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Global Food Prices and Business Cycle Dynamics in an Emerging Market Economy*

Abstract

This paper investigates a perception in the political debates as to what extent poor countries are affected by price movements in the global commodity markets. To test this perception, we use the case of India to establish in a standard SVAR model that global food prices influence aggregate prices and food prices in India. To further analyze these empirical results, we specify a small open economy New-Keynesian model including oil and food prices and estimate it using observed data over the period from 1996Q2 to 2013Q2 by applying Bayesian estimation techniques. The results suggest that big part of the variation in inflation in India is due to cost-push shocks and, mainly during the years 2008 and 2010, also to global food price shocks, after having controlled for exogenous rainfall shocks. We conclude that the inflationary supply shocks (cost-push, oil price, domestic food price and global food price shocks) are important contributors to inflation in India. Since the monetary authority responds to these supply shocks with a higher interest rate which tends to slow growth, this raises concerns about how such output losses can be prevented by reducing exposure to commodity price shocks and thereby achieve higher growth.

Keywords: commodity prices, food prices, New-Keynesian macroeconometric model, inflation, India, structural vector autoregressive model

JEL Classification: C32, E31, Q02

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1 Introduction

Food prices exhibited a large volatility in recent years. In particular, there have been huge price shocks in the years 2007/2008, 2010/2011, and 2012/2013. Since poor people spend a large share of their income on food, higher food prices may lead to hunger of poor people in developing countries. Some of the reasons for rising food prices are bad weather, increasing factor prices, in particular oil prices, or increasing usage of bio-fuels. Sometimes it is also argued that financial speculation on commodity markets is driving up food prices. For example, EU commissioner Michel Barnier said during a hearing of the European Parliament on January 13th 2010: "Speculation in basic foodstuffs is a scandal when there are a billion starving people in the world."[1] In this paper, we analyze to what extent price changes of standard foodstuff commodities are transmitted to local food prices and aggregate inflation in a large emerging market economy. It should be stressed that we are not analyzing whether speculation is driving global food prices. However, a necessary condition for the existence of effects of speculation in basic foodstuffs on poor people in poor countries is that changes in spot prices in global commodity markets are transmitted to local prices. We analyze this transmission for the case of India as an emerging market economy with a large population size. The well-being of around 300 million poor people in India might be hit by higher local food prices.

Food prices have been a major force behind the increase in the overall inflation rate in India in recent years (Anand et al., 2014). Food prices have a weight of about 43% in the Indian consumer price index.[2] Since changes in food prices reflect general inflationary developments and specific food price shocks, the effects of food prices on overall inflation can only be identified using an econometric model. Additionally, it has to be taken into account that inflation does not only depend on domestic factors but also on international developments. Despite the structural differences between advanced and emerging market economies, cyclical fluctuations seem to have been more synchronized in the last decade,

[1] See http://www.europarl.europa.eu/sides/getDoc.do?language=en&type=IM-PRESS&reference=20100112IPR67166.

[2] See http://mospi.nic.in/Mospi_New/upload/cpi_pr_12nov14w.pdf

see, for example, Levine (2012); Mallick and Sousa (2012); Lane (2003); Mishkin (2000). Given the openness of the Indian economy, the monetary and real sectors are no longer immune to external shocks, see for example Bhattacharya et al. (2011). In particular, oil price shocks may have a strong impact on inflation in India. Fuel imports account for around 40% of India's total imports. This external source of inflationary pressure, however, does not explain the structural supply-driven food inflation on the back of endemic rise in food prices due to local factors such as shortage, hoarding and administered pricing strategies of the government.

In the recent years, the volatility of commodity prices has made it difficult for central banks to achieve price stability, as these relative price movements get factored into inflation expectations, making commodity price shocks a possible driver of inflation dynamics in many emerging markets. The monetary authority in India adopts a multiple indicators approach to signal the central bank's assessment of the economy. Changes in the policy environment since the latter half of the 1990s have brought in alternative monetary policy instruments in transmitting policy signals to the financial markets (Bhattacharya and Sensarma, 2008; Bhattacharya et al., 2008)). The central bank also tends to respond by raising the interest rate in order to abate inflation when the source of such inflation appears to be emanating from the supply side. At the same time, the exchange rate policy adopted by India, which results in massive expansion of the central bank's balance sheet and broad money supply, can generate inflationary pressure. In the absence of a commensurate increase in money demand, it can spill over into excess demand for goods and services, putting pressure on overall inflation.

This paper therefore makes a new attempt to understand inflationary dynamics in India.[3] We build a structural macroeconometric business cycle model for India to explain the inflationary dynamics over the time period 1996-2013. We fit the model to Indian data using Bayesian techniques and show that cost-push shocks are important sources of fluctuations in the estimated model. In the context of the model, changes in the output gap

[3]During the second half of last century, many traditional large structural macro-econometric models were estimated for India using annual data, but many of those models suffer from model mis-specification, for an exhaustive critical review of those traditional macro models and for a small macroeconomic policy model for India following the contemporary time series modeling literature, see Mallick (1999).

also account for a big proportion of variation in inflation, reflecting demand pressures.

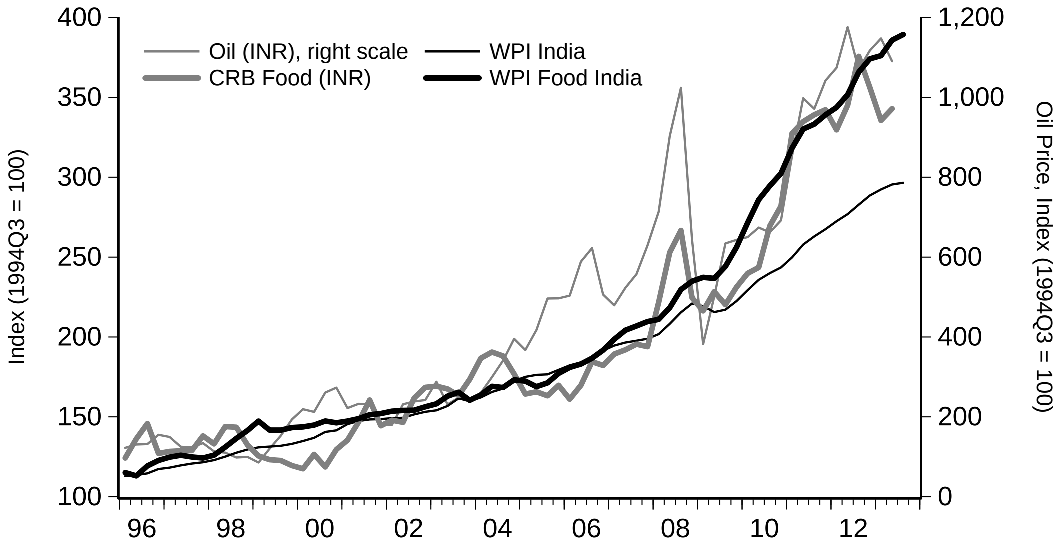
Our empirical analysis is based on two distinct but complementary approaches. In the first step, we identify a shock to commodity prices in a structural vectorautoregressive model (SVAR) and check whether the impulse response function of food prices in India is sensitive to the commodity price shock. There is a huge SVAR literature using short-run zero restrictions to identify structural shocks in the context of advanced countries with aggregate demand-aggregate supply models (see, for example, Cover et al. (2006); Cover and Mallick (2012)). Using a benchmark recursive identification scheme, we show that external price shocks (oil and global food prices) tend to drive inflation in India via imported inflationary shocks. In a second step, we explain the dynamics further using a structural New-Keynesian macroeconometric model that is able to disentangle the impact of several structural shocks on inflation. Overall, our analysis uncovers that global food prices have affected inflation in India in a few periods. However, most of the time other structural shocks have been more important in explaining price development in India.

The remainder of the paper is organized as follows. Section 2 contains the SVAR analysis. Section 3 discusses the structural macroeconometric model and presents the results. A summary and discussion of implications of the findings are provided in Section 4.

2 Do global food prices drive up Indian food prices? Evidence from a structural VARX model

In recent years food prices in India have been soaring, which has motivated researchers to find the causes of food inflation and to what extent it contributes to the near double-digit overall inflation. At the same time, there have been debates as to whether speculative trading in the global commodity markets has led to higher food prices in developing countries affecting poor people who are the net buyers of food. Although supply shocks emanating from institutional factors could contribute to food inflation, we try to disentangle different drivers of food inflation by considering both domestic and external factors. Quarterly ob-

Figure 1: Commodity prices and Indian price level



Notes: Oil price, global food price, WPI food for India, WPI India. Oil price and global food price have been converted into Indian currency using the current nominal exchange rate. Sources: Energy Information Administration (oil price), Commodity Research Bureau (spot price index for food), Ministry of Commerce and Industry India.

servations from 1996Q2 to 2013Q2 have been used to estimate a SVARX model using the following four price variables: oil price (OILP), food spot prices from Commodity Research Bureau (CRBSPFD), which are called global food prices hereafter and could also reflect speculative behavior, Indian WPI as a general index for Indian consumer prices, and a food price index for India (FOOD).[4] Oil and global food price are converted into Indian currency using current nominal exchange rates. WPI and FOOD are seasonally adjusted using CENSUS X12; OILP and CRBSPFD do not exhibit a seasonal pattern. The data are shown in Figure 1. All variables are transformed into logs. Unit root tests reveal that the four variables are integrated of order one. According to Johansen cointegration tests, there is no evidence for cointegration relations between the four variables. Therefore, first differences are taken. Additionally we control for weather shocks by using a quarterly series on the deviation of actual rainfall from normal rainfall (DRAIN).[5] We use one lag as the optimal lag length of the VARX system following several lag selection

[4]Oil prices may be an important common driver of both global food prices and food prices in India, see Baumeister and Kilian (2013), for example. Therefore it is necessary to include oil prices in the VAR model.

[5]Source: India Meteorological Department, Government of India. This is a stationary series.

criteria:

$$x_t = A_1 x_{t-1} + B_0 z_t + B_1 z_{t-1} + u_t, \qquad u_t \sim N(0, \Sigma_u), \tag{1}$$

where x denotes a vector including the four endogenous variables and z the exogenous variable DRAIN.

The estimated four variable reduced-form VARX shows that global food prices are Granger causing food price inflation in India and headline inflation in India (see Table 1). The t-statistic of lagged global food price inflation is larger than two in both the VARX equation for Indian food price inflation and in the VARX equation for Indian wholesale inflation. Shocks to global food prices are accordingly transmitted to inflation in India with a lag of one quarter. This can be visualized using impulse response functions, describing the response of a variable to a shock to one of the endogenous variables. We use a Cholesky decomposition to identify the orthogonalized disturbances. However, while it seems plausible that oil prices and global food prices are not affected contemporaneously by shocks to Indian prices, it is not plausible to assume a recursive ordering for Indian food prices and wholesale prices. Therefore, we estimate two separate four-variable VARXs for oil price, global food price, Indian food price index and oil price, global food price, Indian wholesale price index, respectively. This ordering of the variables implies the following identifying assumptions:

1. Oil prices do not respond contemporaneously to the shocks from other endogenous variables of the model.

2. Global food prices do not respond contemporaneously to Indian aggregate price or food price shocks, while they are contemporaneously affected by the oil price shock.

3. Indian food prices and wholesale prices respond contemporaneously to oil price shocks and global food price shocks, respectively.

We find that global food price shocks have a significant positive effect on Indian food prices and on the aggregate price level in India (see figure 2). However, these shocks

Table 1: Estimated VARX coefficients

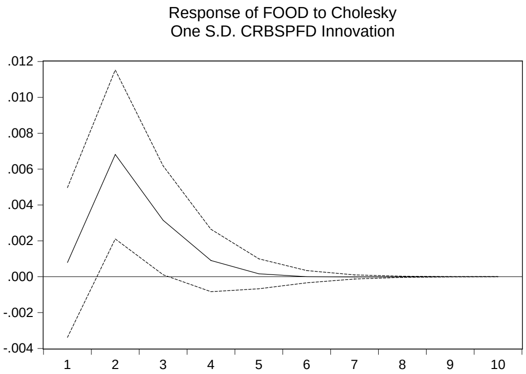
	OILP	CRBSPFD	FOOD	WPI
OILP(–1)	0.027	0.011	0.012	0.012
	0.112	0.052	0.016	0.007
	[0.238]	[0.222]	[0.796]	[1.701]
CRBSPFD(–1)	0.146	0.168	0.111	0.049
	0.271	0.125	0.038	0.017
	[0.538]	[1.340]	[2.929]	[2.865]
FOOD(–1)	0.557	–0.321	0.353	0.117
	1.070	0.495	0.150	0.068
	[0.521]	[–0.648]	[2.359]	[1.723]
WPI(–1)	–3.848	0.327	–0.209	0.235
	2.079	0.962	0.291	0.132
	[–1.851]	[0.340]	[–0.716]	[1.777]
Constant	0.083	0.010	0.012	0.008
	0.028	0.013	0.004	0.002
	[2.974]	[0.746]	[3.131]	[4.309]
DI2008Q4	–0.562	–0.289	–0.003	0.002
	0.138	0.064	0.019	0.009
	[–4.079]	[–4.530]	[–0.141]	[0.281]
DI2008Q4(-1)	–0.477	–0.028	0.032	–0.004
	0.164	0.076	0.023	0.010
	[–2.902]	[–0.372]	[1.383]	[–0.362]
DRAIN	–0.046	0.024	0.002	0.002
	0.072	0.033	0.010	0.005
	[–0.636]	[0.725]	[0.229]	[0.497]
DRAIN(–1)	0.047	–0.046	–0.006	–0.004
	0.070	0.032	0.010	0.004
	[0.674]	[–1.422]	[–0.598]	[–0.821]
R-squared	0.434	0.325	0.226	0.382

Notes: The table shows estimated VARX coefficients, standard errors in parentheses and t-values in brackets. All variables except for DRAIN are transformed to log differences. An autocorrelation LM test shows that the residuals do not exhibit any remaining autocorrelation. Lagged global food prices (CRBSPFD) are significant in the food price inflation (FOOD) equation and in the wholesale inflation (WPI) equation meaning that global food prices are Granger causing food price inflation and wholesale inflation in India. DI2008Q4 denotes an impulse dummy which is equal to one in the fourth quarter of 2008 and zero in all other quarters.

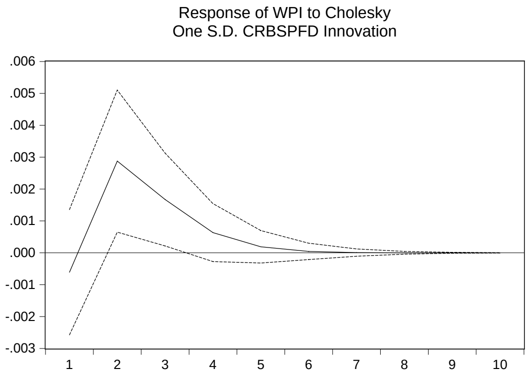
explain only a minor share in the variance of food and aggregate inflation as forecast error variance decompositions for the two variables show (see figure 3). After two quarters, about 12% of the forecast error variance of food price inflation and about 10% of the forecast error variance of wholesale inflation can be attributed to shocks in global food prices. These values increase slightly with the forecast horizon to about 14% and 12%,

Figure 2: Impulse responses from the estimated three-variable VARXs

(a) Food price inflation



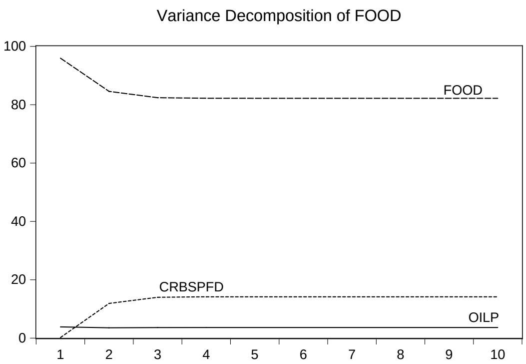
(b) Wholesale price inflation



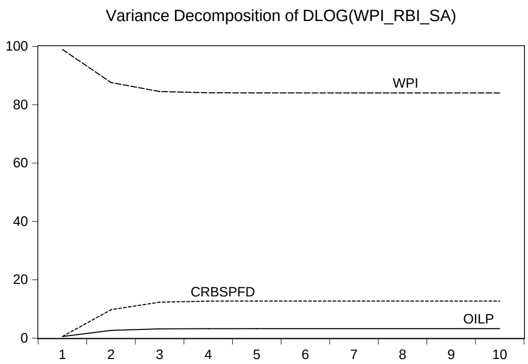
Notes: Impulse responses from two separate VARX models (OILP, CRBSPFD, FOOD and OILP, CRBSPFD, WPI) with one lag, respectively. All variables are in log differences. Structural shocks are identified by a Cholesky decomposition.

Figure 3: Forecast error variance decompositions for food price inflation and wholesale price inflation

(a) Food price inflation



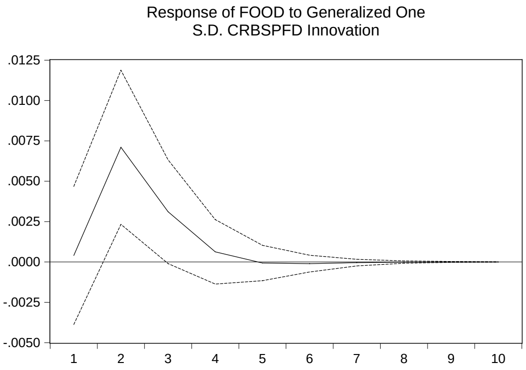
(b) Wholesale price inflation



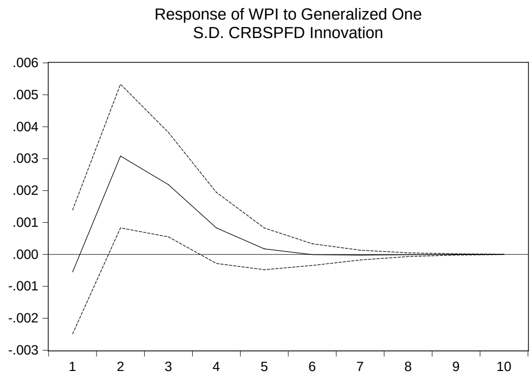
Notes: Forecast error variance decompositions from two separate VARX models (OILP, CRBSPFD, FOOD and OILP, CRBSPFD, WPI) with one lag, respectively. All variables are in log differences. Structural shocks are identified by a Cholesky decomposition.

Figure 4: Generalized impulse responses from the estimated four-variable VARX

(a) Food price inflation



(b) Wholesale price inflation



Notes: Generalized impulse responses from a VARX model for OILP, CRBSPFD, FOOD and WPI with one lag.

respectively. These results are robust with respect to reasonable modifications of the model. Increasing the number of lags in the VAR models does not change the qualitative results, for example. The main findings do not depend on the ordering of the variables because contemporaneous correlations of the VAR residuals are very low. Generalized impulse responses from a VAR model including all four variables show essentially the same picture (see figure 4). In the next section, we specify a New-Keynesian business cycle model in which wholesale inflation in India is explained by a hybrid open-economy Phillips curve augmented by oil price, local food price and global food price shocks and further explore the importance of global commodity prices for inflation dynamics in India.

3 Alternative sources of inflationary shocks in an estimated macroeconomic model for India

3.1 A New-Keynesian small open-economy model for India

In this section, we analyze inflation in India in a standard New-Keynesian macroeconometric model. We use the model of Carabenciov et al. (2008a,b) as a starting point and augment the model with oil prices, global food prices and relative food prices in India

(FOOD deflated using WPI). The dynamics of the latter three variables are determined by a reduced-form VAR model in log differences of order one meaning that we assume that the Indian business cycle dynamics have no impact on global oil prices, global food prices and relative Indian food prices. It is reasonable to impose exogeneity of relative food prices because the changes in food prices that are not due to general inflation are mostly dominated by non-economic factors like the weather.

In the model, potential (flexible price) real GDP ($\overline{y}$) is determined by a random walk with drift,

$$\overline{y}_t = \overline{y}_{t-1} + g_t^{\overline{y}}/400 + \varepsilon_t^{\overline{y}}. \tag{2}$$

$\varepsilon_t^{\overline{y}}$ denotes a serially uncorrelated exogenous shock. The drift term $g_t^{\overline{y}}$ follows an autoregressive process of order one,

$$g_t^{\overline{y}} = (1-\rho^{\overline{y}})g_{ss}^{\overline{y}} + \rho^{\overline{y}} g_{t-1}^{\overline{y}} + \varepsilon_t^{g^{\overline{y}}}, \tag{3}$$

where the steady state growth rate $g_{ss}^{\overline{y}}$ is estimated by the mean of real GDP growth in the sample period 1996Q2 to 2013Q2 and is equal to 6.8% (year-on-year percentage change) and $\varepsilon_t^{g^{\overline{y}}}$ is a serially uncorrelated exogenous shock. Actual output is determined by a hybrid New IS equation relating the output gap ($\tilde{y}_t = y_t - \overline{y}_t$) to lagged output gap, expected future output gap, real interest rate gap (difference between actual, r_t and equilibrium real interest rate, $\overline{r}_t$), and real effective exchange rate gap (difference between actual, q_t and equilibrium real effective exchange rate, $\overline{q}_t$),

$$\tilde{y}_t = \alpha_2 E_t \tilde{y}_{t+1} + (1-\alpha_2)\tilde{y}_{t-1} - \alpha_3(r_t - \overline{r}_t) - \alpha_4 \tilde{q}_t + \varepsilon_t^{\tilde{y}}, \tag{4}$$

where $\varepsilon_t^{\tilde{y}}$ is a serially uncorrelated exogenous shock, and E_t denotes the expectation operator. Equilibrium real interest rate ($\overline{r}_t$) and equilibrium real effective exchange rate ($\overline{q}_t$) follow univariate time series models,

$$\overline{r}_t = (1-\rho^{\overline{r}})\overline{r}_{ss} + \rho^{\overline{r}}\overline{r}_{t-1} + \varepsilon_t^{\overline{r}} \tag{5}$$

and

$$\overline{q}_t = \overline{q}_{t-1} + \varepsilon_t^{\overline{q}}, \tag{6}$$

where $\varepsilon_t^{\overline{r}}$ and $\varepsilon_t^{\overline{q}}$ are serially uncorrelated exogenous shocks. Monetary policy follows a standard interest rate rule with interest rate smoothing: the interest rate increases if the output gap is positive or if the expected inflation rate is larger than steady state inflation,

$$i_t = \tau_1 i_{t-1} + (1-\tau_1)\left(\overline{r}_t + \pi_{t+1} + \tau_2 \tilde{y}_t + \tau_3(\pi_{t+1} - \pi_{ss})\right) + \varepsilon_t^i, \tag{7}$$

where ε_t^i is a serially uncorrelated exogenous shock. Although monetary aggregates were important as instruments of policy in the past, the cost of money or the interest rate has become the key instrument since the mid-1990s. For example, stronger rural demand on account of higher rural incomes can produce demand-led inflationary pressures, leading to a rate-hike. Steady state inflation π_{ss} is estimated by the mean of observed inflation in the sample 1996 to 2013 and is equal to 5.6% (year-on-year percentage change). In many emerging market economies, central banks tend to be particularly concerned about food price inflation. However, in an economy as large as that of India, with continued existence of market imperfections in factor and product markets between regions, the focus of monetary policy continues to be managing inflation expectations.[6] Nominal and real interest rates are connected via the Fisher equation

$$i_t = r_t + E_t \pi_{t+1}. \tag{8}$$

In an augmented Phillips curve framework, both demand and supply factors are seen as key drivers of inflation. In the literature on Indian inflation, the importance of sectoral aspects of inflation has been strongly emphasized, see Balakrishnan (1991), Sen and Vaidya (1995), Dutta Roy and Darbha (2000); Callen (2001), Nachane and Lakshimi (2002), Mallick (2004), indicating the importance of accounting for supply shocks in explaining inflation in India. One of the well-established findings in this line of literature on Indian

[6] The indicators of inflationary expectations that the RBI implicitly monitors are output growth, capacity utilization, inventory, corporate performance, industrial/investment expectations and other indicators of aggregate demand.

inflation is that cost-push factors have a greater predictive power than demand-pull factors. Goyal and Pujari (2005) identify a supply curve using data on inflation and industrial output growth and find that supply shocks have a large impact on inflation, whereas demand has large and persistent effects on output.[7] Further, inflation is also driven by many supply side factors like the effect of monsoon on agriculture. Wholesale price inflation in the model therefore follows an open-economy hybrid New-Keynesian Phillips curve,

$$\pi_t = \beta_1 \pi_{t-1} + \beta_2 E_t \pi_{t+1} + \beta_3 \tilde{y}_t + \beta_4 \Delta q_t + x_t^{\pi}, \tag{9}$$

Where π_t is wholesale inflation, $\tilde{y}_t$ is the output gap and Δq_t is the change in the log real effective exchange rate. Given the openness of the Indian economy, any change in the exchange rate has a direct effect on prices. In the recent literature, the importance of supply-side channel for the transmission of monetary policy has been emphasized.[8] By following the same logic, when the central bank aims at keeping its currency at a depreciated level, it makes imported goods expensive and thus affects firms' marginal cost and their pricing decisions, which in turn can cause inflation and thereby changes in nominal interest rates. The cost-push shock x_t^{π} is decomposed into relative global food price changes (x_t^1), relative food price changes in India (x_t^2), relative oil price changes (x_t^3), rainfall (z_t) and other serially uncorrelated cost-push shocks (ε_t^{π}):

$$x_t^{\pi} = \beta_5 x_t^1 + \beta_6 x_{t-1}^1 + \beta_7 x_t^2 + \beta_8 x_{t-1}^2 + \beta_9 x_t^3 + \beta_{10} x_{t-1}^3 + \beta_{11} z_t + \beta_{12} z_{t-1} + \varepsilon_t, \tag{10}$$

[7] In a more recent paper, Patra and Ray (2010) emphasize that although inflationary pressures emanating from higher food prices may limit the scope for monetary policy action, eventually the monetary authority has to respond to this even if it is an inflationary supply shock. From our impulse responses, it is noted that monetary policy does significantly respond to this type of inflationary supply shock.

[8] See Batini et al. (2010) for a discussion on these issues. Aizenman et al. (2011) find that both inflation and real exchange rates are important determinants of policy interest rates in many emerging markets. Also see Mohanty and Klau (2005) who emphasize the importance of exchange rate in policy rules in emerging markets.

where x^1, x^2 and x^3 follow a structural vector autoregressive model of order one,

$$\begin{pmatrix} 1 & 0 & 0 \\ -\phi_{21,0} & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x_t^1 \\ x_t^2 \\ x_t^3 \end{pmatrix} = \begin{pmatrix} \phi_{11} & \phi_{12} & \phi_{13} \\ \phi_{21} & \phi_{22} & \phi_{23} \\ \phi_{31} & \phi_{32} & \phi_{33} \end{pmatrix} \begin{pmatrix} x_{t-1}^1 \\ x_{t-1}^2 \\ x_{t-1}^3 \end{pmatrix} + \begin{pmatrix} 0 \\ \phi_{24,0} \\ 0 \end{pmatrix} z_t + \begin{pmatrix} 0 \\ \phi_{24} \\ 0 \end{pmatrix} z_{t-1} + \begin{pmatrix} \varepsilon_t^{x^1} \\ \varepsilon_t^{x^2} \\ \varepsilon_t^{x^3} \end{pmatrix}. \tag{11}$$

Rainfall is exogenous and is described by an autoregressive process,

$$z_t = \theta_0 + \theta_1 z_{t-1} + \varepsilon_t^z. \tag{12}$$

Finally, the actual real effective exchange rate q_t adjusts towards its long-run equilibrium value $\overline{q}_t$ and is affected by domestic inflation in the short-run,

$$\Delta(q_t - \overline{q}) = -\gamma_1(q_{t-1} - \overline{q}_{t-1}) + \gamma_2(\pi_t - \pi_{ss}) + \gamma_3(\pi_{t-1} - \pi_{ss}) + \gamma_4 \Delta(q_{t-1} - \overline{q}_{t-1}) + \varepsilon_t^q, \tag{13}$$

where ε_t^q is a serially uncorrelated exogenous shock.

3.2 Estimation of the model

Real GDP (at constant market prices), short term interest rate (91-day T-bills), and real effective exchange rate (REER), have been gathered from Datastream and RBI. GDP data have been seasonally adjusted using the US Census Bureau's X12 seasonal adjustment method. Although the RBI uses both repo and reverse repo rates as short-term interest rates, given the limited sample on this rate, we use the 3-month T-bill yield as a proxy for the domestic interest rate. The REER is used because it captures imported inflationary pressures and changes in competitiveness more comprehensively than a bilateral exchange rate.[9] The data is depicted in figure 5.

Overall, together with the four variables described in section 2, seven variables are used for estimation. The estimation has been carried out with the Dynare toolkit for MatLab. The steady state growth rates of the non-stationary variables (real GDP, WPI, oil price index and global food price index) have been estimated separately and imposed in the model estimation (see Appendix). The priors have been chosen in a sophisticated way by either taking values that have been used in other studies (however, mostly for different countries) or by taking univariate ordinary least-squares estimates where feasible. The priors and the estimates of all model parameters are given in table 2. The estimates for the contemporaneous components of the cost-push shock (β_5, β_7 and β_9) have been insignificant and therefore excluded from the model. The coefficients of the lagged cost-push shock components are all significantly different from zero. In the equations for oil price inflation, global food price inflation and Indian food price inflation, insignificant variables have also been deleted. The only non-autoregressive coefficient remaining is ϕ_{21} which captures the effect of lagged global food price changes on Indian food price changes. Accordingly global food price changes are transmitted directly to Indian wholesale inflation (β_{10}) and indirectly via Indian food prices (β_6).

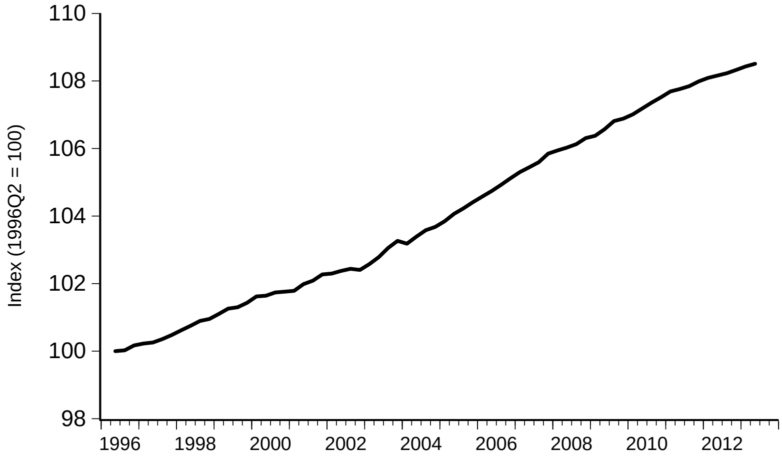
3.3 Impulse response analysis

The dynamic effects of an increase in global food prices on inflation in India can be visualized using estimated impulse response functions. In order to derive the posterior distribution of the impulse responses, the Metropolis-Hastings algorithm has been applied with 20,000 replications and two blocks. The responses to a shock in global food prices are depicted in figure 6. Like in the SVAR analysis, the peak impact is in the second quarter after the occurrence of a shock. Moreover, it can be seen that global food price increases do not only affect Indian food prices and Indian wholesale inflation but also

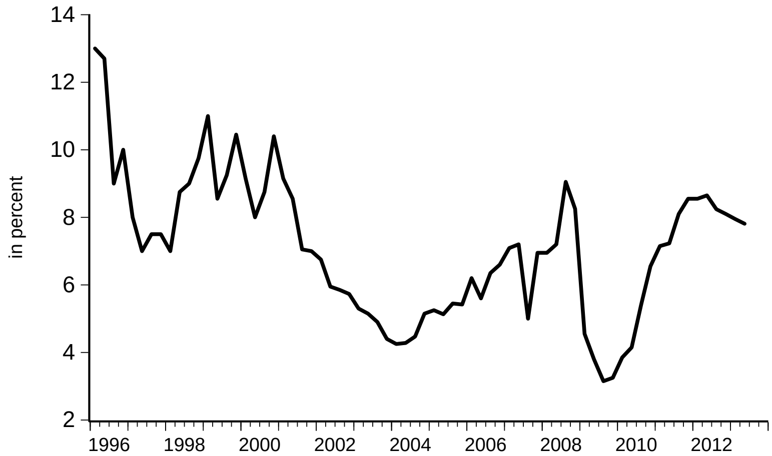
[9] Scholl and Uhlig (2008) use the exchange rate in nominal terms. It is possible that the nominal and the real exchange rates may respond in a very similar way to monetary policy shocks in the case of advanced economies. But in emerging markets, one may find a different pattern due to a relatively higher level of inflation in these countries.

Figure 5: Macroeconomic Data for India

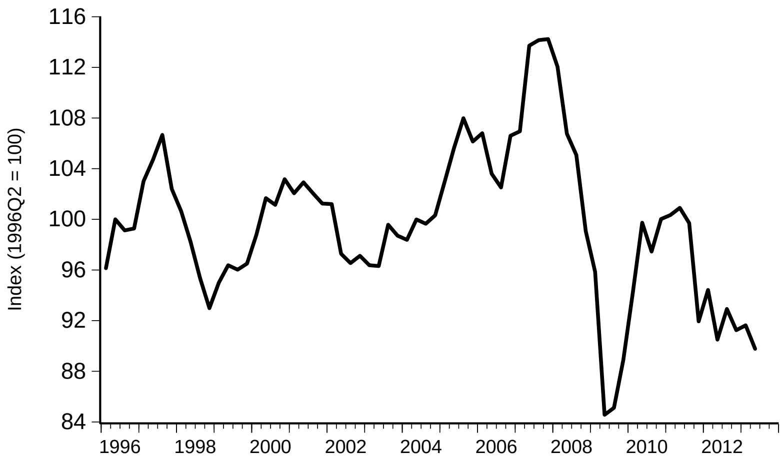
(a) Log real GDP (seasonally adjusted)



(b) Short-term interest rate (T-Bill rate)



(a) Real effective exchange rate

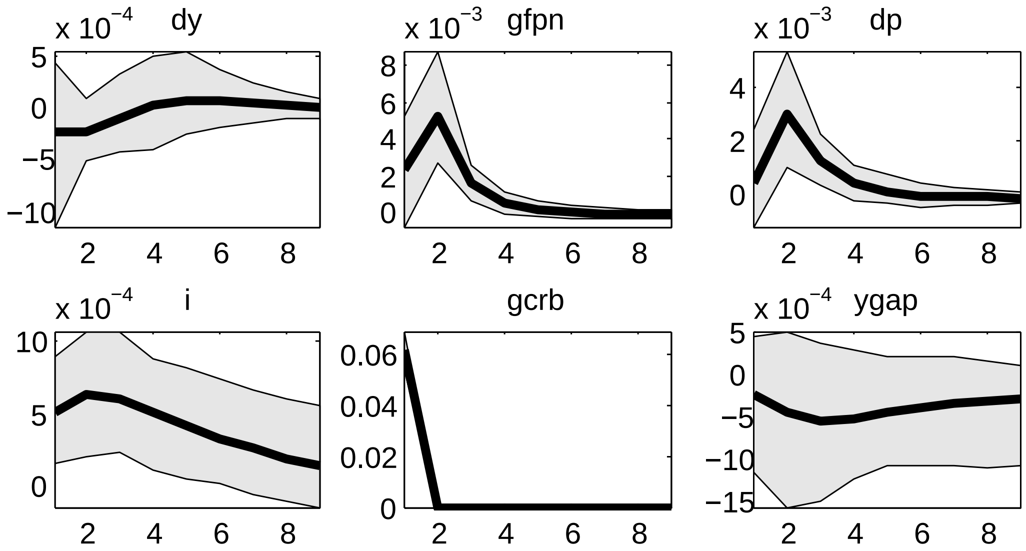


Sources: Reserve Bank of India and International Monetary Fund.

Table 2: Estimated structural parameters

	Prior			Posterior		
	mean	s.d.	distribution	mode	s.d.	t-statistic
			Standard deviations of shocks			
ε^{z}	0.2300	2.0000	Inv. Gamma	0.1081	0.0442	2.4436
ε^{x^1}	0.0570	2.0000	Inv. Gamma	0.0610	0.0051	11.9443
ε^{x^2}	0.0150	2.0000	Inv. Gamma	0.0125	0.0021	5.9771
ε^{x^3}	0.1240	2.0000	Inv. Gamma	0.1521	0.0127	11.9314
$\varepsilon^{g^{\overline{y}}}$	0.0090	2.0000	Inv. Gamma	0.0041	0.0017	2.4626
$\varepsilon^{\overline{y}}$	0.0090	2.0000	Inv. Gamma	0.0083	0.0008	9.7952
$\varepsilon^{\tilde{y}}$	0.0090	2.0000	Inv. Gamma	0.0029	0.0006	4.5197
ε^{π}	0.0090	2.0000	Inv. Gamma	0.0032	0.0008	4.2063
ε^{i}	0.0030	2.0000	Inv. Gamma	0.0015	0.0008	1.9221
$\varepsilon^{\overline{r}}$	0.0090	2.0000	Inv. Gamma	0.0151	0.0059	2.5533
$\varepsilon^{\overline{q}}$	0.0100	2.0000	Inv. Gamma	0.0223	0.0030	7.3729
ε^{q}	0.0200	2.0000	Inv. Gamma	0.0114	0.0044	2.5764
			Parameters			
$\overline{r}_{ss}$	0.0030	0.1000	Normal	0.0046	0.0016	2.9389
$\phi_{21,0}$	0.0200	0.0300	Normal	0.0292	0.0213	1.3723
ϕ_{21}	0.0300	0.0300	Normal	0.0294	0.0202	1.4544
ϕ_{22}	0.2000	0.1000	Normal	0.2114	0.0897	2.3569
$\phi_{24,0}$	0.0000	0.5000	Normal	–0.0650	0.0432	1.5052
ϕ_{24}	0.0000	0.5000	Normal	–0.0265	0.0262	1.0125
ϕ_{44}	0.0000	0.5000	Normal	0.0797	0.3369	0.2367
τ_1	0.7000	0.1000	Beta	0.8661	0.0291	29.7780
τ_2	0.5000	0.2500	Gamma	0.4183	0.2495	1.6765
τ_3	0.5000	0.2500	Gamma	0.2227	0.1281	1.7385
α_2	0.5000	0.2500	Beta	0.9013	0.1215	7.4169
α_3	0.2000	0.1000	Gamma	0.0581	0.0322	1.8017
α_4	0.2000	0.1500	Normal	0.0134	0.0209	0.6423
β_1	0.5000	0.1500	Beta	0.5067	0.0733	6.9162
β_2	0.5000	0.1500	Beta	0.4070	0.1320	3.0836
β_3	0.2500	0.1000	Gamma	0.1851	0.0834	2.2180
β_4	0.2000	0.2000	Normal	0.0044	0.0202	0.2167
β_5	0.0000	0.2000	Normal	0.1749	0.1129	1.5500
β_6	0.0000	0.2000	Normal	–0.0748	0.0760	0.9848
β_7	0.0000	0.2000	Normal	–0.0068	0.0069	0.9940
β_8	0.0000	0.2000	Normal	0.0182	0.0061	2.9931
β_9	0.0000	0.2000	Normal	–0.0219	0.0182	1.2026
β_{10}	0.0000	0.2000	Normal	0.0358	0.0141	2.5298
β_{11}	0.0000	0.2000	Normal	0.0571	0.0266	2.1494
β_{12}	0.0000	0.2000	Normal	–0.0340	0.0194	1.7507
γ_1	0.5000	0.2500	Beta	0.2346	0.0818	2.8680
γ_2	0.0000	0.5000	Normal	0.7354	0.2601	2.8269
γ_3	0.0000	0.5000	Normal	–0.1793	0.2730	0.6567
γ_4	0.0000	0.5000	Normal	0.6665	0.1952	3.4148

Figure 6: Responses to a shock in global food prices



Notes: The figure shows impulse responses together with 90% confidence bands. The posterior distribution of the impulse responses has been calculated using the Metropolis-Hastings algorithm with 20,000 replications and 2 blocks. dy is the log difference of real GDP, gfpn the log difference of the Indian food price index, dp the log difference of the Indian wholesale price index, i the nominal interest rate, and gcrb the log difference of the global food price index.

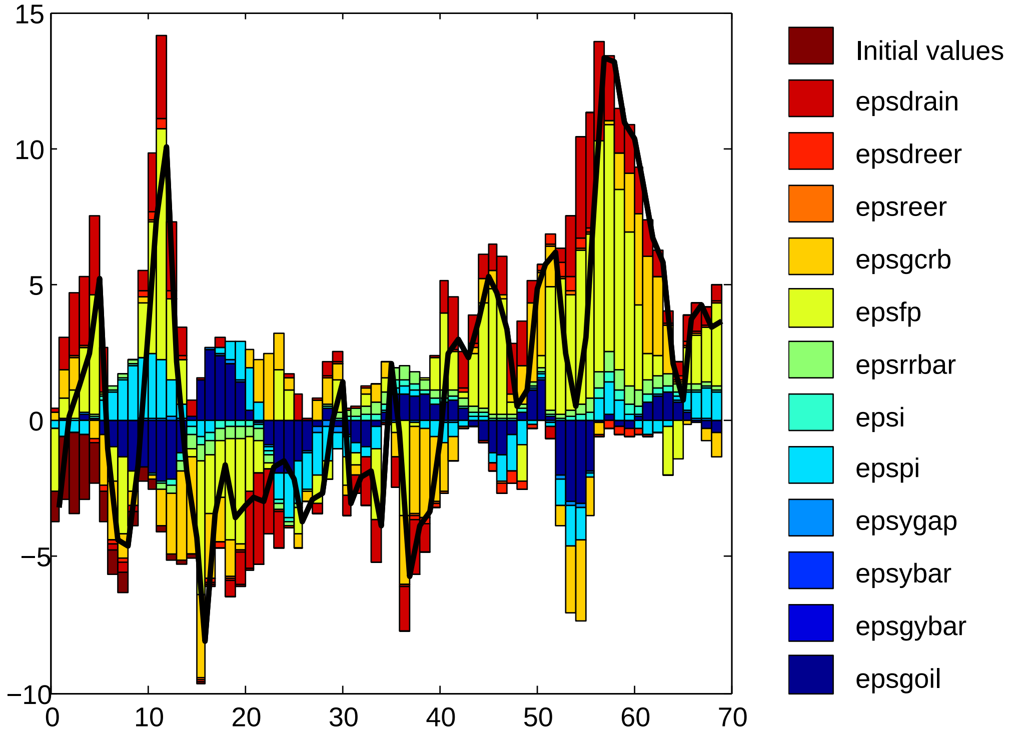
real growth. This can be explained by the monetary policy reaction to increasing prices. Since wholesale inflation is an argument in the monetary policy reaction function, the increase in inflation triggers an increase in the interest rate which in turn has a negative effect on real GDP growth. Similar findings can be reported for the responses to domestic cost-push shocks (ε^{π}), oil price shocks and Indian food price shocks.[10] According to these results, temporary exogenous cost-push shock of different kinds trigger restrictive monetary policy responses in India which reduce real GDP growth.

3.4 Historical decomposition

In the previous subsection it has been shown that global food price shocks have significant effects on Indian food price inflation and Indian wholesale inflation. How important are these effects? The SVAR analysis in section 2 suggests that global food prices are on average of minor importance for inflation in India. However, most interesting in the recent

[10]The corresponding impulse responses are shown in the appendix.

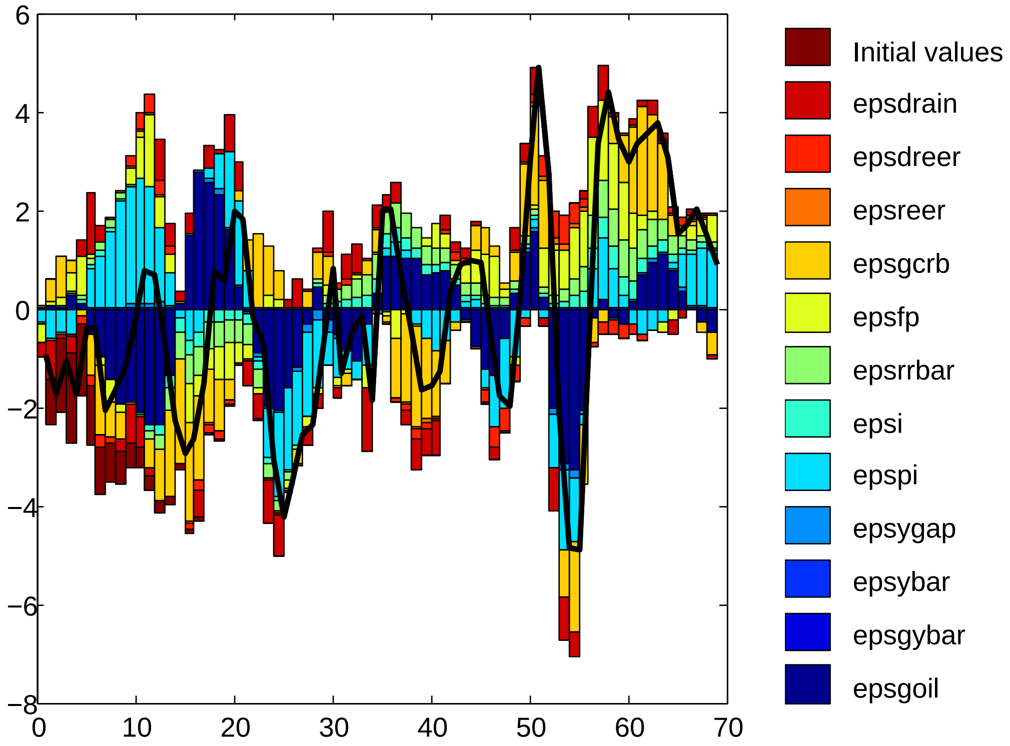
Figure 7: Historical decomposition of year-on-year percentage food price changes in India



Notes: epsdrain denotes the shock in rainfall, epsdreer the shock in the actual real effective exchange rate, epsreer the shock in the long-run equilibrium real effective exchange rate, epsgcrb the shock in global food prices, epsfp the shock in Indian food prices, epsrrbar the shock in the equilibrium real interest rate, epsi the monetary policy shock, epspi the Phillips equation shock, epsygap the IS equation shock, epsybar permanent potential output shocks, epsgybar transitory shocks in the growth rate of potential output, and epsgoil shocks in the growth rate of oil prices.

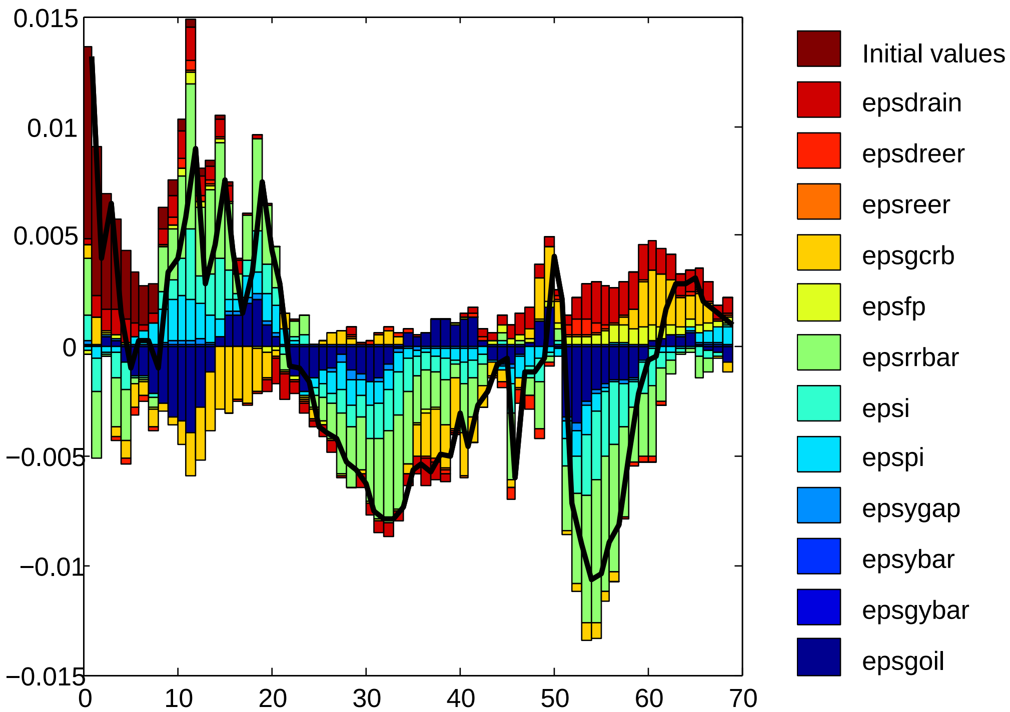
debate have been the periods with sharp increases in global food prices as measured in our model by global spot prices. Figures 7 and 8 show historical decompositions of food price inflation and wholesale inflation in India. Figure 7 shows that food price inflation in India is mainly driven by idiosyncratic shocks (epsgfp) and rainfall (epsdrain). However, in the years 2008 and 2010, when global food prices have been increasing strongly, these changes have contributed to a certain extent to food price inflation in India. A similar result is found for wholesale price inflation (figure 8). In the peak periods in the years 2008 and 2010, global food price increases have also contributed to Indian aggregate price inflation. Accordingly, these changes have also had an impact on the interest rate set by the central bank (see figure 9) and therefore a negative effect on output.

Figure 8: Historical decomposition of year-on-year percentage changes in the Indian wholesale price index



Notes: epsdrain denotes the shock in rainfall, epsdreer the shock in the actual real effective exchange rate, epsreer the shock in the long-run equilibrium real effective exchange rate, epsgcrb the shock in global food prices, epsfp the shock in Indian food prices, epsrrbar the shock in the equilibrium real interest rate, epsi the monetary policy shock, epspi the Phillips equation shock, epsygap the IS equation shock, epsybar permanent potential output shocks, epsgybar transitory shocks in the growth rate of potential output, and epsgoil shocks in the growth rate of oil prices.

Figure 9: Historical decomposition of Indian short-term interest rate



Notes: epsdrain denotes the shock in rainfall, epsdreer the shock in the actual real effective exchange rate, epsreer the shock in the long-run equilibrium real effective exchange rate, epsgcrb the shock in global food prices, epsfp the shock in Indian food prices, epsrrbar the shock in the equilibrium real interest rate, epsi the monetary policy shock, epspi the Phillips equation shock, epsygap the IS equation shock, epsybar permanent potential output shocks, epsgybar transitory shocks in the growth rate of potential output, and epsgoil shocks in the growth rate of oil prices.

4 Conclusions

This paper provides empirical evidence on the sources of inflationary dynamics in India. Over a 17 years (69 quarters) time horizon during the post-reform period, impulse responses both from SVARX models and from a structural macroeconomic model for India show that global food price shocks have inflationary effects on food price inflation and wholesale inflation in India. This effect is mainly important in periods, in which global food prices increase strongly as it has been the case in the years 2008 and 2010. Since the monetary authority responds to these supply shocks with a higher interest rate which tends to slow growth, this raises concerns about how such output losses can be prevented by reducing exposure to commodity price shocks and thereby achieve higher growth. It is therefore an important future research question what factors drive global food prices. In particular, it should be further investigated to what extent global food prices are affected by non-fundamental financial trading strategies.

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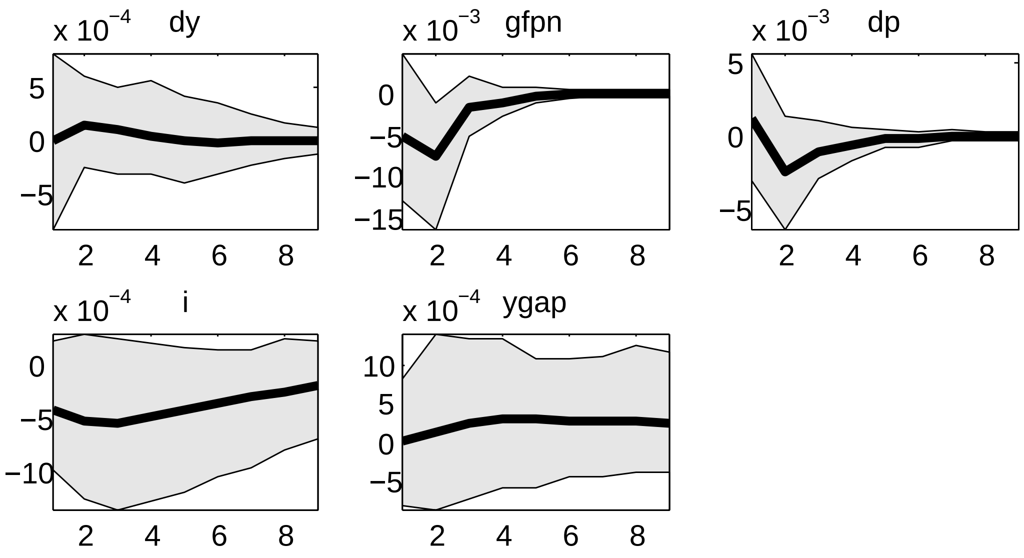
Appendix

Pre-set parameters

Parameter	Description	Value
drainss	average of drain	−0.068690
ppss	steady state quarterly growth rate of wholesale price index	0.014000
goilss	steady state quarterly growth rate of nominal oil price index in INR	0.045285
gcrbss	steady state quarterly growth rate of nominal global food prices	0.018646
gyss	steady state quarterly growth rate of real GDP	0.017000

Selected impulse responses

Figure 10: Responses to a shock in rainfall



Notes: The figure shows impulse responses together with 90% confidence bands. The posterior distribution of the impulse responses has been calculated using the Metropolis-Hastings algorithm with 20,000 replications and 2 blocks. dy is the log difference of real GDP, gfpn the log difference of the Indian food price index, dp the log difference of the Indian wholesale price index, i the nominal interest rate.

Figure 11: Responses to a monerary policy shock in India

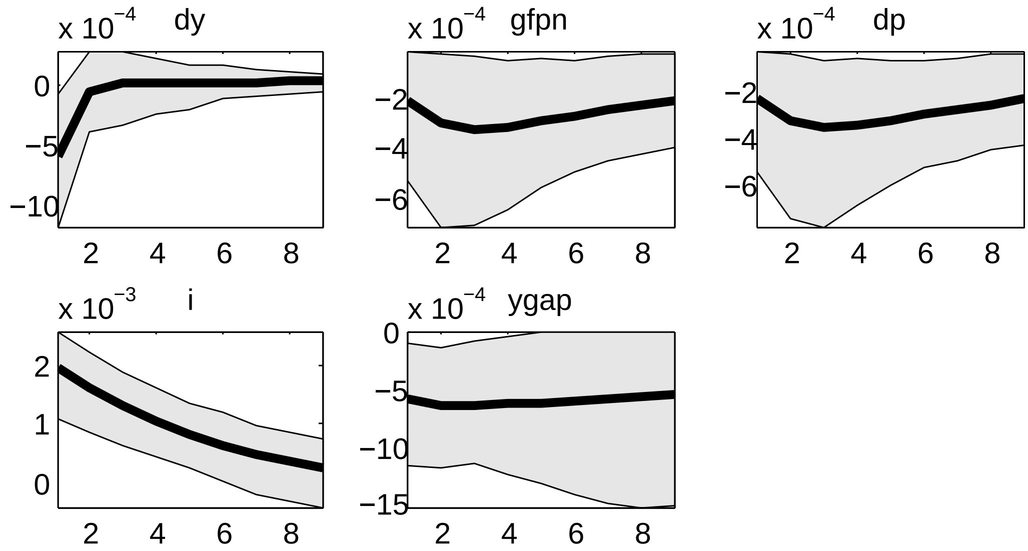


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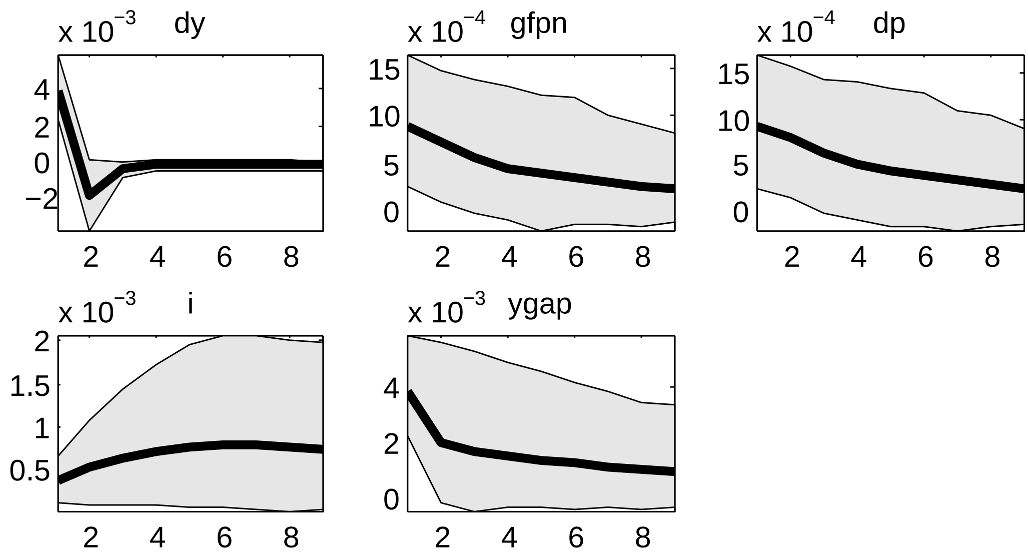
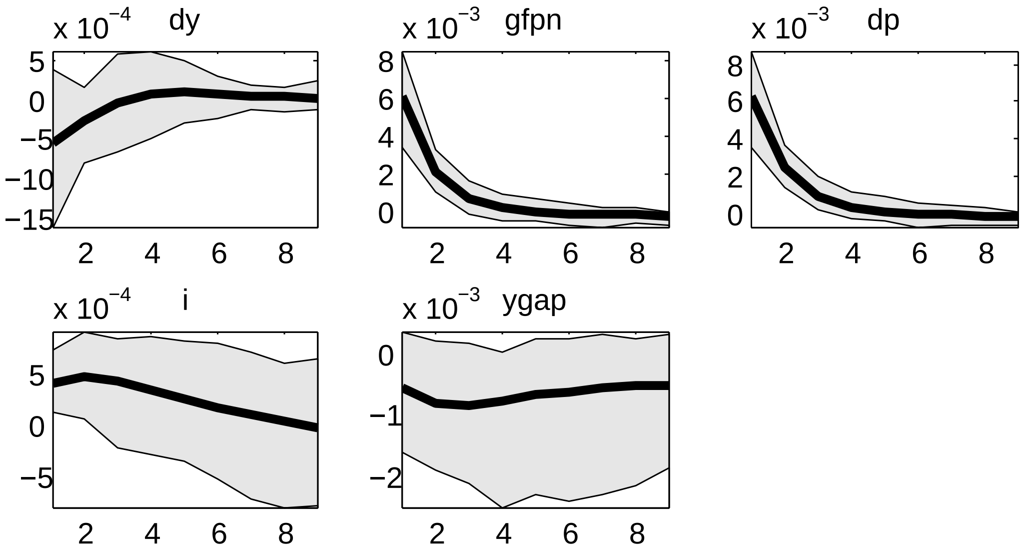
Figure 12: Responses to an aggregate demand shock in India



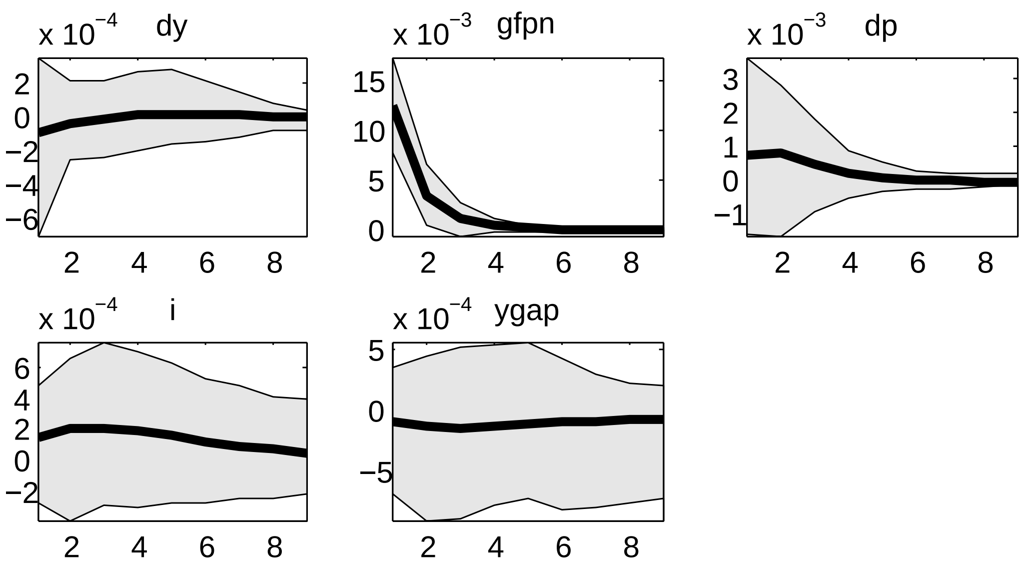
Notes: The figure shows impulse responses together with 90% confidence bands. The posterior distribution of the impulse responses has been calculated using the Metropolis-Hastings algorithm with 20,000 replications and 2 blocks. dy is the log difference of real GDP, gfpn the log difference of the Indian food price index, dp the log difference of the Indian wholesale price index, i the nominal interest rate.

Figure 13: Responses to a general cost-push shock in India



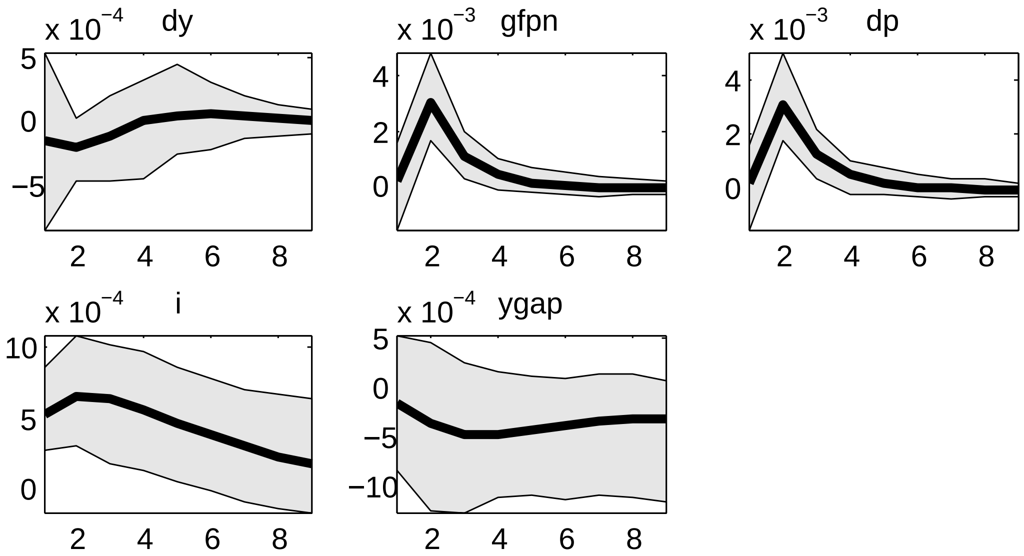
Notes: The figure shows impulse responses together with 90% confidence bands. The posterior distribution of the impulse responses has been calculated using the Metropolis-Hastings algorithm with 20,000 replications and 2 blocks. dy is the log difference of real GDP, gfpn the log difference of the Indian food price index, dp the log difference of the Indian wholesale price index, i the nominal interest rate.

Figure 14: Responses to a food price shock in India



Notes: The figure shows impulse responses together with 90% confidence bands. The posterior distribution of the impulse responses has been calculated using the Metropolis-Hastings algorithm with 20,000 replications and 2 blocks. dy is the log difference of real GDP, gfpn the log difference of the Indian food price index, dp the log difference of the Indian wholesale price index, i the nominal interest rate.

Figure 15: Responses to an oil price shock



Notes: The figure shows impulse responses together with 90% confidence bands. The posterior distribution of the impulse responses has been calculated using the Metropolis-Hastings algorithm with 20,000 replications and 2 blocks. dy is the log difference of real GDP, gfpn the log difference of the Indian food price index, dp the log difference of the Indian wholesale price index, i the nominal interest rate.