and Sen, 2013). Indirect losses from child undernutrition are caused by poor cognitive function, grade repetitions, and lower school attainment.[2] The economic cost of hunger is estimated to range from 2 to 3 percent of Gross Domestic Product (GDP) in low income countries, to as much as 16 percent of GDP in most affected countries. Food is a necessity for the poor and an important component of standard poverty measures (Dreze and Sen, 1989; Anand and Harris, 1994; Sen, 2001).[3] Despite their importance, food insecurity and hunger have received less attention in the practice and conduct of monetary policy.

In this paper, we study the impact of monetary policy on food inequality in India, a low income country. Food plays an indispensable role in the survival and welfare of a large share of poor households in India. Nearly 25% of the population or close to 300 million people live below the national poverty line and spend about 65-70% of their income on food, see Figures 3-4. Despite spending such a large proportion of income on food, they still remain substantially food deprived. The per capita per day intake of calories for poor households

[1] Food and Agriculture Organization (FAO) defines "hunger" as chronic undernourishment and food intake less than 2100 Kcal, over a period of one year. About 795 million people, 11% of the world's population suffer from chronic undernourishment and almost all the hungry people, 780 million, live in developing countries (FAO).

[2] A 'poverty trap' can exist with people who are undernourished making it difficult to gain employment because they are unproductive, and continue to remain so because they are unemployed, Dasgupta (1997). Many other studies have examined how physical productivity of labor and, thereby, employment and wages are related to food intake (Dasgupta, 1995; Haddad and Bouis, 1991; Sahn and Alderman, 1988; Behrman and Deolalikar, 1988; Dasgupta and Ray, 1986; Stiglitz, 1976).

[3] Productivity losses as a result of undernutrition have been conservatively estimated in low income countries to be at least 2-3 percent of GDP annually (Behrman et al., 2004). However in Africa, these losses are very high. The economic costs of undernutrition have been estimated to be 16.5% of GDP in Ethiopia and 10.3% of GDP in Malawi (The Cost of Hunger in Africa-COHA study, African Union Commission, 2013).

(bottom 20% of the expenditure distribution) is 1933 Kcal in rural India and 1856 Kcal in urban India, which is significantly below the biological minimum intake of 2,400 Kcal in rural India and 2,100 Kcal in urban India (Nutritional Intake Survey, 2011-12). Despite years of robust economic growth, poverty and hunger continue to remain India's compelling challenge.[4]

Using the most recent household consumption expenditure survey data from 1996 to 2013, spanning all rounds of National Sample Survey Organization (NSSO), we estimate the dynamic effects of monetary policy on relative food prices and the distribution of food consumption in rural and urban India.[5] We utilize the dynamic common factor model (Bernanke, Boivin, and Eliasz, 2005 and Stock and Watson, 2011), and identify monetary policy shocks using the sign restriction approach of Uhlig (2005). We report three principal findings from our empirical study. First, expansionary monetary policy shocks substantially increase the relative price of food (with respect to the general price level). Second, expansionary monetary policy shocks have significant and negative effects on the distribution of food consumption in the short run. There is strong heterogeneity in food consumption responses to the policy shocks faced by households across different expenditure classes in rural and urban India. Food consumption for poor households (bottom 20% of the expenditure distribution) falls much more relative to the the rich households (top 20% of the expenditure distribution). Expansionary monetary policy shocks therefore increase food consumption inequality by disproportionately hurting the poor relative to the non-poor. Finally, monetary policy shocks seem to play a non-trivial role in accounting for fluctuations in the distribution of food consumption. Forecast error variance decompositions suggest that the contribution

[4]India has been ranked 97 among 118 developing countries (ranked from least to most hungry) in the 2016 Global Hunger Index. The GHI, adopted and developed by the International Food Policy Research Institute (IFPRI) in 2006, is a multidimensional statistical tool used to describe the state of a country's hunger situation. The GHI combines 4 component indicators: 1) the proportion of the undernourished as a percentage of the population; 2) the proportion of children under the age of five suffering from wasting; 3) the proportion of children under the age of five suffering from stunting; 4) the mortality rate of children under the age of five.

[5]Time series studies on development issues such as poverty and inequality for low income countries are particularly challenging due to data limitations.

of monetary policy shocks to fluctuations in food consumption of households is around 15%, the same order of magnitude as the contribution of these shocks to any other macroeconomic variable like GDP or inflation.

This is the first study to provide evidence of a *"food price channel"* in monetary policy transmission to understand food inequality. Following a monetary expansion, food prices, being relatively more flexible, increase more relative to the general price level in the economy, increasing the *relative* price of food. Even within the food sector, all food prices do not respond uniformly to the policy shock. Monetary policy shocks have *distortionary* effects on the food prices of individual food items. We observe that prices of agricultural food articles like cereals, lentils, vegetables, fruits, animal proteins, and spices increase more than those of manufactured food items. Since the poor households (bottom 20%) of the population in India are net buyers of food and spend a disproportionate share of their income on food, this relative price response generates a *negative* real income/wealth effect. Thus, an increase in relative food prices reduces the food consumption of poor households significantly (from their biological minimum) and hurt the poor disproportionately relative to the non-poor. While expansionary monetary policy is a potent tool to stimulate the economy, it may come with an unwanted side effect: a fall in food consumption of the poor, and an increase in food consumption inequality in the short run.

Previous literature provides evidence that agricultural wages in India tend to be sticky in the short run (Ravallion, 1998; Ravallion, 2000). Further, poor households mostly work in the informal sector, are credit constrained, and consume their current labor income (Dreze and Sen, 2013; Anand and Prasad, 2015). Informal employment, dependence on the market for food, short run wage stickiness and credit constraints tend to make poor households vulnerable to relative food price distortions. Thus, evidence of a *food price channel* is particularly relevant to low income countries, due to the following features of poor households in these countries: being net buyers of food, having a high share of food expenditure in total consumption expenditure, informal employment, and credit constraints. This study holds important policy implications for Indian central bankers and policymakers as well as for those in similar low income countries. We discuss the related literature in section 2 and characteristics of the poor households in section 3.

2 Related Literature

Previous literature examining the impact of monetary policy on inequality through various channels has focused mostly on advanced countries (Easterly and Fischer, 2001; Albanesi, 2007; Williamson, 2008; Ledoit, 2011; Saiki and Frost, 2014; Carpenter and Rodgers, 2004; Yannick and Ekobena, 2014; Coibion et al., 2017; Romer and Romer, 1998). Monetary policy is transmitted through different both direct and indirect channels and recent studies have focused on its redistributional effects (Coibion et al., 2012; Williamson, 2009; Ledoit, 2009, Erosa and Ventura, 2002; Kakar and Daniels, 2019; Albanesi, 2007; Saiki and Frost, 2014; Doepke and Schneider, 2006; Carpenter and Rodgers, 2004; Heathcote et al., 2010).

Households in developing countries differ significantly from those in advanced countries in many respects: income, wealth, employment status, financial inclusion, institutions, patterns of consumption expenditure, savings etc. (Easterly and Fischer, 2001; Yannick and Ekobena, 2014). Thus, channels through which monetary policy affects households in advanced countries may not be relevant to developing countries. For instance, on average, the share of food in total household expenditure is 40-50% in developing countries as compared to 10-15% in advanced countries (Figure 1). More than half the population in developing countries does not have access to a formal banking and financial system, while in advanced countries, almost all households have such access (Figure 2). Due to differences in the degrees of development across countries, monetary policy transmission channels affect households in developing countries differently from those in developed countries.

Food and non food prices do not adjust with the same frequency to monetary policy shocks. It is argued that as agricultural prices are less rigid, they respond faster to changes in money supply than non-agricultural prices (Frankel, 1986; Bordo,1980). This varying degree of price adjustments to monetary shocks has been empirically validated by a number of studies for different countries. Previous literature confirms the tendency of agricultural prices to be more flexible and more volatile relative to the prices of other goods in the economy, (Chambers and Just, 1982); Hercowitz, 1982; Barnett et al., 1983, Orden, 1986; Orden and Fackler, 1989; Cho et al.,1993; Dorfman and Lastrapes, 1996; Lastrapes, 2006 and Balke and Wynne, 2007). A majority of poor households in developing countries depend significantly on agriculture for employment and income as well as spend a high proportion of their income on food. Thus, linkages between monetary policy and food prices hold significant implications for their welfare.

A few studies have focused on the short run welfare effects of a change in the relative price of food on across various income groups. Mellor (1978) finds that the income effect of foodgrain price changes on low income households is larger relative to high income households in India due to their very large food share in income. Ravallion (1990) finds that an increase in the relative price of foodgrains is very unlikely to be passed on to the agricultural wage rate even in the long-run, and therefore the distributional effects of an increase in the relative price of foodgrains are similar to Mellor (1978). The rural rich are likely to gain and the rural poor lose from an increase in the relative price of foodgrains. Apart from differential effects on real income of the rich and the poor, higher relative food prices also generate differential effects on the real income of net buyers and net sellers of food, hurting the poor disproportionately relative to the non-poor. This is due to the small size of landholding and high degree of wage stickiness of poor households (Dev and Ranade, 1998; Krishna and Kapila, 2009; Ravallion, 1998, 2000). Robles and Torero (2010) in their welfare study of 'food crisis' on four Latin American countries find that the 'poverty incidence' increases by 1% point in Guatemala, Honduras and Peru, and 4% points in Nicaragua from rise in relative food prices. Ivanic and Martin (2008) use household survey data for ten low-income countries and find that poverty increases in response to an increase in relative food prices after accounting for net food sellers among the poor. Thus, previous literature confirms the adverse short-term welfare effects of higher relative food prices on the poor in low-income countries.

3 Characteristics of the Urban and Rural poor in India

In this section, we present some stylized facts that provide evidence of the dominant role played by food prices in the welfare of the poor households in India. Nearly 25% of the Indian population or close to 300 million people, live below the national poverty line of Rupees 33 (50 cents) per person per day in urban areas and Rs 27 (40 cents) per person per day in rural areas. These poor households rely heavily on cash purchases of food, and spend a very large portion of their income, about 65-70%, on food, particularly on cereals and vegetables. Figures 3-4 present the food expenditure shares of households in rural and urban India. In rural India, poor households allocate an average of 70% of their total consumption expenditures to food and rich households allocate about 35%. In urban India, poor households allocate about 65% and rich households 25%. These statistics suggest that food expenditures comprise the largest component of poor households' budget. Further, Figure 6 reports the fraction that poor allocate to different food types - cereal, lentils, vegetables, fruits, milk products, animal proteins, spices, sugar, salt, edible oils and beverages. Poor households spend maximum on cereals (32 %), followed by vegetables (17 %), the two cheapest source of nutrition in India.

Despite spending such a large portion of their income on food, poor households still remain substantially food deprived. The Public Distribution System in India distributes rice, wheat, and sugar through fair price shops but is able to satisfy only a fraction of their caloric requirement (Figure 7). As the government procures more grain for redistribution, the mark-up that grain producers charge over their marginal costs of production increases leading to higher prices in the open grain market, and overall inflation in the grain sector, Ghate et al. 2018. Poor households also have to rely on the market for consumption of other essential food commodities such as lentils, milk, fruits, and animal proteins that provide important micro nutrients to the human body.

The extent of gains or losses to the poor from higher relative prices of agricultural goods in rural India depend on many factors such as the distribution of land, access to credit and infrastructure, and the dynamics of wage adjustment from the agricultural sector. The bottom 37% of the rural population comprise the landless laborers (less than .002 hectare of land), and laborers with very little land (Figure 5) who mostly are net buyers of food (Dev and Ranade, 1998; Krishna and Kapila, 2009). Dev and Ranade (1998) find that by a very conservative estimate, the entire urban population and at least 50 per cent of the total rural population in India is adversely affected by an increase in relative prices of food. Ravallion (1998, 2000) finds prevalence of a strong degree of wage 'stickiness' in the Indian agricultural sector. Financial inclusion in India is very low, more than half of the population lack access to the formal financial and banking system (Figure 2). The poor live hand-to-mouth, i.e., do not have no access to credit markets and simply consume their current labor income. Thus, their ability for consumption smoothing is limited, they cannot insure against idiosyncratic shocks, and market fluctuations (Anand and Prasad, 2015).

Further, India is characterized by the presence of a large informal sector (Dreze and Sen, 2013). Thus, higher relative food prices acts as an implicit tax on the poor: in the informal sector wages are not indexed to inflation and workers don't have much bargaining power vis-a-vis their employers (Easterly and Fischer, 2001; Rada, 2010; Gulati and Saini 2013; Rajan, 2016). Despite robust economic growth in India, mean real wages rose at a slow rate of only 1.03% in rural India and 2.6% in urban India (Dreze and Sen, 2013). Dreze and Sen (2013) argue that the reason why economic growth in India has led to so little increase in wages is owing to 'jobless growth'.[6] Thus, poor households in India remain net buyers of

[6]India's rapid economic growth during the last twenty years has been driven mainly by the 'service sector' which in heavily skill intensive industries (software development, financial services etc.) rather than more traditional labor intensive sectors. While this has helped, the educated class to earn higher wages, the bulk of the labor force has been left behind in agriculture and other informal sectors (which employs more than

food, spend a disproportionate share of their income on food, mostly work in the informal sector, and are credit constrained. All these characteristics poor households vulnerable to fluctuations in relative food prices that are indirectly affected by monetary policy shocks.

4 Data

We utilized quarterly macroeconomic data and household consumption expenditure survey data from 1996 to 2013.[7] We measured aggregate output as real GDP (seasonally adjusted), the general price level as the overall consumer price index, the nominal interest rate as the overnight prime lending rate, and the stock of nominal money as M3.[8] Quarterly data on the above macro variables were taken from the Federal Reserve Bank of St. Louis Data Base (FRED) and household consumption expenditure data were taken from the National Sample Survey Organization (NSSO). All variables were log transformed prior to use.

India witnessed a robust real GDP growth of 6.7% per year over the time period under consideration. Nominal money supply and the overall consumer price index had average annual growth rates of 16.5% and 7.1% respectively. We used the highest level of disaggregated wholesale food price data from the Ministry of Statistics and Programme Implementation, Central Statistical Organization. There are over 150 series of individual food prices which includes prices of both agricultural and manufactured food articles. However, many of these series have incomplete coverage and missing data. The sample we use contains 98 food prices that have complete quarterly observations from 1996 to 2013. The list of the food price series along with the summary statistics is reported in the Appendix.

90 percent of the labor force) where wages remained very low.

[7]The time period of study has been selected based on the availability of the most recent data.

[8]The Reserve Bank of India (RBI), India's central bank introduced a full-fledged liquidity adjustment facility (LAF) in 2004, which was later reinforced in 2011, with the overnight call money rate (also known as the central bank rate) being explicitly recognised as the operating target of monetary policy and the repo rate, as the only one independently varying policy rate to influence the operating target (Mohanty, 2011). Since the monetary policy framework in India underwent periodic modifications and shifts based on experience and development of financial markets, we use the overnight prime lending rate as an indicator of monetary policy in India. Significant unidirectional causality has been found from the policy interest rate to various measures of liquidity, providing evidence of a high degree of monetary policy transmission in India (Mohanty, 2012).

The household consumer expenditure surveys, published by India's NSSO, reports the distribution of average nominal monthly per capita food consumption expenditure for different expenditure groups across rural and urban India.[9] Households who meet the national poverty line requirements are present in the 20-30% of expenditure distribution in India.[10] Consistent with the poverty definitions of world bank (Poverty Manual, ch 4, World Bank) and poverty line estimates of the Planning Commission of India, *"poor households"* are identified as those who live below the national poverty line i.e. located in the 0-20% of expenditure distribution. Keeping in mind our focus on food inequality, we select two expenditure classes for this study: poor households in the bottom quintile of the expenditure distribution (0-20%) and rich households in the top quintile of the expenditure distribution (80-100%). We compute quarterly averages of nominal monthly per capita food consumption expenditures of the poor and rich households and deflate by the aggregate food price index, to obtain quarterly averages of real per capita food consumption expenditures. We use the difference between the 80th percentile and the 20th percentile of the log levels in food consumption distribution as a measure of food inequality following Coibion et al., 2017.

5 Empirical Framework

5.1 Empirical Model and Identification

We estimate the dynamic responses of relative food prices and the distribution of food consumption to monetary policy shocks in India. We utilize a factor-augmented vector auto regression (FAVAR) framework (Bernanke, Boivin, and Eliasz, 2005 and Stock and Watson, 2011). A FAVAR model is particularly well-suited for this study because it provides a parsimonious framework for incorporating a large set of individual food prices without losing

[9] We have used, all rounds of consumer expenditure surveys and have used both the thick rounds i.e. surveys conducted once in 5 years and the thin rounds i.e. surveys conducted every year.

[10] The Planning Commission of India quantifies, in terms of money, an ideal poverty line basket which should suffice the food and a non-food component, based on which it characterizes poor and non-poor households.

too many degrees of freedom. It also allows for heterogeneity in the responses across relative prices of the different food types to monetary policy shocks. The dynamic factor model summarizes information from a large sample of disaggregated food prices into one estimated food price index through factor analysis. It then allows us to examine the dynamic effects of monetary policy shocks on food prices.

Let X_t be a n-dimensional vector stochastic process for a set of nominal wholesale price indices of food and a set of "informational" variables represented by Z_t and F_t be an q-dimensional vector of latent common factors. Λ is a $n \times q$ matrix of "factor loadings". The informational variables are primarily used in estimation to help extract the common latent factors. Given a time series realization for X_t and the observable subset of F_t, we estimate the following dynamic factor model:

$$X_t = \Lambda F_t + \upsilon_{xt} \tag{1}$$

$$\begin{bmatrix} Y_t \end{bmatrix} = \begin{bmatrix} Z_t \\ F_t \end{bmatrix} = B(L) \begin{bmatrix} Z_t \\ F_t \end{bmatrix} + \begin{bmatrix} \epsilon_t \end{bmatrix} \tag{2}$$

where, Y_t follows the following linear dynamic process

$$Y_t = B_1 Y_{t-1} + ...B_p Y_{t-p} + \epsilon_t \tag{3}$$

Y_t is a $m \times 1$ vector of data at date $t = 1, ..., T$, B_i are coefficient matrices of size $m \times m$ and ϵ_t is the one-step ahead prediction error with variance-covariance matrix Σ.

The system in Eq. (3) is in reduced form, obtained from a dynamic structural model. We focus on identifying how the variables in Y_t respond to structural shocks, not reduced form shocks. The structural counterpart to Eq. (3) in moving average form is given by:

$$Y_t = (I - B_y L)^{-1} D_y u_t \tag{4}$$

$$Y_t = (D_0 + D_1 L + D_2 L^2 + ...) u_t \tag{5}$$

where u_t is a vector of aggregate structural shocks, $E\left(u_t u_t^{'}\right)$ is normalized to be the identity matrix.[11] The mapping from the reduced form to the structural form thus entails restrictions on the covariance structure:

$$\Sigma = E\left(\epsilon_t \epsilon_t^{'}\right) = D_y E\left(u_t u_t^{'}\right) D_y^{'} = D_y D_y^{'} \tag{6}$$

Once we identify the $m \times m$ matrix D_y from this mapping, we obtain the dynamic multipliers of interest from equation (3) using (4) and (5). We do not fully identify D_y because we are solely interested in the monetary policy shock. We impose identifying restrictions to identify only the column of matrix D_y which corresponds to the monetary policy shock. We use the robust sign restrictions approach of Uhlig (2005) for identification. In particular, we identify an expansionary monetary policy shock as one that does not lead to a decrease in real GDP, CPI, and nominal money, or an increase in the interest rates over a selected horizon.[12]

[11] There are m fundamental innovations which are mutually independent and normalized to be of variance 1: they can therefore be written as a vector u_t of size $m \times 1$ with $E\left[u_t u_t'\right] = I_m$.

[12] Many studies in the literature identify monetary policy shocks using zero restrictions in the short run and long run. However, there is a wide disagreement regarding the use of such identification strategies. Faust and Leeper(1997) show that substantial distortions in the estimations are possible due to small sample biases and measurement errors when using zero restrictions in the long run. On the other hand, Canova and Pina (1999) argue that there isn't enough theoretical evidence to justify a zero contemporaneous impact of nominal shocks on output, and such a restriction is also not consistent with a large family of general equilibrium models. As an alternative Uhlig (2005), Scholl and Uhlig (2008), Canova and De Nicolo (2002), Mountford (2005), Peersman (2005), and Abdallah and Lastrapes (2013) among many others use sign restrictions to identify structural shocks. The advantage of the sign restrictions approach is that shocks are identified not based on a zero restriction in the short run or long run, but based on the direction of their impact on the variables in the system; this eliminates price puzzles. Peersman (2005) shows that if conventional identification strategies (based on zero restrictions) produce impulse responses which are consistent with the sign restrictions, then these responses mostly lie in the tails of the distributions of the set of all impulse responses that satisfy the sign restrictions.

5.2 Model Specification and Estimation

Following Bernanke, Boivion, and Eliasz (2005), we use a two-step estimation method, in which the latent factor is first estimated by principal components prior to estimation of the factor-augmented vector auto regression model (FAVAR).

5.2.1 Model Specification

Step I: X_t in Eq. (1) contains the nominal wholesale price indices of 98 different food types. We estimate F_t as the first principal component of X_t: $\hat{F}_t = \left(\frac{1}{n}\right)\hat{\Lambda}'X_t$, where $\hat{\Lambda}$ contains the eigenvectors of X_t, normalized so that $\left(\frac{1}{n}\right)\Lambda'\Lambda = I$. Thus, $\hat{F}_t$ is the estimated common latent factor that serves as the nominal food price index for my study. We deflate $\hat{F}_t$ by the overall CPI to obtain the *relative* food price index.[13]

Step II: With the common latent factor of food price in hand from Step I, the next strategy depends on how we specify the macro subsystem (Z_t) in Eq. (2). Our aim is to estimate the dynamic responses of the distribution of food consumption to monetary policy shocks in rural and urban India respectively. Keeping in mind our objective, we include the following six macro-variables in the macro sub-system (Z_t): real GDP, consumer price index (CPI), interest rate, nominal money supply, and the food consumption of the bottom and top quintile respectively.

5.2.2 Estimation

The FAVAR (Y_t) given by Eq. (3) includes the latent factor from step I, and the macro subsystem (Z_t) from step II . Once we have specified the FAVAR, next we proceed to estimating the FAVAR using the sign restrictions approach. We run FAVAR estimation separately for rural and urban India. We have fitted a VAR with 4 lags in levels of the logs of all the series,

[13]By including $\hat{F}_t$ in the VAR, we augment the standard VAR model with an estimated latent factor; this makes the standard VAR a factor-augmented VAR.

except for using the interest rate directly. We add a constant and a time trend to Eq. (3). The horizon over which we impose the sign restrictions to identify monetary policy shocks is $k = 2$ quarters, including the initial period of the shock. These restrictions are imposed only on the real output, consumer price index, interest rate, and nominal money supply.[14] No restrictions are imposed on relative food prices and the distribution of food consumption. We remain agnostic about these two variables under investigation which are the main interest in this study. We use Bayesian method to estimate the posterior densities of the concerned parameters, conditional on observing the sample data, for the baseline model and alternatives to check for robustness of the model specification. None of the results in section 6 are sensitive to increasing the common lag in the VAR to five lags, and to assuming the sign-restriction horizon as three quarters. Our results discussed in section 6, for the baseline VAR model are robust to changes in model specification.

We estimate the posterior density using the sign restriction approach of Uhlig (2005, Appendix B.1, pp 409-412) as also generalized by Rubio-Ramirez, Waggoner, and Zha (2010). Observe in particular that B and Σ are directly identified from estimation of the parameters in Eq. (3) via OLS. We assume a Gaussian likelihood function and a standard diffuse (Jefferey's) prior on the reduced form parameters B and Σ, which implies that the joint posterior density of the parameters is of the Normal-Wishart form (Uhlig 2005, pp. 409-410):[15]

$$\Sigma^{-1} \sim W\left[\left(T\hat{\Sigma^{-1}}\right), T\right] \tag{7}$$

$$(B|\Sigma) \sim N\left[\hat{B}, \Sigma \times \hat{\Omega}\right] \tag{8}$$

[14] One problem confronting the estimation is that the variables in my model are characterized as non-stationary $I(1)$ variables. Therefore, we conduct a robustness check by estimating the model in first differences. We find that our results discussed in section 6, for the baseline VAR model (estimating the VAR in log levels) are robust to changes in model specification (estimating the VAR in log first differences). We present the robustness results in Appendix Figures 1-4.

[15] see Uhlig(1994) for a detailed discussion on the properties of Normal-Wishart distribution

where T is the time series sample , $\hat{B}$ and $\hat{\Sigma}$ are the OLS estimates of the dynamic factor model with observable factors, and $\hat{\Omega} = \frac{1}{T}\sum_{t=1}^{T} Y_{t-1}Y_{t-1}'$. The algorithm entails the following steps:

1. Estimate $\hat{B}$ and $\hat{\Sigma}$ from Eq. (3) by OLS. OLS is efficient given the restrictions of the model.

2. Draw $\bar{B}$ and $\bar{\Sigma}$ from the posterior distribution given by Eq. (7) and (8) and conditional on the OLS estimates from step 1.

3. Using the values from this draw, impose the sign restrictions to identify structural shocks using the following algorithm of Rubio-Ramirez, Waggoner, and Zha (2010, section 6.4, pp. 688)

   (a) Draw a $m \times m$ matrix M, element by element, from a standard normal density, and use its "Q-R" factorization to set $M = QR$, where Q is an orthogonal matrix ($QQ^{'} = I$) and R is normalized to have positive diagonal elements.

   (b) Set $D_y = \tilde{D}Q$ which from Eq. (5) implies values for $\bar{D}_k$ for $k = 1, ..., K$, where $\tilde{D}$ denotes the lower-triangular Cholesky factor of Σ.

   (c) If the $\bar{D}_k$ estimates *do not satisfy* the sign restrictions for monetary policy shocks over the chosen horizon K, return to substep 3(a), draw a new value of Q, and continue until the draw of Q yields responses that satisfy the sign-restrictions.

   (d) If the $\bar{D}_k$ estimates *satisfy* the sign restrictions, compute and save the corresponding impulse response coefficients relating to the variables in Y_t and X_t to these shocks. Then return to step 2 and draw a new set of reduced form parameters.

4. Iterate on steps 2 through 3(d) until 20,000 draws from the posterior distribution of the dynamic responses of all the variables to monetary policy shocks (that satisfy the conditions of step 3(d)) are produced.

We report the median as well as the 16% and the 84% quantiles for the sample of impulse responses.[16]

6 Empirical Results

6.1 Dynamic Responses to Monetary Policy Shocks

We begin by discussinng the dynamic responses of the *relative* prices of food and the distribution of food consumption to monetary policy shocks. The impulse responses are presented in Figures 8-12. Figure 8 represents the dynamic responses of all variables to an expansionary monetary policy shock for rural India while Figure 9 represents the responses for urban India. Figures 10-11 represent the effects of an expansionary monetary policy shock to food inequality for rural and urban India respectively. The impulse responses for the relative prices of selected agricultural food articles (at the disaggregate level) are presented in Figure 12.

We first discuss the results for rural India, Figure 8. An expansionary monetary policy shock causes the interest rate to fall by 30 basis points and the nominal money supply to rise by .40% on impact. Output responds positively reaching a peak impact of .40% at a one-quarter horizon, and then makes a gentle descent back to its original value by the end of five quarters. The aggregate consumer price index increases permanently by .80% in

[16] Paustian (2007) and Fry and Pagan (2011) note that the "pure sign-restriction" approach successfully identifies only the structure but not the model. There is a multiple models problem because there are many set of impulse vectors that satisfy the sign restrictions, and will yield the same VAR and give the same fit to the data. One solution to overcome the model identification problem suggested by Fry and Pagan (2011) is to use quantitative information about the magnitude of the impulse responses and reduce the set of models. The "penalty function" method by Uhlig (2005) solves the model identification problem, by minimizing a given criterion function on the space of all impulse vectors, which penalizes any sign restriction violation. While pure sign restriction approach provides a range of impulse vectors consistent with sign restrictions, the penalty function approach uniquely identifies the model and selects the best of all impulse vectors. Given a choice among many candidate monetary impulse vectors the "penalty function" approach picks the one which generates the most decisive response of the variables (Uhlig 2005, p. 414). We use the "penalty function" approach of Uhlig (2005, Appendix B.2, pp. 413-417) as a solution to the model identification problem and as a robustness check for my main empirical method. We find that my results from the baseline model are robust to empirical specification.

response to the same shock.[17] In response to the expansionary monetary shock, the relative food price index increases monotonically, reaching a peak impact of .50% at a one-quarter horizon, continues to remain high for the next two quarters, and then gradually approaches its original value at the end of eight quarters. Results of this paper provide empirical evidence that following the monetary expansion, food price being *relatively* more flexible overshoot relative to the general price level in the economy by .50%.

Further, even within the food sector all prices do not respond uniformly to the policy shock, i.e., monetary policy shocks have *distortionary* effects on the different individual food prices (Figure 12). In particular, we observe that prices of agricultural food articles like cereals, lentils, vegetables (especially onion), fruits, and animal proteins which primarily constitute the food basket of the Indian poor (eg. cereals, lentils and vegetables that form 50% of the poor households' budget), increase more than most manufactured food articles.[18] These observations are consistent with standard microeconomic evidence in the new-Keynesian literature (Bils and Klenow, 2004; Dhyne at al., 2006; and Nakamura and Steinsson, 2008) that first, food prices change more frequently than the general price level in the economy and second, that prices of unprocessed food items change with markedly higher frequency than manufactured food prices.[19]

The impulse response functions of the distribution of food consumption is the main focus of this research. In rural India (Figure 8), the distribution of food consumption responds negatively to expansionary monetary shocks in the short run, with larger negative effects observed at the lower end of the distribution. There appears to be strong heterogeneity in the response of food consumption experienced by different households. Poor households

[17]The impulse responses of the interest rate, nominal money, GDP, and CPI series discussed above lend validity to the identification scheme employed in this paper (sign-restriction), suggesting reliability in the results for all the other series.

[18]For brevity, we only present the impulse responses of the relative prices of certain selected agricultural food articles- cereals, lentils, salt, sugar, oil, vegetables, fruits, spices, and animal proteins in Figure 12. The matrix of factor loading is provided in Appendix, Table 1. Note that the factor loadings of agricultural commodities are larger than manufactured articles.

[19]This asymmetric effect of monetary policy on individual food prices holds potential implications for poor households, especially since their ability to substitute across food items is limited in the presence of expansionary monetary shocks.

witness a much larger decline in food consumption than the rich. Given an expansionary monetary policy shock that increases the relative food price index by .50%, reduces the the food consumption of poor households by 1.30%, that of rich households by only .50%. The response of food consumption for poor households remains negative for first four quarters. For rich households, the negative response is relatively more persistent and remains negative for eight quarters. Thus, we observe that for poor households the sensitivity to policy shocks is higher but less persistent.

We present the response of food consumption inequality in Figure 10. Using the difference between the 80th percentile and the 20th percentile of the log levels in the food consumption distribution as a measure of food consumption inequality, we report that food consumption inequality increases in response to an expansionary monetary policy shock in rural India in the short run, with the largest impact observed in the initial quarters following the shock (.80% on impact).

Next, we discuss the results for urban India (Figure 9, Figure 11). The results for urban India and rural India are quite similar. An expansionary monetary policy shock causes the interest rate to fall by 30 basis points, and the money supply to increase by .40% on impact. Relative food price increases monotonically, reaching a peak impact of .50% at a one-quarter horizon, continue to remain high for the next two quarters, and then gradually starts falling. Consistent with rural India, we find that the distribution of food consumption responds negatively to expansionary monetary shocks. Following the expansionary monetary shock, the food consumption of poor households falls by 1.10% but that of high income households fall by .35%. Figure 11 plots the food consumption response of the top quintile relative to the bottom quintile; the results again indicate that expansionary monetary policy shocks are associated with higher levels of food inequality (.75%) in urban India in the short run. Thus, expansionary monetary policy shocks increase the relative food price and food inequality in India in both rural and urban India in the short run.

6.2 How much variation do monetary policy shocks explain?

We further examine the economic significance of monetary policy shocks in accounting for the dynamics of the distribution of food consumption in India. We present the share of the variance accounted for by monetary policy shocks in the distrbution of food consumption. According to the median estimates presented in Figures 13-14, monetary policy shocks account for 5-10% of the variation in relative food price index and 13-15% of the distribution of food consumption in most forecast horizons. Monetary policy shocks appear to have played a non-trivial role in accounting for fluctuations in food consumption of households in rural and urban India over the study period. Figures 13-14 also plot equivalent variance decompositions for all other macroeconomic variables over the same time period. Monetary policy shocks account for upto 15% of the variation in real GDP, and upto 25% of the variations in interest rate, and CPI at all horizons. The forecast error variance decompositions show that the contribution of monetary policy shocks to fluctuations in food consumption of poor households is of the same order of magnitude as the contribution of these shocks to other macroeconomic variables like GDP and inflation, suggestive of the evidence that these shocks are important.

6.3 The Food Price Channel: Discussion

This paper documents that the *relative* price of food responds positively and the distribution of food consumption responds negatively to expansionary monetary policy shocks in the short run in India. In addition, there appears to be strong heterogeneity in the food consumption responses faced by households across different expenditure classes to monetary policy shocks. Poor households experience a much larger decline in food consumption relative to the rich. The increase in relative food prices following a monetary expansion hurt the poor disproportionately relative to the non-poor. Since the food consumption at the lower end of the distribution falls more than that at the upper end, inequality in food consumption increases . Interestingly, results of this paper point towards a plausible channel through which these distributional effects occur: *"a food price channel"*. The mechanism is as follows: food prices being relatively more flexible, adjust quicker than the overall price level in the economy. Thus, expansionary monetary policy shocks generate an increase in the aggregate *relative* price of food. The relative price increase is not uniform across the different food types. Agricultural food prices like cereals, lentils, vegetables, fruits, and animal proteins which form the major sources of nutrition and the largest share of the diet of poor households, increase more than manufactured food items.[20] Since poor households are mostly net buyers of food and spend a disproportionate share of their income on food, this relative price response is equivalent to a negative real income/wealth effect. This is because poor households have limited ability to substitute to other less expensive goods. Further, short run sticky wages, credit constraints, and informal employment exacerbate this limited ability to hedge against relative food inflation. An expansionary monetary policy shock via an increase in relative food prices reduces food consumption of poor households and hurts them disproprtionately in the short run.

7 Conclusion

"The analysts cheer every cut in interest rates because markets are assumed to have a Pavlovian positive response to them. Even the poor are inured to their fate of seeing real incomes erode, and are only aggrieved when the price of some food staple sky-rockets." Rajan, 2016

There is an increased interest in understanding monetary policy transmission in emerging market economies. Time series studies on development issues such as poverty and inequality for emerging market economies are particularly challenging due to data limitations. To the best of our knowledge, this is one of the first time series study on the effects of monetary policy on food inequality. Using the most recent expenditure survey data for India, we find

[20]Cereals and vegetables alone comprise more than 50% of their food basket.

that expansionary monetary policy shocks have significant *negative* effects, in the short run, on the distribution of food consumption. The *negative* effects vary systematically across the expenditure distribution in rural and urban India: food consumption for poor households falls far more relative to rich households. Thus, expansionary monetary policy shocks are associated with higher levels of food consumption inequality. We present evidence of a *food price channel* in the transmission of monetary policy. While expansionary monetary policy is a potent tool to stimulate the economy, it may come with an unwanted side effect in a developing country like India: a decline in the food consumption of the poor and an increase in food inequality in the short run. This study is relevant for the Reserve Bank of India and central banks in other emerging market economies where relative food prices play a dominant role. An important policy implication of this study, and consistent with arguments of Anand and Prasad (2015) is that, monetary policy in emerging market economies, should aim at stabilizing headline inflation instead of core inflation.

Future work on this issue would benefit from integrating a food price channel into a dynamic stochastic general equilibrium (DSGE) model with heterogenous agents that match credit constraints, consumption behavior, and capture income and wealth inequality. It is possible that the *food price channel* will be more dominant in low-income African economies, where poor households spend an even larger portion of their income on food (75%). International comparisons of the asymmetries in the effects of monetary policy on food inequality is another avenue for future research.

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Supporting Evidence

Emerging Markets		*Advanced Economies*	
Indonesia	53.0	Japan	14.7
Vietnam	49.8	Germany	11.5
India	48.8	Australia	10.8
China	36.7	Canada	9.3
Russia	33.2	United Kingdom	8.8
Malaysia	28.0	USA	5.7
Average	**41.6**	**Average**	**10.1**

Figure 1: Cross Country Comparison, Share of Food in Total Expenditure (%).

Source: Anand and Prasad, 2015.

Selected EMs	*Percent with access*	*Selected EMs*	*Percent with access*
Argentina	33	Nigeria	30
Brazil	56	Philippines	27
Chile	42	Poland	70
China	64	Russia	48
India	35	South Africa	54
Indonesia	20	Thailand	73
Kenya	42	Turkey	58
Malaysia	66		
Median (29 Emerging Markets): 42		**Median (27 Advanced Economies): 96**	

Figure 2: Cross Country Comparison, Financial Inclusion (%).

Source: Anand and Prasad, 2015.

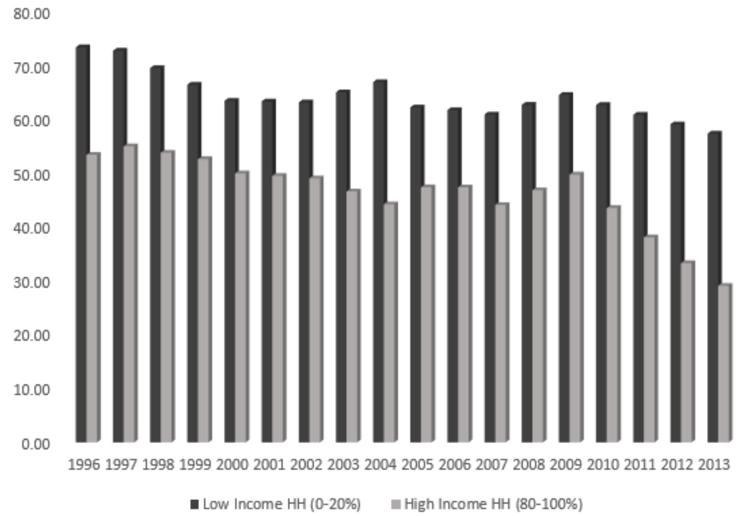

Figure 3: Share of Food in Total Expenditure, Rural India (%)

Source: Household Consumer Expenditure Survey Reports, NSSO, India.

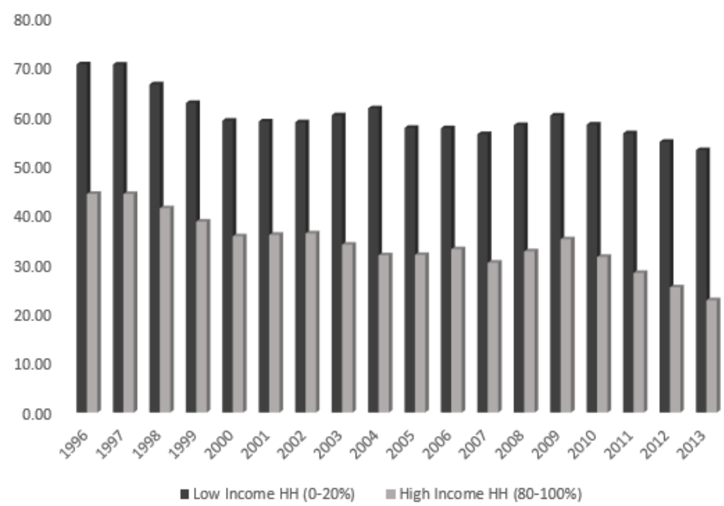

Figure 4: Share of Food in Total Expenditure, Urban India (%)

Source: Household Consumer Expenditure Survey Reports, NSSO, India.

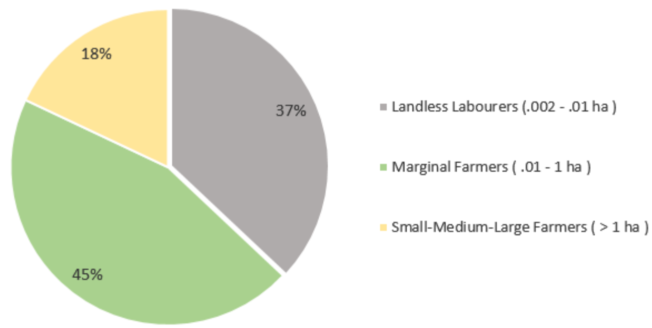

Figure 5: Net Buyers vs. Net Sellers of Food, Rural India

Source: Key Indicators of Land and Livestock Holdings in India, NSSO, India.

Notes: The bottom 37% of the rural population comprise the landless laborers (less than .002 hectare of land), and laborers with very little land (less than .01 hectare of land). Poor households in rural India are identified as net buyers of food (Dev and Ranade, 1998; Krishna and Kapila, 2009; Ravallion,1998, Ravallion, 2000).

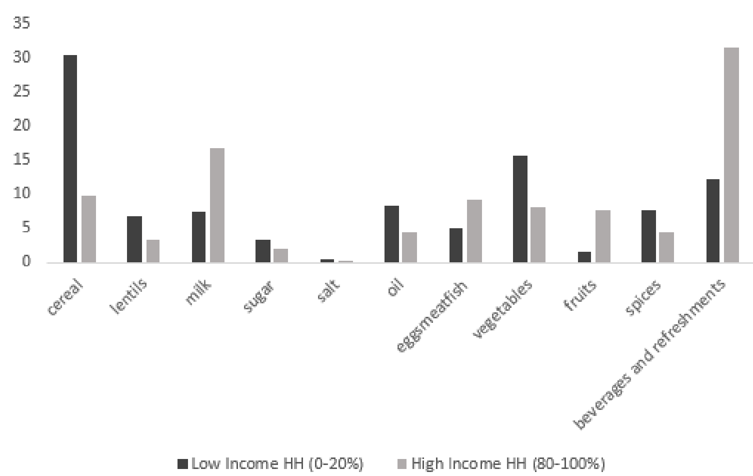

Figure 6: Composition of Food Budget, India (%)

Source: Household Consumer Expenditure Survey Reports, NSSO, India.

Notes: Composition of food budget for the rich vs. poor indicates the proportion of income allocated by the two expenditure classes towards different food types.

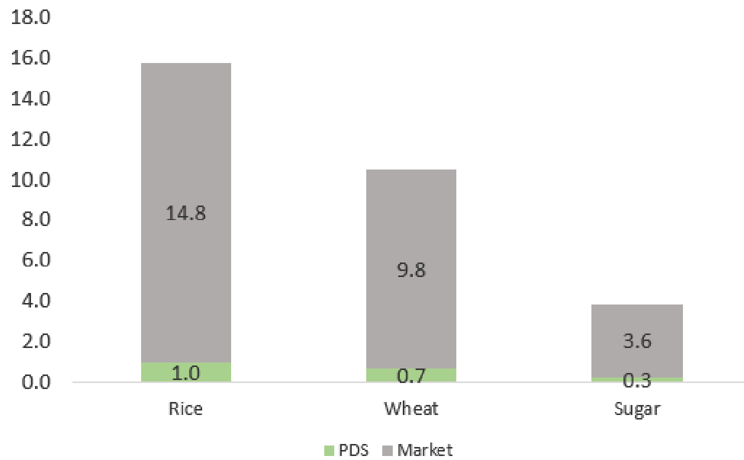

Figure 7: Public Distribution System, India (%)

Source: Household Consumer Expenditure Survey Reports, NSSO, India.

Notes: Proportion of income that poor households spend towards purchasing food (rice, wheat and sugar) from the market vs. fair price shops.

Main Results

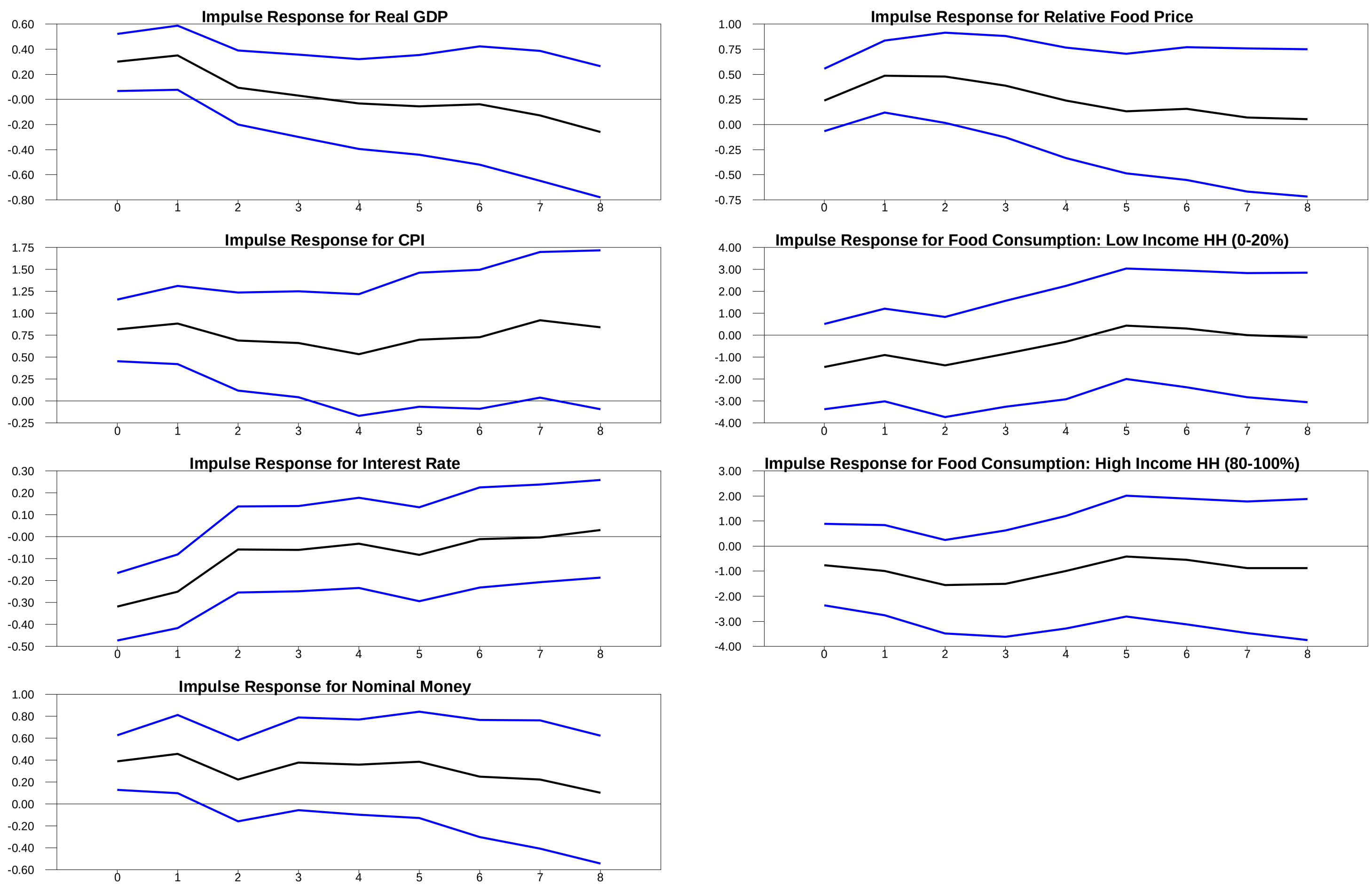

Figure 8: Impulse Responses to Expansionary Monetary Policy Shock, Rural India

Notes: Impulse responses to an expansionary monetary policy shock in rural India using sign restriction approach with $K = 2$ (2 years). That is the responses of the CPI, the real GDP and nominal money supply has been restricted not to be negative and the interest rate not to be positive for quarters k, k=0,1,2 after the shock. The three lines are 16 % quantile, the median and the 16 % quantile of the posterior distribution.

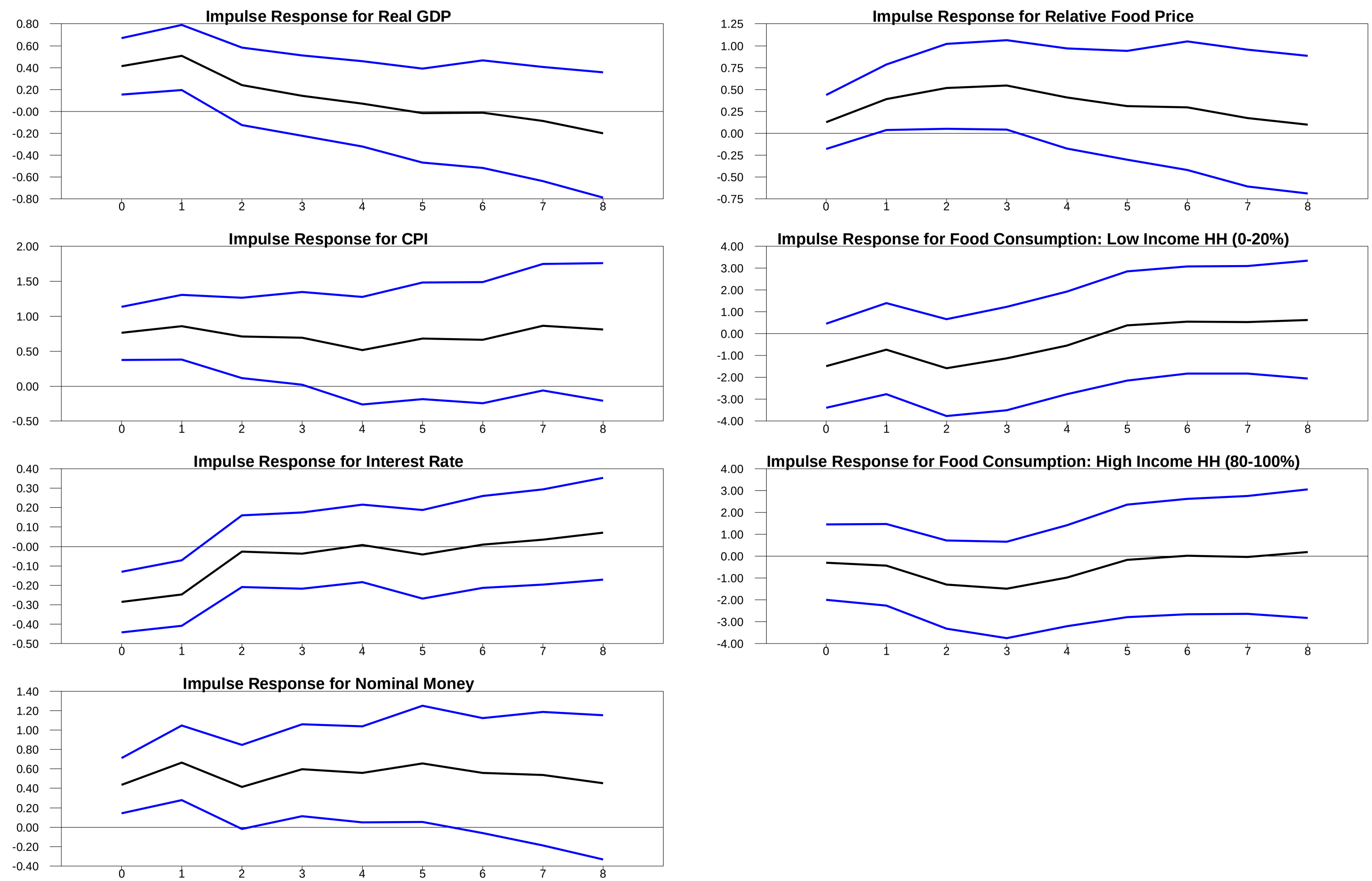

Figure 9: Impulse Responses to Expansionary Monetary Policy Shock, Urban India

Notes: Impulse responses to an expansionary monetary policy shock in urban India using sign restriction approach with $K = 2$ (2 years). That is the responses of the CPI, the real GDP and nominal money supply has been restricted not to be negative and the interest rate not to be positive for quarters k, k=0,1,2 after the shock. The three lines are 16 % quantile, the median and the 16 % quantile of the posterior distribution.

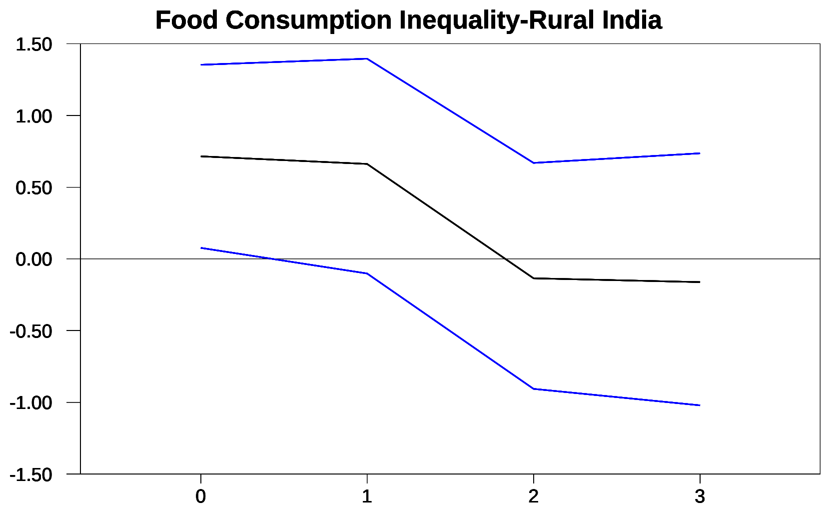

Figure 10: Impulse Response for Food Consumption Inequality, Rural India

Notes: Figure 10 plots the food consumption response of the top quintile relative to the bottom quintile for the first four quarters to the expansionary monetary policy shock (estimated from the FAVAR in Figure 8) in rural India.

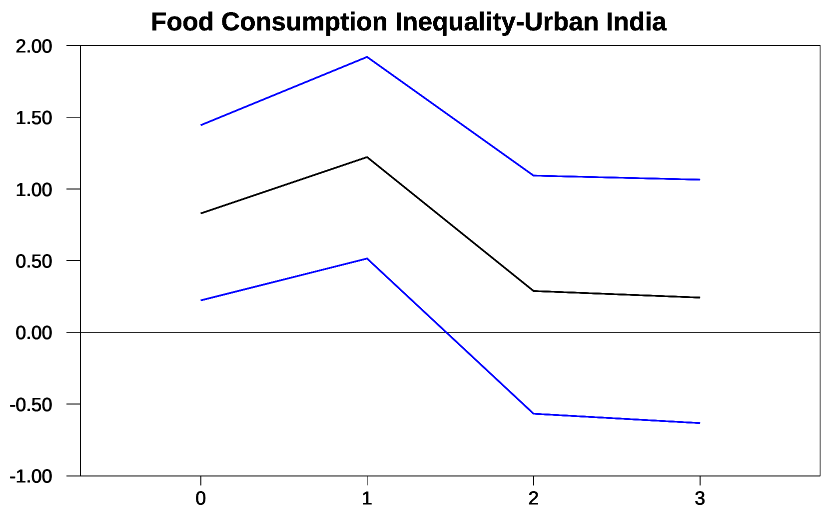

Figure 11: Impulse Response for Food Consumption Inequality, Urban India

Notes: Figure 11 plots the food consumption response of the top quintile relative to the bottom quintile for the first four quarters to the expansionary monetary policy shock (estimated from the FAVAR in Figure 9) in urban India.

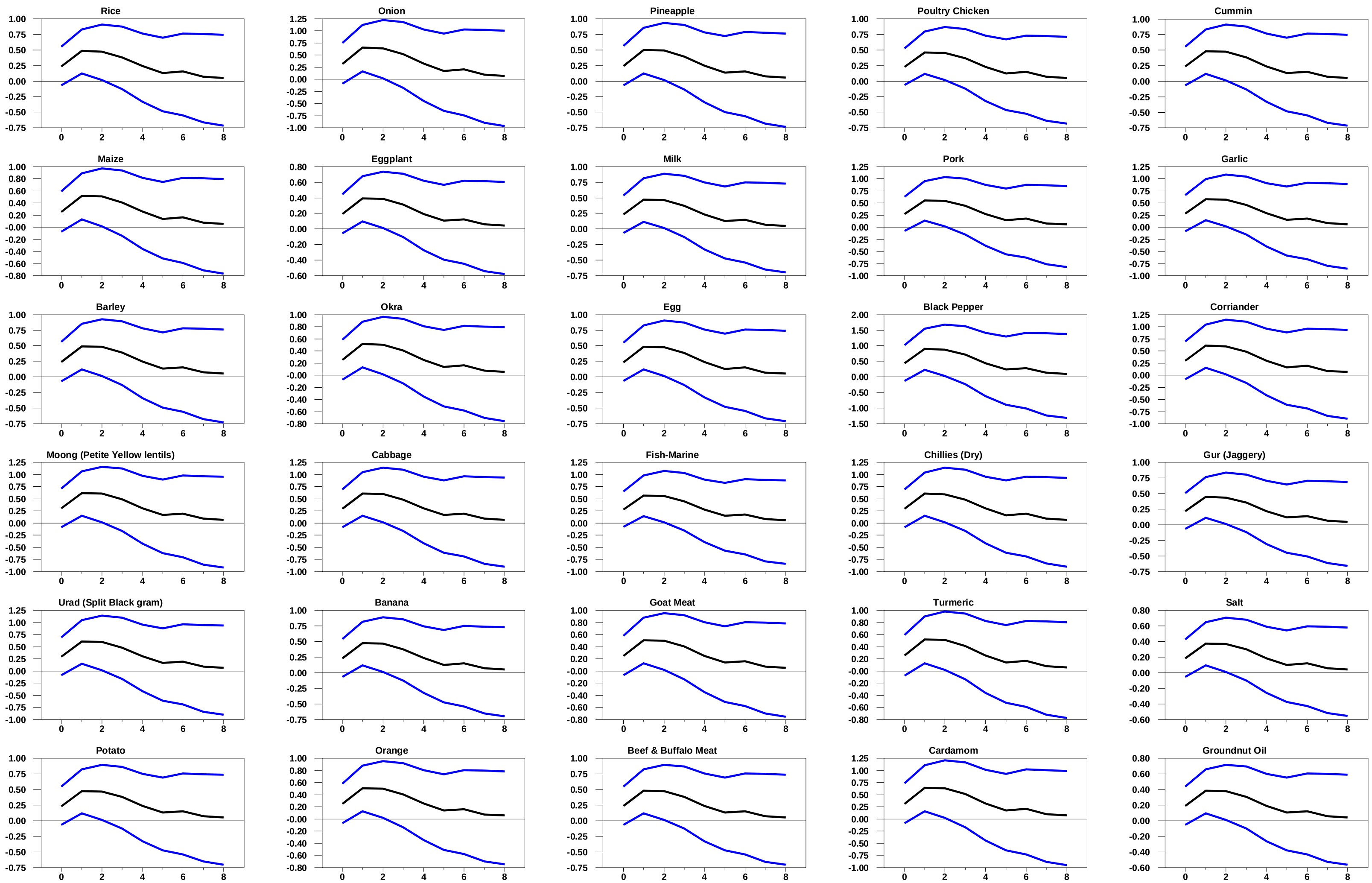

Figure 12: Impulse Responses for Relative Food Prices at the disaggregate level.

Notes: Impulse responses to an expansionary monetary policy shock using sign restriction approach with $K = 2$ (2 years). The three lines are 16 % quantile, the median and the 16 % quantile of the posterior distribution.

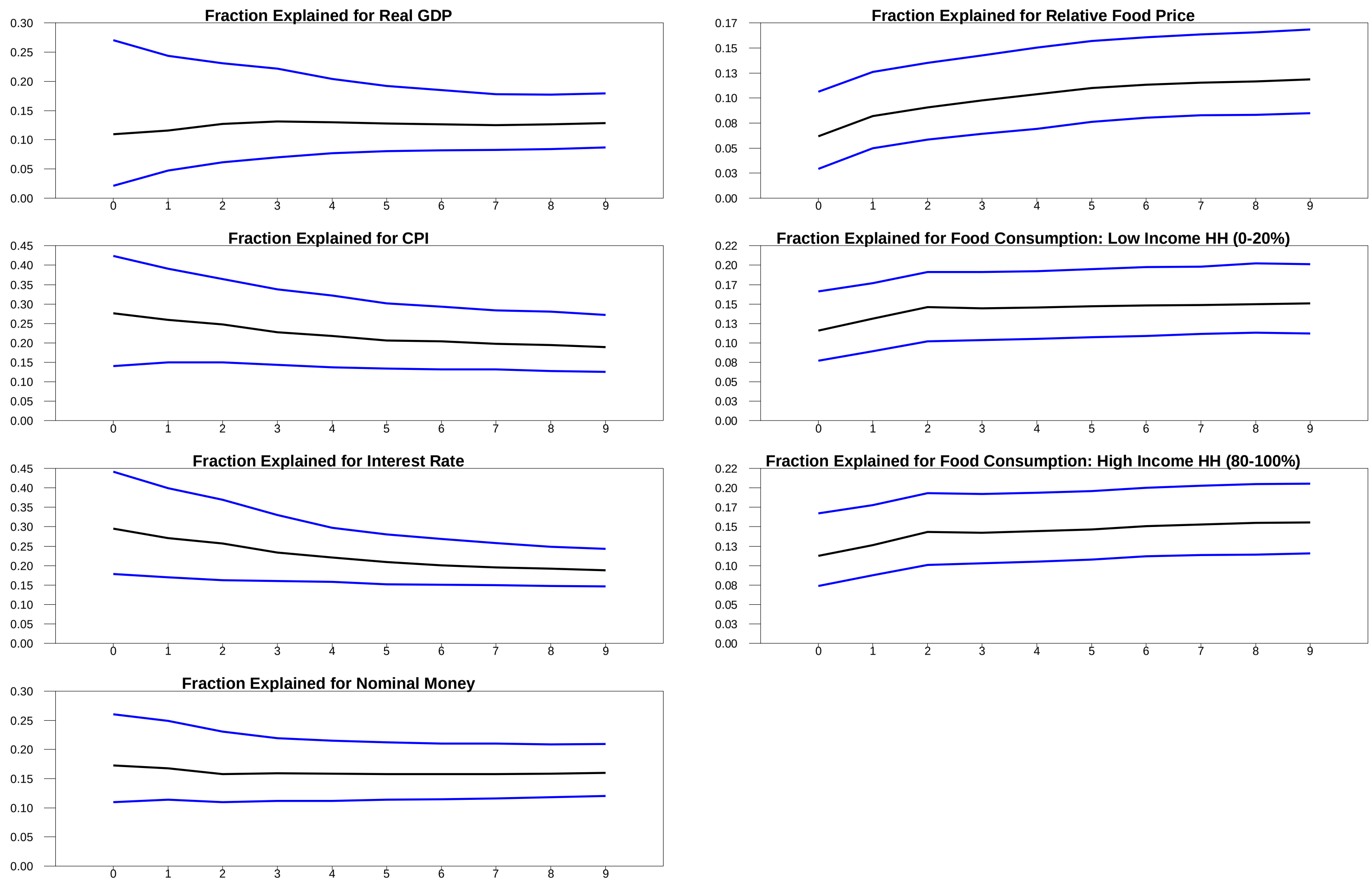

Figure 13: Fraction of the forecast error variance explained by monetary policy shock, Rural India.

Notes: These plots show the fraction of the variance of the k - step ahead forecast revision explained by a monetary policy shock, using sign restriction approach with $K = 2$ (2 years). The three lines are 16 % quantile, the median and the 16 % quantile of the posterior distribution.

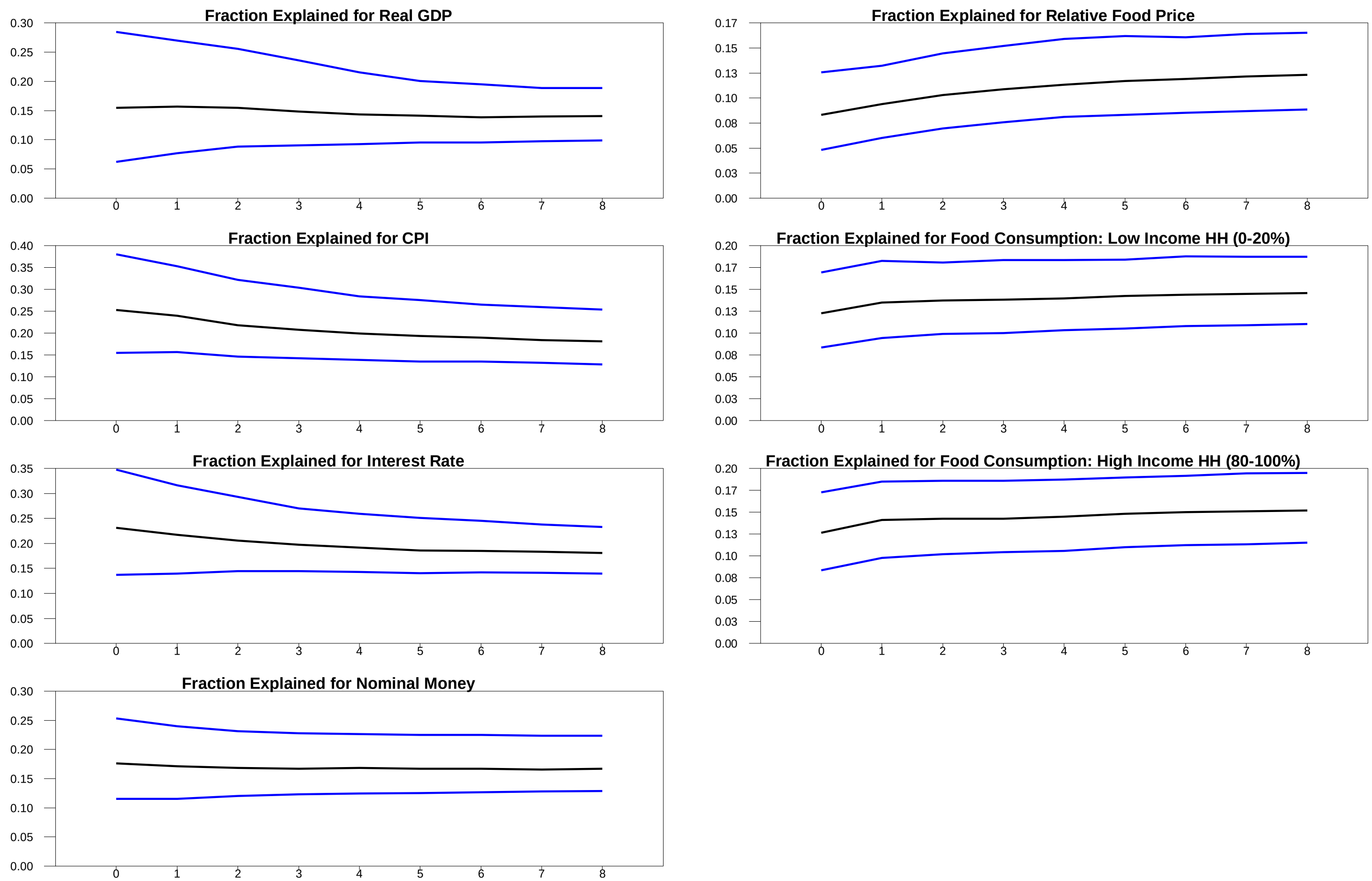

Figure 14: Fraction of the forecast error variance explained by monetary policy shock, Urban India.

Notes: These plots show the fraction of the variance of the k - step ahead forecast revision explained by a monetary policy shock, using sign restriction approach with $K = 2$ (2 years). The three lines are 16 % quantile, the median and the 16 % quantile of the posterior distribution.