Monetary Policy and Distribution of Food Consumption in China: The Role of Food Prices

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Abstract

Despite concerns of food security in China, the distributional consequences of monetary policy on household food consumption have been largely ignored in the practice and conduct of monetary policy. In this paper, I study how monetary policy affects the distribution of food consumption in China. Using data from the household surveys conducted by China's National Bureau of Statistics, I estimate the dynamic effects of monetary policy shocks on the *relative* food price and the distribution of food consumption in rural and urban China from a vector auto regression (VAR) model, and identify monetary policy shocks using the sign restriction approach of Uhlig (2005). VAR results show that the *relative* price of food responds positively, and the distribution of food consumption responds negatively to expansionary monetary policy shocks in China. Further, the negative effects on food consumption vary systematically across the income distribution in rural and urban China: food consumption at the lower end of the distribution falls less than that at the upper end. Overall, results of this study provide evidence of the impact of a *"food price channel"* of monetary policy on the distribution of food consumption and declining inequality in China.

Keywords: Monetary Policy, Food Prices, Food Subsistence, Poverty, Inequality, Development
JEL Classification Numbers : D63, E31, E5, E63, I32, O11, O23

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1 Introduction

In company with rapid economic growth, China has been facing strong upward pressure in food prices. Historically, China experienced huge fluctuations in food prices over the last two decades. Food price inflation measured by CPI of food, fluctuated more than the headline inflation measured by overall CPI in the economy (Figure 1). Whereas the period 1996 to 2003 witnessed a negative growth rate in food prices of .50%, the period 2004 to 2013 recorded a large and positive growth rate in food prices of 7%. The increase in food prices in China since 2004 raised concerns over food security in the country and the world.[1] With 1.3 billion inhabitants, the Chinese government places food security as a foremost priority in its domestic policy agenda, so that the domestic food market especially the grain market continues to remain heavily intervened, and still retains characteristics of a centrally planned economy (Wang, 2001; Yang et al., 2008; Tang et al., 2009; Yu and Jensen, 2010; Yu, 2014).[2] The food share of expenditures in China is less than the average in low-income countries, but more than six times the food budget share in the United States (Figure 2). Clearly, food represents a major expense for Chinese households especially the poor (Figures 3-4), and likely influences their spending on other items, and their overall welfare. Changes in relative food prices can have great impacts on Chinese farmers' income and consumers' cost of living (Peng, Marchant and Reed, 2004). Absorbing short run fluctuations in relative food prices and managing cash flow optimally can be a challenge especially for poor households due to *subsistence* and limited *substitutability* of food. There is also evidence of strong correlation between higher relative food prices, poverty, lower caloric intake, lower quality diet, and

[1] The most widely accepted definition of food security proposed during the 1996 World Food Summit defines it as follows: Food security exists when all people, at all times, have physical and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life.

[2] Even though through the past 20 years of reform, China's grain marketing system has been largely liberalised, however the state still plays an important role in the grain market. It is argued that due to the Cobweb Effect, the grain market is subject to large fluctuations without government intervention. The instability could have serious repercussions on the consumers and producers in China who rely heavily on foodgrains. The Government is therefore highly involved in the grain market to keep it steady and stable (Wang, 2001; Huang et al., 1993; Findlay and Chen, 2001).

an increase in child malnutrition (Mellor, 1978; Ravallion, 1998; Friedman and Levinsohn, 2002; Alderman, Hoddinott, and Kinsey 2006; Christiaensen and Demery, 2007; Wodon et al. 2010).[3] All these could have potential long term impact on the human capital and productivity of the country, thereby reducing the pace and durability of economic growth (Dreze and Sen, 1989; Horton, 1999; Behrman et al., 2004; Deaton and Dreze, 2009; Dreze and Sen, 2013).

Traditionally, research studies have analysed fluctuations in food prices through supply and demand gap, however recent literature has also given a great deal of emphasis on the impact of macroeconomic variables, especially monetary and financial factors, on food prices (Chambers and Just, 1982; Orden, 1986; Orden and Fackler, 1989; Dorfman and Lastrapes, 1996; Cho et al., 2004, Lastrapes, 2006; and Balke and Wynne, 2007). These studies show that agricultural prices are relatively more flexible, and following a monetary expansion adjust quicker than the overall price level in the economy; therefore major changes in monetary policy can have *real* short run and long run effects on food prices.

Despite the dominant role played by relative food price changes in developing countries, and evidence of strong interlinkages between monetary policy variables and relative food prices, studies in empirical monetary economics have largely ignored the distributional consequences of monetary policy that could arise from *relative* food price distortions. To the best of my knowledge, there is no study that empirically investigated this causal channel i.e. the *"food price channel"* of monetary policy. It is conceivable that the distributional impacts of monetary policy from this channel could be negligible in developed countries given the

[3] Apart from reduction in food consumption, the loss in purchasing power affect buying of other goods and services which are essential for sheer physical survival such as water, sanitation, education, lighting, health care etc. Adjustment in wages, employment and capital flows to agriculture take time to reach the poor. The adverse impact of high food prices on poor is also seen in terms of (a) poor nutrition status of pregnant and lactating women and of pre-school children; (b) poor health status of women and children; (c) increase in child labour and withdrawal of children from school; (d) the distress sale of productive assets (Mahendra Dev, 2012).

small share of food in the CPI basket, however with almost 50% share of food in the CPI basket, these effects could be substantially large in developing countries.

In this paper, I seek to fill the gaps in the literature by examining the impact of the *"food price channel"* of monetary policy on the distribution of food consumption in China. My primary reason for selecting China is because India and China currently stand as two of the fastest growing large economies of the world. Both developing countries, even though have recorded robust GDP growth rates in the last 20 years, are strikingly different with regards to their demography, structure, household characteristics, and economic policies. While De (2017) investigates the impact of the *"food price channel"* monetary policy on the distribution of food consumption in India, the current paper conducts a similar empirical analysis for China; this allows me to compare and contrast the results for the two countries, and thereby draw conclusions about the relative importance of the *"food price channel"* in emerging market economies.

Using household survey data from 1996:Q1 to 2013:Q4, I estimate the dynamic effects of monetary policy shocks on the *relative* price of food and the distribution of food consumption in rural and urban China from a VAR model, and identify monetary policy shocks using the sign restriction approach of Uhlig (2005). VAR results show that expansionary monetary policy shocks increase the *relative* price of food and have heterogeneous *negative* effects on household food consumption which vary systematically across the income distribution: food consumption at the lower end of the distribution falls less than that at the upper end. More specifically, in rural China food consumption at the lower end of the distribution remains unaffected (on average) while that at the upper end falls, and in urban China food consumption at the lower end of the distribution falls, but much less than that at the upper end. 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, I find that expansionary monetary policy shocks reduce the observed inequality across households in food consumption in rural as well as urban China.[4]

Overall, I find evidence of the impact of the *"food price channel"* of monetary policy on the distribution of food consumption, and inequality in China. The mechanism is straightforward. Food prices being relatively more flexible, following a monetary expansion, adjust quicker than the overall price level in the economy. So, expansionary monetary shocks lead to an increase in the *relative* price of food. Poor households in China respond very little to the increase in *relative* food price, and consequently following the monetary expansion witness a much smaller decline in food consumption compared to the rich.[5] Two factors contribute to the above heterogeneous response. First, poor households have very low levels of initial food consumption *(subsistence)*. Food is more a *necessity* for them and so their food demand is relatively price inelastic (Portillo et al., 2016). Second, rural poor households rely heavily on self-produced food (Figure 5); food self sufficiency appears to be quite effective at insulating the responses of many rural households in the bottom of the income distribution from the effects of policy shocks. Therefore, expansionary monetary shocks in China via the *"food price channel"* are found to decrease the observed inequality across households in food consumption.

De (2017), relying on a factor augmented vector auto regression (FAVAR) model, conducts a similar empirical analysis for India. There is evidence of the impact of *"food price channel"* of monetary policy on inequality in both emerging market economies i.e. India and China, however the sign of the impact differs strikingly in the two economies.[6] While in India expansionary monetary shocks via the *"food price channel"* increase food consump-

[4]Coibion at al. (2012) uses the difference between the 90th percentile and the 10th percentile of the log levels in income and consumption distribution as a measure of inequality.

[5]The rich households are identified as those who lie in the top 20% of income distribution (top quintile) and poor households in the bottom 20% (bottom quintile). See data section for details.

[6]see section for details 7.

tion inequality, in China expansionary monetary shocks via the same channel reduce food consumption inequality. Results for India and China show that poor households (bottom quintile) in India are far more sensitive to the *"food price channel"* of monetary policy than those in China. This is primarily because of differences in certain characteristics and features of poor households across the two countries: (i) while in India the bottom quintile allocates on average roughly 65-70% of their total income towards food expenditures, in China they allocate about 50-55% ; (ii) while in India the rural poor rely largely on cash purchases of food *(food purchased from the market)* to meet their daily food requirements which make them more sensitive to fluctuations in relative food prices, in China they rely heavily on self-produced food which plays a key role in dampening the effects on them of relative food price changes; (iii) while in India the poor live hand-to-mouth, i.e., they have no access to credit markets and simply consume their current labor income, in China the poor have significantly higher access to the formal financial institutions that hedge in some way against inflation (Figure 6; Anand and Prasad, 2015; Sparreboom and Duflos, 2012; Fungacova et al., 2015). Due to differences in the degree of financial inclusion, poor households in the two countries differ significantly in terms of their ability to smooth consumption behaviour in the face of idiosyncratic shocks. Finally, India is characterized by the presence of a huge informal sector (90%) compared to China (50%); higher relative food price acts as an implicit tax for the Indian poor engaged in the informal sector where wages are not indexed to inflation, and where workers don't have much bargaining power vis-a-vis their employers. (Easterly and Fischer, 2001; Rada, 2010; Gulati and Saini 2013; Rajan, 2016).

The main point from the above discussion is that, even though food is a *necessity* for the poor in both countries (due to their subsistence caloric intake), however due to the above influences, the privation imposed on the poor in India by rise in relative food prices from expansionary monetary shocks is large enough that their food demand seems to be far more elastic with respect to price, than the poor in China. Expansionary monetary policy shocks, which increase the relative price of food, have stronger adverse effects on the Indian poor. Aside from the above mentioned factors, differences in other household characteristics (with regard to socioeconomic and demographic factors, such as age and education, rural-urban migration, income, wealth, employment status, tax and housing status, patterns of food consumption) between the two economies could also potentially have implications for differences in their responses to changes in monetary policy. Many mechanisms through which monetary policy affects households in different ways may be at play, and it is a daunting task to disentangle and identify these effects empirically (Yannick and Ekobena, 2014). Results for India and China suggest that in emerging market economies the impact of the *"food price channel"* of monetary policy on inequality is a priori ambiguous. The effects of monetary policy on the rich versus the poor is specific to the institutions and histories of each economy; in sum the question is an empirical one, and the answer may well differ among economies (Easterly and Fischer, 2001).

In the next section I give a brief review of the literature.

2 Literature Review

In addition to the large body of literature on the distributional consequences of monetary policy (Romer and Romer, 1998; Erosa and Ventura, 2002; Carpenter and Rodgers, 2004; Doepke and Schneider, 2006; Albanesi, 2007; Heathcote et al., 2010; Coibion et al., 2012), this paper is related to two separate literatures, that I summarize below:

2.1 Monetary Policy and Food Price

The main question is whether food and non food prices adjust proportionately to monetary policy shocks or not. It is theoretically argued that as agricultural prices are less rigid, they respond faster to changes in money supply than non-agricultural prices (Frankel, 1986;

Bordo, 1980). Chambers and Just (1981), Orden (1986), Orden and Fackler (1989), Cho et al. (1993), and Dorfman and Lastrapes (1996) provide empirical evidence of the tendency of agricultural (food) prices to be more flexible relative to the general price level in the economy. The authors show that an increase in money supply raises agricultural prices relative to the general price level in the economy. Further, Hercowitz (1982), Debell and Lamont (1997), Lastrapes (2006), and Balke and Wynne (2007) go beyond the relative price effects and also report that monetary disturbances lead to an increase in the dispersion of the cross-section distribution of prices. While most of the above studies focus on the US economy, several studies have also found similar evidence in many emerging market economies. In Hungary, Slovenia, South Africa, India, Pakistan, China, Korea, the Philippines, and Thailand, authors have shown that monetary changes have real short- and long-run effects on agricultural prices (Saghaian et al., 2002; Peng, Marchant and Reed, 2004; Asfaha and Jooste, 2007; Saghaian, Hye and Siddiqui, 2010; Khundrakpam and Das, 2011; Bakucs and Ferto, 2013).[7] In sum, the literature provides evidence of short run and long run monetary non-neutrality. Commodity prices do not respond proportionately to monetary shocks; in particular, food prices being relatively more flexible, adjust more quickly to changes in monetary disturbances than do prices of other goods.

2.2 Food Price, Poverty and Income Distribution

In low income countries, the most direct distributional consequence of change in relative food prices emerge from the differential income effects on the absolute and relative income levels of various household income classes. Mellor (1978), Ravallion (1998), Rao (1998), and Pons (2011), among many others, show that an increase in relative food prices increases poverty and inequality in low-income countries like India and Bangladesh, through adverse distributional effects on the real income of poor households. Research studies done on Latin

[7] In the case of China, Peng, Marchant and Reed (2004) find the existence of a long-run equilibrium relationship between monetary policy and food prices, however the author argues that in China the effects are stronger from money supply than interest rates due to controlled interest rate regime and underdeveloped nature of financial markets.

American countries - Guatemala, Nicaragua, Honduras, and Peru show that an increase in relative food prices represents a negative shock for poor households, primarily, due to their disproportionately high share of food expenditure (Robles and Torero, 2010). 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. This has already been studied to some context for low-income countries, and the results appear to be quite mixed, as household consumption choices and patterns, sources of income, and geography mattered greatly in determining the specific impact.[8] Friedman and Levinsohn (2002) investigate the welfare impact of large food price increases during the Indonesian currency crisis of 1997, both across geographical areas and along the income distribution, and find that the rural poor who rely largely on self produced food suffered a smaller welfare loss than the rural rich, while the urban poor who rely mainly on cash purchases of food, fared the worst under the price changes. In contrast to this, Barrett and Dorosh (1996) in their study of rice price changes in Madagascar find that up to one-third of the rural poor (rice farmers) lose, in net terms, from higher prices. Using data from a number of African countries, Christiaensen and Demery (2007) study the second-round effects of relative food price changes by including an additional effect of increased farm productivity, and find that higher relative food prices lead to a rise in the poverty index in Africa, even after factoring in countervailing wage and productivity effects. Wodon et al. (2010) also provide empirical evidence that rise in relative food prices lead to higher poverty in Sub-Saharan Africa primarily because the negative impact on net consumers outweighed the benefits to producers.[9] Given

[8]Understanding the net effect on rural households of a rise in relative food price is complex since rural households are both consumers and producers of food. High food prices reinforce the substitution effect of a price increase by encouraging farm households to sell their food produced to the market instead of consuming them on farm. However, higher food prices also benefit farmers by increasing their overall profits from farm sales. This income effect potentially increases farmers' demand for food, offsetting the substitution effect. The net effect of higher food prices on food consumption of rural households could be either positive or negative, depending on whether the substitution effect or income effect is larger (Singh et al., 1986; Han et al., 2001; Gale et al., 2005).

[9]The authors note that the poor in rural areas were often constrained by small land holdings, input costs, and distance to markets, and hence were generally unable to produce the marketable surplus required to exceed their food expenditures.

these previous literatures as discussed above, a conclusion is reached: change in relative food prices is, in the short run, one of the most important determinants of change in the relative and absolute real income of poor households in developing countries, because they allocate a disproportionate share of their total expenditures towards food. The urban poor who are net buyers of food are more vulnerable to rising food prices; effects on the rural poor who may rely on self produced food are more country specific, but on average they are worse off when relative price of food rises.

Despite the dominant role played by changes in relative food prices in developing countries, and evidence of strong interlinkages between monetary policy variables and relative food prices in the literature, research studies in empirical monetary economics have largely ignored the distributional consequences of monetary policy that could arise from fluctuations in relative food prices. In this paper, I seek to fill the gaps in the literature by investigating how monetary policy via distortions in *relative* food prices affect the distribution of food consumption in China - one of the fastest growing emerging market economies in the world. Results of my study provide empirical evidence of the impact of the *"food price channel"* of monetary policy on the distribution of food consumption, and inequality in China.

3 Data and Stylized Facts

The data sample I use for this study is quarterly and ranges from 1996:Q1 to 2013:Q4.[10] I measure aggregate output as real GDP, the general price level as the overall consumer price index, the food price as the consumer price index of food, the nominal interest rate as the less than 24 hour Central Bank Rate (the primary monetary policy instrument of the *People's Bank of China*), and the stock of nominal money as M2. I obtain the quarterly data on China's real GDP from Chen, Higgins, Waggoner, and Zha (2016). Quarterly data on all other macro-variables are taken from the Federal Reserve Bank of St. Louis Data Base

[10]The primary reason for selecting the given time period is to maintain consistency with De (2017).

(FRED). I compute the relative price of food as the consumer price index of food deflated by the overall consumer price index in the economy. Figure 1 compares the growth rates in CPI and the food price; I note that the food price in China fluctuated far more than the general price level in the economy. Table 1 reports the average annual growth rates of the macro variables over the sample period. I note that while real GDP and money supply grew at 9% and 17% per annum respectively, food prices grew at 3.5% per annum over the study period. Figures 7-8 plot the movements in interest rate and money supply growth respectively over the study period.

For data on the distribution of food consumption, I rely on the household consumer expenditure surveys published by National Bureau of Statistics of China (NBS). The surveys report the average annual nominal per capita food consumption expenditure in five income quintile across rural and urban China.[11] NBS defines the top quintile or high income households (rich households) as those who fall in the 80-100% of income distribution (80^{th} percentile), and the bottom quintile or low income households (poor households) as those who fall in the 0-20% of income distribution (20^{th} percentile). I take the annual nominal per capita food consumption expenditures of the top and bottom quintile from NBS, then convert them into quarterly figures (assuming there is no quarterly variation in food expenditures for any given year), and finally deflate them by the consumer price index of food to obtain the quarterly real per capita food consumption expenditures of the respective quintile groups. Figure 9 plots the quarterly real per capita food consumption expenditures across the distribution in rural and urban China respectively. Following Coibion at al. (2012) who uses the difference between the 90th percentile and the 10th percentile of the log levels in consumption distri-

[11]All households in the sample are grouped, by per capita disposable income of the household, into groups of low income, lower middle income, middle income, upper middle income and high income, each group consisting of 20%, 20%, 20%, 20%, and 20% of all households respectively. Data for nominal food expenditures by income groups (discussed above) is available only from 2002-2012. So, for the years 1996-2001 and 2013 when the data was not available, I compute (interpolate) the annual figures for nominal food consumption expenditures using information (growth rates) from the total consumption expenditure series which is available from 1996-2013. By doing so, I make an implicit assumption in my study that food consumption expenditures of households is roughly proportional to their total consumption expenditures.

bution, I use the difference between the 80th percentile and the 20th percentile of the log levels in food consumption distribution as a measure of food consumption inequality *(also popularly known as the Kuznets ratio).*

Household survey data in China suggests that food expenditures comprise the largest component of household budget especially among the poor, accounting for nearly half of their total expenditures. Figures 3-4 plot the share of food expenditure in the total budget of the top and bottom quintile in rural and urban China respectively. In rural China the bottom quintile allocates on average about 55% of their total consumption expenditures to food and the top quintile allocates about 35%, while in urban China the bottom quintile allocates roughly 45% and the top quintile 30%. Even though the food share in rural China is higher than in urban China, but food expenditures in absolute terms is very low in rural China. This is because Chinese rural households are able to meet most of their basic nutritional requirements at minimal expenses by consuming self-produced food, largely grains and vegetables. Households at all income levels in rural China rely on self-produced food, however this is especially higher for the lower income groups as they have limited cash (Gale et al., 2005).[12] Further, lack of market development constraints the consumption choices of Chinese rural low income households; in remote rural areas transportation costs may prevent market participation by driving a wedge between effective purchase prices and sale prices. Lack of off-farm cash-generating employment opportunities also may force poor households to rely on self-produced food. Therefore, food self-sufficiency is more a rational response to the lack of cash income and limited access to retail food markets for rural low income households in China (Gale et al., 2005).

[12]China's rural poor spends very little on food, yet is very well-fed. More than 80 percent of grains, beans, and potatoes consumed are self-produced; and 70 percent of vegetables consumed are self-produced. Other important food items are also largely self-produced, including milk (68 percent), beef and mutton (54 percent), poultry and eggs (48 percent), pork (44 percent), fruit (39 percent), and edible oil (32 percent). Consumption of self-produced food frees up scarce cash income for non-food purchases like housing, schooling, transportation, and other nonfood goods and services (Gale et al., 2005).

Comparing the degree of food self-sufficiency between low-income and high-income households, I note that over the period 1996-2013 cash expenditures *(share of food purchased from market)* accounted for only 50% of total food expenditures for the rural low income households (Figure 5). The remaining 50 percent were noncash expenditures: the imputed value of food grown by the farm family itself plus the value of food obtained through informal exchange or other non-purchased sources. Relative to low income households, high income households had high cash and noncash food expenditures, but cash expenditures were particularly high accounting for 80 percent of their total food expenditures over the same sample period (Figure 5).[13]

4 Empirical Framework

4.1 Empirical Model and Identification

The aim of this paper is to estimate the dynamic responses of relative food price and the distribution of food consumption to monetary policy shocks in China. To achieve my objective, I make use of a vector auto regression (VAR) framework. Let Y_t be the m-dimensional vector stochastic process of aggregate macroeconomic variables. Assume that Y_t follows the following linear dynamic process:

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

$$\Sigma = E\left(\epsilon_t \epsilon_t^{'}\right) \tag{2}$$

[13]The share of self-produced food shows a declining trend from 1996 to 2013; the switch from self-produced to purchased food has been driven by structural changes in the rural economy over the past decade - a phenomenon referred to as *market development* (Huang and Rozelle, 1998). Better access to food markets as a result of better transportation and communications, greater mobility of the rural population, expansion of food retail outlets into rural areas, rural-urban migration, the rising ownership of home refrigerators, and other factors enabled rural households especially the rich to shift away from self production to the market for meeting their food requirements (Gale et al., 2005).

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. (1) is the reduced form, from a dynamic structural model. My interest lies not in the reduced form shocks but in identifying how the variables in Y_t respond to the aggregate structural shocks.

The structural counterpart to Eq. (1) in moving average form is given by:

$$Y_t = (I - B_y L)^{-1} D_y u_t \tag{3}$$

$$Y_t = (D_0 + D_1 L + D_2 L^2 + ...)u_t \tag{4}$$

where u_t is a vector of aggregate structural shocks, $E\left(u_t u_t^{'}\right)$ is normalized to be the identity matrix.[14] The mapping from the reduced form to the structural form thus entails restrictions on the covariance structure:

$$\Sigma = E\left(\epsilon_t \epsilon_t^{'}\right) = D_y E\left(u_t u_t^{'}\right) D_y^{'} = D_y D_y^{'} \tag{5}$$

Once I identify the $m \times m$ matrix D_y from this mapping, I obtain the dynamic multipliers of interest from equation (1) using (3) and (4). In my study, I do not fully identify D_y because I am solely interested in the monetary policy shock.[15] So, I impose identifying restrictions to identify only the column of matrix D_y corresponding to the monetary policy shock.

I identify monetary policy shocks using the "sign-restriction" approach of Uhlig (2005).[16]

[14] 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 $E\left[u_t u_t{}'\right] = I_m$.

[15] I do not identify the other $m - 1$ fundamental innovations.

[16] Faust (1998) uses sign restrictions to identify monetary policy shocks, imposing them only at the time of impact, however Canova and De Nicol (2002) identify monetary shocks using sign restrictions on impulse response correlations. More recently, Dedola and Neri (2007) have used sign restrictions to identify technology shocks and Mountford (2005), Peersman (2005), Benati and Mumtaz (2007), Dungey and Fry (2009) and Fry and Pagan (2007) have addressed the issues pertaining to identification of multiple shocks using sign restrictions.

I 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. My primary reason for adopting "sign-restriction" as a method of identification is because it eliminates any prize puzzle by construction.

In particular, I follow the "penalty-function" approach of sign restriction for my identification strategy instead of the "pure-sign restriction" approach (Uhlig 2005, Appendix B.2, pp. 413-417). This is because the "pure sign restriction" method fails to address the multiple models problem, which could result in excess uncertainty about the model's estimates and ultimately incorrect policy inference (Fry and Pagan, 2007 and Liu and Theodoridis, 2012).[17] The "penalty function" approach on the other hand uniquely identifies the model by minimizing a penalty for the impulse responses that violate the sign restrictions, and rewarding responses that satisfy the constraints. The penalty function is defined as follows (Uhlig 2005, Appendix B.2, pp. 413-417):

$$f\left(x\right)=\begin{cases} x & if \quad x\leq 0 \\ 100*x & if \quad x\geq 0 \end{cases} \tag{6}$$

where x is the impulse response. It is important to note here that the penalty function explained above is asymmetric, in which wrong responses are penalized more times (at a slope 100 times larger) than correct responses are rewarded. Due to the asymmetry in the numerical specification, this method is able to select the best of all impulse vectors, i.e., given a choice among many candidate monetary impulse vectors it picks the one which generates the most decisive response of the variables (Uhlig 2005, p. 413).

[17] 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.

In sum, the "penalty function" approach goes as far as possible in imposing the sign restrictions and delivers impulse response functions with small standard errors, thus reducing the uncertainty of the identification procedure (Liu and Theodoridis, 2012). I therefore adopt the "penalty-function" over the "pure-sign restriction" approach for identification in this paper.

4.2 Model Specification and Estimation

4.2.1 Model Specification

Keeping in mind my objective i.e. estimate the dynamic responses of relative food price and the distribution of food consumption to monetary policy shocks in rural and urban China, I include the following seven endogenous variables in my baseline VAR model Y_t: real GDP, consumer price index, interest rate, nominal money supply, relative food price, and the real per capita food consumption expenditures of the top quintile and the bottom quintile respectively.

I have fitted a VAR with 4 lags in levels of the logs of all the series, except for using the interest rate directly. I add a constant and a time trend to Eq. (1). The horizon over which I 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.[18] I use a Bayesian method to estimate the posterior densities of the parameters of interest, conditional on observing the sample data, for the baseline model as well as alternatives to check for robustness of the model specification. None of the results in section 5 are sensitive to increasing the common

[18] A problem confronting my estimation is that the variables in my model are all characterized as non-stationary $I(1)$ variables (Table 2, Appendix Figures 18-19). Therefore, in the appendix I conduct a robustness check for my results; prior to estimation, I transform all data to log first-differences except for interest rate which is just first differenced to impose stationarity. Due to first differencing, I impose the sign restrictions on the cumulative impulse responses. I find that my results discussed in section 5 for the baseline VAR model (estimating the VAR using variables in log levels) are robust to changes in model specification (estimating the VAR using variables in log first differences) (Appendix Figures 20-23).

lag in the VAR to five lags, and to assuming the sign-restriction horizon as three quarters. My results discussed in section 5, for the baseline VAR model are robust to changes in model specification.

4.2.2 Estimation

I estimate the posterior density using the "penalty function" approach of Uhlig (2005, Appendix B.2, pp 409-417). Note in particular that B and Σ are directly identified from estimation of the parameters in Eq. (1) using OLS. I 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):[19]

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

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

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. (1) 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 "penalty function" approach of Uhlig (2005, Appendix B.2, pp 413-417)

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

(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. (4) implies values for $\bar{D}_k$ for $k = 1, ..., K$, where $\tilde{D}$ denotes the lower-triangular Cholesky factor of Σ.

(c) Let $d_{j,k}$ be the impulse responses of variable j at horizon k to the impulse vector $\bar{D}_k$, where $k = 0, .., K$. σ_j is the standard deviation of the variable j, such that the impulse responses are re-scaled.[20] Let $l_j = 1$ if j is the index of interest rate, and else, let $l_j = -1$.[21] The monetary impulse vector $\bar{D}_k$ is defined as one that minimizes the criterion function $\psi\left(\bar{D}_k\right)$, which penalizes negative impulse responses of real GDP, consumer price index, nominal money supply, and positive impulse responses of interest rate at horizons $k = 0, ..., K$. The horizon over which I impose these restrictions is $k = 2$ quarters, including the initial period of the shock.

$$\psi\left(\bar{D}_k\right) = \sum_{j \in \left\{ \begin{array}{lll} \text{``}real & GDP\text{''} & \\ \text{``}consumer & price & index\text{''} \\ \text{``}interest & rate\text{''} & \\ \text{``}nominal & money & supply\text{''} \end{array} \right\}} \sum_{k=0}^{K} f\left(l_j \frac{d_{j,k}}{\sigma_j}\right) \tag{9}$$

4. Since the true VAR is not known, I find the monetary policy impulse vector for each draw from the posterior, and accordingly calculate the statistics based on all the draws.

I show the median as well as the 16% and the 84% quantiles for the impulse responses.

[20] This makes it possible to compare deviations across the various impulse responses.

[21] Note that the sign of the penalty function is flipped for the interest rate.

5 Empirical Results

5.1 Dynamic Responses to Monetary Policy Shocks

My interest is how the relative food price and the distribution of food consumption respond to monetary policy shocks. I run VAR estimation separately for rural and urban China. The impulse responses are presented in Figures 10-13. Figures 10-11 present the impulse responses for rural China, while Figures 12-13 present the same for urban China.

I first discuss the results for rural China (Figures 10-11). Given an expansionary monetary policy shock, the interest rate falls by roughly 15 basis points on impact, then begins a slow asymptote towards its original value. The money supply increases by .40% on impact (liquidity effect), and further by .60% over the next two quarters. Output responds positively reaching a peak impact of .25% at a two-quarter horizon, and then makes a gentle descent back to its original value at the end of five quarters. The overall consumer price index also responds positively to the monetary policy shock. The peak elasticity is approximately .35, meaning that an expansionary monetary policy shock which results in a decline in interest rate by 15 basis points increases the general price level in the economy by .35% at a four-quarter horizon. The impulse responses of the interest rate, nominal money, GDP, and CPI series conform with standard dynamic macroeconomic theory, lending validity to the identification scheme employed in this paper (sign-restriction), and suggesting reliability in the results for the other series i.e., relative food price and the distribution of food consumption.

The estimated response functions for relative food price and the distribution of food consumption series is the main focus of this paper. The relative price of food rises fairly monotonically reaching a peak impact of .50 at a four-quarter horizon, and then gradually approaches its original response at the end of seven quarters. Consistent with several earlier studies, this study provides empirical evidence that food price is relatively more flexible than the overall price level, and so expansionary monetary policy shocks cause an increase in the *relative* price of food. Given an expansionary monetary shock, that leads to an increase in the *relative* price of food, the per capita real food consumption expenditures of low-income households (bottom quintile) remain unchanged (on average), however that of high-income (top quintile) households fall and remain in the negative region for roughly six quarters. The peak negative impact for high income households is .75 at a four-quarter horizon. Results for rural China are suggestive of the evidence that the food demand of low income households is more price inelastic compared to high income households. There are two reasons contributing to this result. First, low income households who are close to *subsistence* caloric intake have very limited ability to substitute into other less expensive goods when *relative* price of food increases. Food is more a *necessity* for them and consequently their food demand is price inelastic (Portillo et al., 2016). Second, household food self-sufficiency among the rural low income households allow them to minimize their food expenditures, and at the same time meet their *subsistence* nutritional needs without having to rely on risky markets.

Thus, I observe strong heterogeneity in the food consumption responses faced by households across different income classes. Figure 11 plots the difference between the estimated food consumption responses of high-income and low income households in rural China. 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, this paper reports that food consumption inequality decreases from expansionary monetary shocks to an economically meaningful extent in rural China.

Second, I look at urban China (Figures 12-13). An expansionary monetary policy shock causes the interest rate to fall by roughly 5-10 basis points, and the money supply to increase by .70% on impact. The *relative* price of food increases monotonically, reaching a peak impact of .60 at a two-quarter horizon, continues to remain high for the next two quarters, and then gradually starts falling. In response to the expansionary monetary shock, I note that the real food consumption expenditures of both low-income and high-income households fall, however the latter falls more than the former. While the peak decline in food consumption is .80 for the top quintile, it is .60 for the bottom quintile at the two-quarter horizon.

Thus, results for urban China point to expansionary monetary shocks having heterogeneous negative effects on the distribution of food consumption which reduce food consumption at the lower end of the distribution much less than that at the upper end, again suggestive of the evidence that low income households who survive on subsistence food are more price inelastic compared to high income households. Figure 13 plots the difference between the estimated food consumption responses of high-income and low income households in urban China. Because food consumption at the lower end of the distribution falls less than that at the upper end, inequality in food consumption decreases from expansionary monetary shocks in urban China as well.

Overall, results of my study provide empirical evidence in favor of the impact of the *"food price channel"* of monetary policy on the distribution of food consumption in China. I find evidence of somewhat stronger impact in urban China compared to rural China, reflecting the protective effect of agricultural activities.

5.2 How much variation do monetary policy shocks explain?

In this sub section, I consider the extent to which monetary policy shocks in China can account for the dynamics of the food price fluctuations and the distribution of food consumption. That is, whereas the previous sub section focused on characterizing whether monetary policy shocks affect relative food prices and the distribution of food consumption, I now turn to the question of assessing the economic importance of this relationship. I do so by studying the share of the variance in the food consumption distribution which can be accounted for by monetary policy shocks over the given time period. According to the median estimates shown in the middle lines of Figures 14-15 , monetary policy shocks account for 15-20 % of the variation in relative food price index, and the distribution of real per capita food consumption expenditure for majority of the forecasting horizons. Monetary policy shocks appear to have played a non-trivial role in accounting for fluctuations in food consumption distribution in rural and urban China over the study period. Figures 14-15 also plot equivalent variance decompositions for all other macroeconomic variables over the same time period. The contribution of monetary policy shocks to the variance of these variables is also in the 10-20 percent range for most horizons. The forecast error variance decompositions show that the contribution of monetary policy shocks to fluctuations in the distribution of food consumption is of the same order of magnitude as the contribution of these shocks to other macroeconomic variables like GDP and inflation.

6 Comparison: India and China

In related work, De (2017) by relying on a factor augmented vector auto regression (FAVAR) model investigates the dynamic effects of monetary policy shocks on relative food prices and the distribution of household food consumption in India over the same sample period i.e. 1996-2013, and finds empirical evidence of the impact of *"food price channel"* of monetary policy on the distribution of food consumption in the country.

Comparing the results of India with China, I note that the relative food price responds *positively* and the distribution of food consumption responds *negatively* to expansionary monetary policy shocks in both countries, however the differential effects of policy shocks on the rich vs. poor are strikingly different in the two emerging market economies. Following an expansionary monetary policy shock, while in India the poor witness a markedly greater fall in food consumption than the rich, in China it is found to be otherwise. This means that while in India *"the food price channel"* of monetary policy increases food consumption inequality, in China the same channel reduces inequality (Figures 16-17).

Results for India and China also show that poor households (bottom quintile) in India are far more sensitive to the *"food price channel"* of monetary policy than those in China. This difference could be attributed to the high degree of heterogeneity in the characteristics of poor households across the two countries. In particular, there are four differential features that are noteworthy: (i) while in India the bottom quintile (poor households) allocate on average roughly 65-70% of their total budget towards food, in China they allocate about 50-55%; (ii) while in India the rural poor rely largely on cash purchases of food *(food purchased from the market)* to meet their daily food requirements which make them more sensitive to fluctuations in relative food prices, in China they rely heavily on self-produced food which plays a key role in dampening the effects of relative food price changes on them; (iii) while in India the poor live hand-to-mouth, i.e., they have no access to credit markets and simply consume their current labor income, in China the poor have significantly higher access to the formal financial institutions that hedge in some way against inflation (Anand and Prasad, 2015; Fungacova et al., 2015; Sparreboom and Duflos, 2012). Due to differences in the degree of financial inclusion, poor households in the two countries differ significantly in terms of their ability to smooth consumption behaviour in the face of idiosyncratic shocks. Finally, India is characterized by the presence of a huge informal sector (90%) compared to China (50%); higher relative food price acts as an implicit tax for the Indian poor engaged in the informal sector where wages are not indexed to inflation, and where workers don't have much bargaining power vis-a-vis their employers. (Easterly and Fischer, 2001; Rada, 2010; Gulati and Saini 2013; Rajan, 2016). Due to the above factors, the privation imposed on the poor in India, by rise in relative food prices from expansionary monetary shocks is large enough, that their food consumption (despite being at subsistence) seems to be far more elastic with respect to price, than the poor in China. Therefore, in response to monetary expansion poor households in India witness a much greater fall in food consumption than poor households in China.

7 Summary and Conclusion

"The relative effects of inflation on the rich versus the poor must be specific to the institutions and histories of each economy. The question must be an empirical one, and the answer may well differ among economies."
Easterly and Fischer, 2001

Using household survey data and vector auto regression (VAR) framework, this paper empirically investigates the impact of monetary policy shocks on the distribution of food consumption in China. Results of this study show that expansionary monetary policy shocks in China have heterogeneous *negative* effects on the distribution of food consumption which reduce food consumption at the upper end of the distribution more than that at the lower end. There seems to be evidence of the presence of the *"food price channel"* of monetary policy, through which these distributional effects occur. The mechanism is simple: food prices being relatively more flexible, following a monetary expansion, adjust quicker than the overall price level in the economy. So, expansionary monetary policy shocks generate an increase in the *relative* price of food. Rich households in China respond significantly more to this *relative* food price change compared to the poor. The poor in China are found to be much more demand inelastic with respect to food price primarily because of their subsistence caloric intake *(necessity)* and high degree of food self-sufficiency. Therefore, following monetary expansion poor households witness a much smaller decline in food consumption than the rich, leading to an overall decline in inequality.

This paper documents that expansionary monetary policy shocks in China via the *"food price channel"* have statistically significant *negative* effects on food consumption inequality. Interestingly, the results observed for China are a striking contrast to those observed for India. In India while expansionary monetary shocks via the *"food price channel"* increase food consumption inequality, in China expansionary monetary shocks via the same channel reduce inequality. This observed difference in the results between India and China could be attributed to the differences in the characteristics and features of poor households across the two countries. Relative to China, poor households in India are characterized by a higher share of food in total budget, dependence on cash purchases of food, financial constraints, and informal employment; all these make them more vulnerable to fluctuations in relative food prices. Consequently expansionary monetary policy shocks, which increase the relative price of food, have stronger adverse effects on the Indian poor.

Aside from these factors, other differences in household characteristics (with regard to socioeconomic and demographic factors, such as age and education, rural-urban migration, income, wealth, employment status, tax and housing status, patterns of food consumption) between the two economies could also potentially have implications for their response to changes in monetary policy. Many mechanisms through which monetary policy affects households in different ways may be at play, and it is a daunting task to disentangle and identify these effects empirically (Yannick and Ekobena, 2014). In conclusion, results for India and China suggest that in emerging market economies the impact of *"food price channel"* of monetary policy on inequality is ambiguous, and rather specific to the household characteristics, institutions and histories of each economy.

Figures and Tables

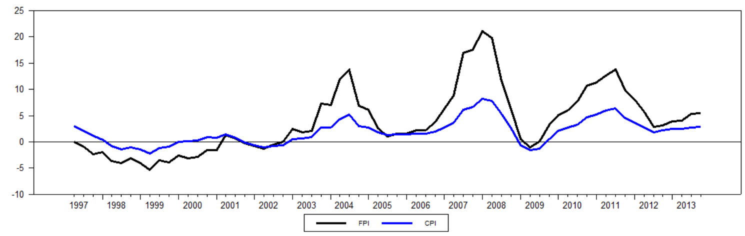

Figure 1: Growth Rate of FPI vs. CPI, China (%)

Source: Federal Reserve Bank of St. Louis Data Base (FRED).

Notes: FPI (food price index) is the consumer price index of food; CPI is the overall consumer price index in the economy.

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 2: Cross Country Comparison, Share of Food in Total Expenditure (%)

Source: Anand and Prasad, 2015

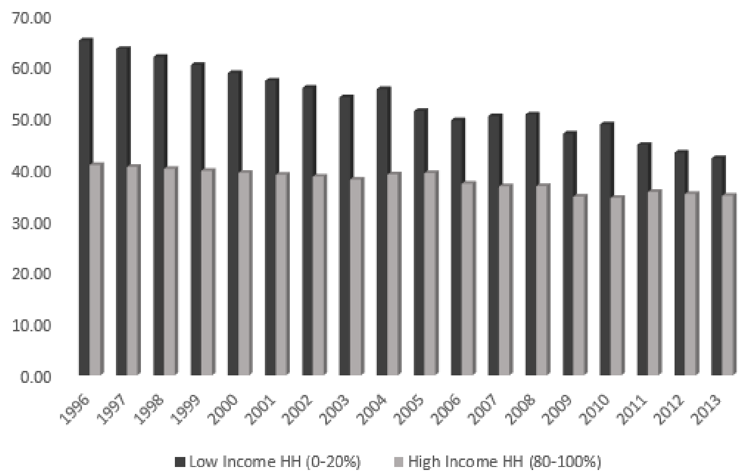

Figure 3: Share of Food in Total Expenditure, Rural China (%)

Source: National Bureau of Statistics, China

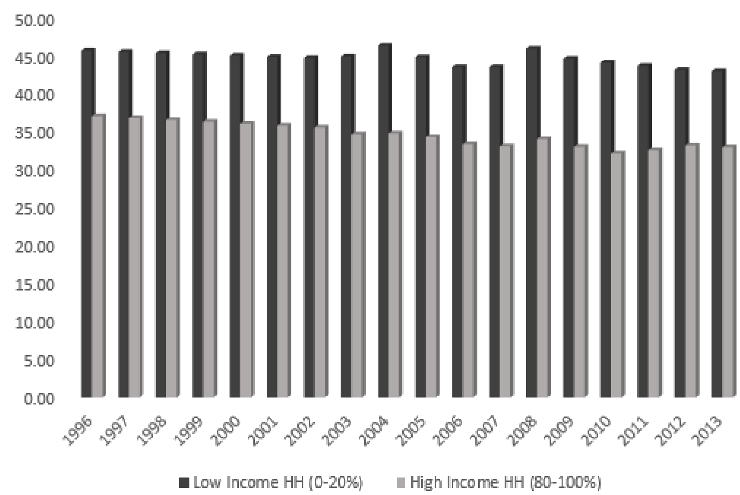

Figure 4: Share of Food in Total Expenditure, Urban China (%)

Source: National Bureau of Statistics, China

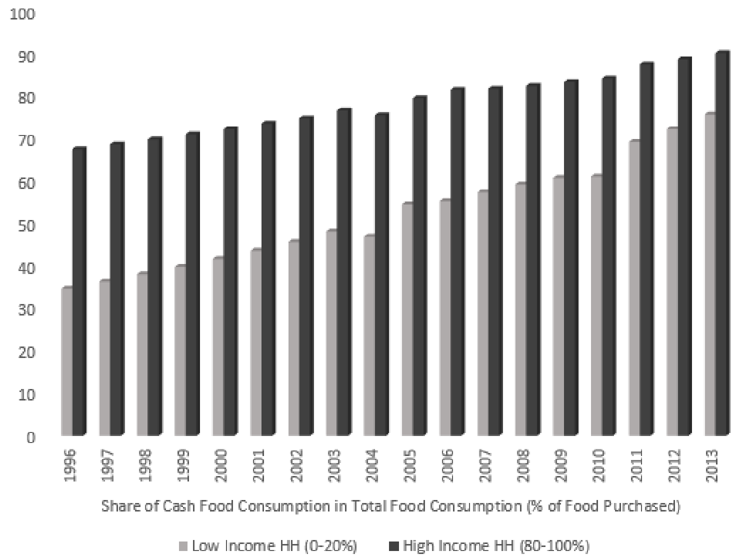

Figure 5: Share of Cash Food in Total Food Expenditure, Rural China (%)

Source: National Bureau of Statistics, China

Notes: Share of Cash Food indicates the share of food purchased from market.

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 6: Cross Country Comparison, Financial Inclusion (%)

Source: Anand and Prasad, 2015

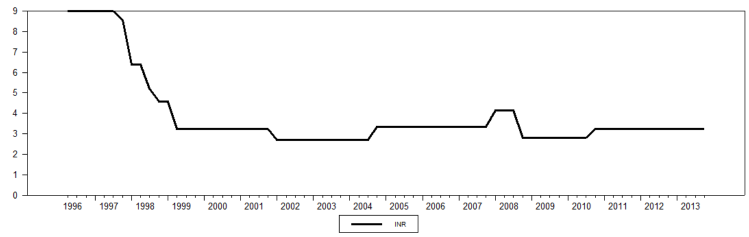

Figure 7: Central Bank Rate, China (%)

Source: Federal Reserve Bank of St. Louis Data Base (FRED).

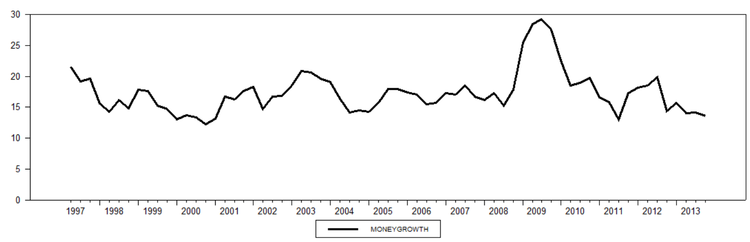

Figure 8: Growth Rate of Nominal Money Supply (M2), China (%)

Source: Federal Reserve Bank of St. Louis Data Base (FRED).

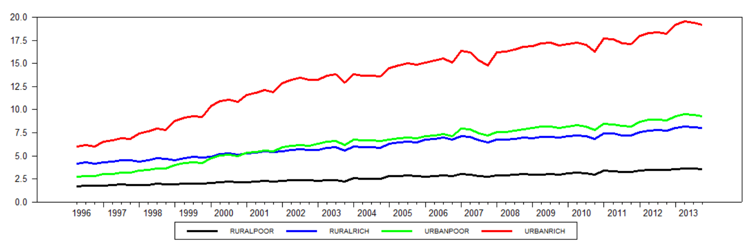

Figure 9: Distribution of Real Per Capita Food Consumption Expenditure, China

Source: National Bureau of Statistics, China.

Notes: Poor households feature those who lie in the 0-20% of income distribution (bottom quintile or 20^{th} percentile). Rich households feature those who lie in the 80-100% of income distribution (top quintile or 80^{th} percentile).

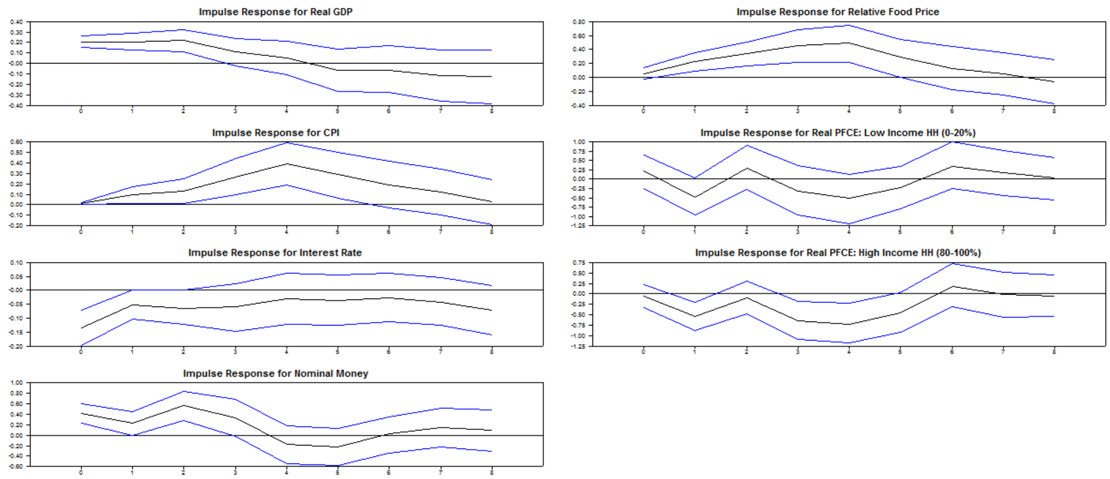

Figure 10: Impulse Responses to Expansionary Monetary Policy Shock, Rural China

Notes: Impulse responses to an expansionary monetary policy shock in rural China using penalty function approach with $K = 2$ (2 years). 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. Real PFCE refers to quarterly real per capita food consumption expenditures.

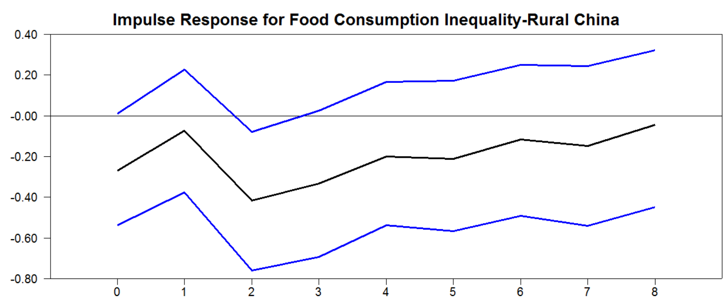

Figure 11: Impulse Response for Food Consumption Inequality, Rural China

Notes: Food consumption inequality is measured by the difference between the top quintile (80th percentile) and the bottom quintile (20th percentile) of the log levels in food consumption distribution.

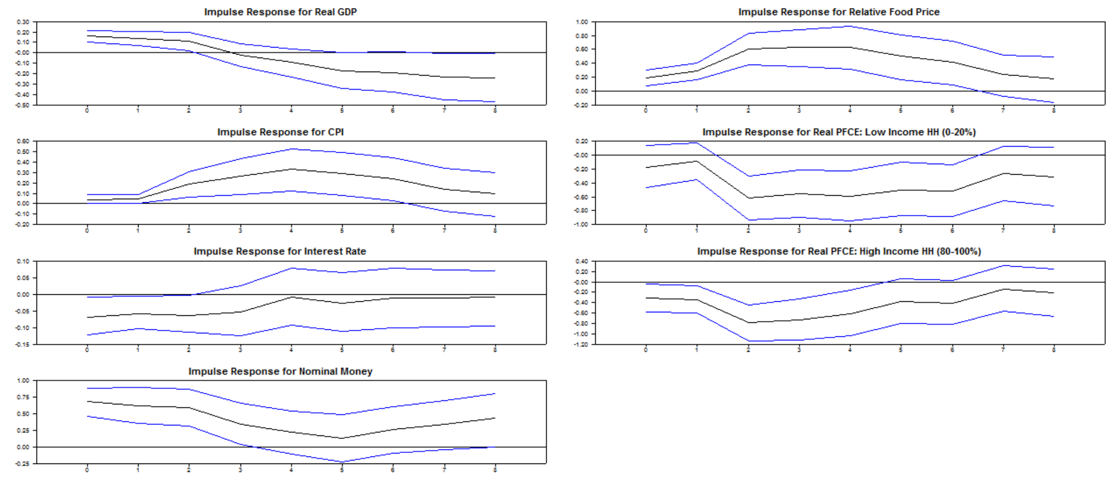

Figure 12: Impulse Responses to Expansionary Monetary Policy Shock, Urban China

Notes: Impulse responses to an expansionary monetary policy shock in urban China using penalty function approach with $K = 2$ (2 years). 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. Real PFCE refers to quarterly real per capita food consumption expenditures.

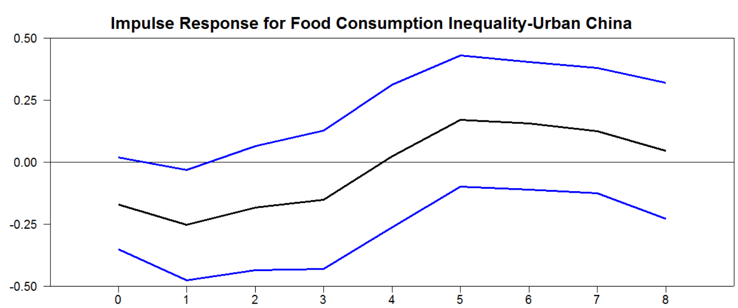

Figure 13: Impulse Response for Food Consumption Inequality, Urban China

Notes: Food consumption inequality is measured by the difference between the top quintile (80th percentile) and the bottom quintile (20th percentile) of the log levels in food consumption distribution.

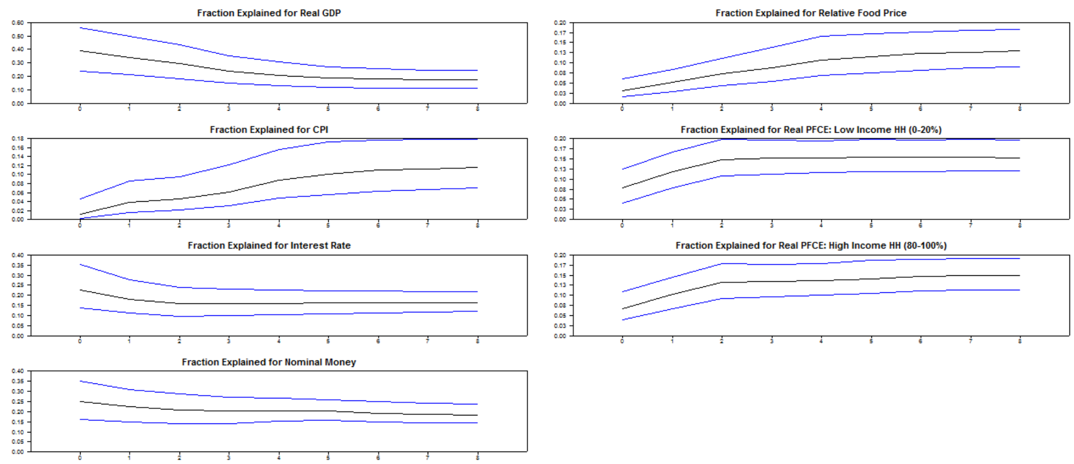

Figure 14: Fraction of the forecast error variance explained by monetary policy shock, Rural China

Notes: These plots show the fraction of the variance of the k - step ahead forecast revision explained by a monetary policy shock, using penalty function approach with $K = 2$ (2 years). The three lines are 16 % quantile, the median and the 16 % quantile of the posterior distribution. Real PFCE refers to quarterly real per capita food consumption expenditures.

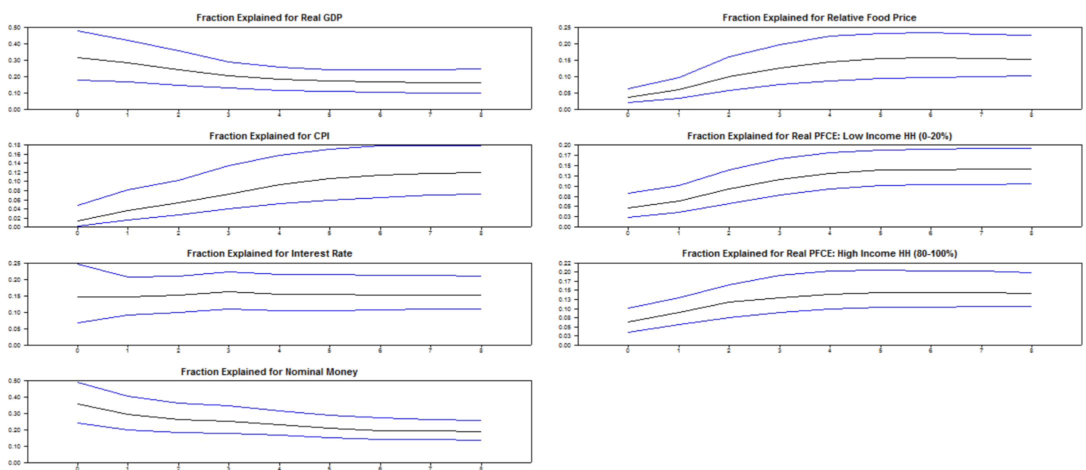

Figure 15: Fraction of the forecast error variance explained by monetary policy shock, Urban China

Notes: These plots show the fraction of the variance of the k - step ahead forecast revision explained by a monetary policy shock, using penalty function approach with $K = 2$ (2 years). The three lines are 16 % quantile, the median and the 16 % quantile of the posterior distribution. Real PFCE refers to quarterly real per capita food consumption expenditures.

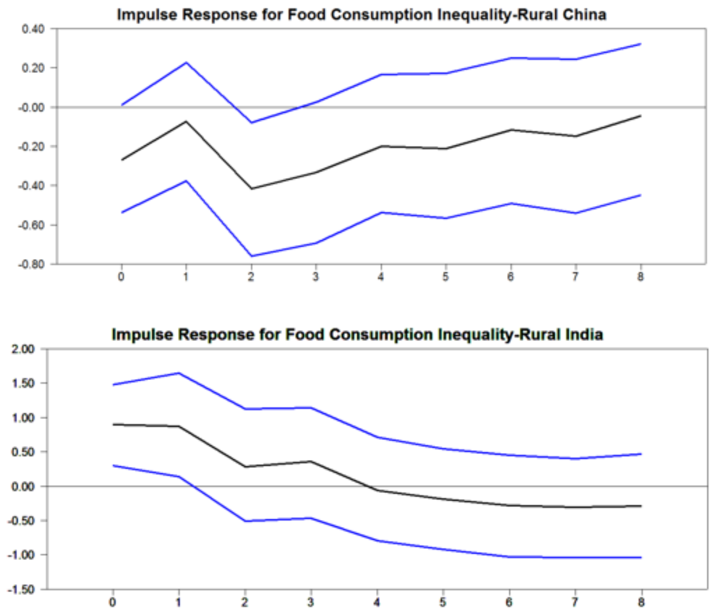

Figure 16: Food Consumption Inequality, Rural China vs. Rural India

Notes: Impulse response of food consumption inequality to an expansionary monetary policy shock, rural China vs. rural India.

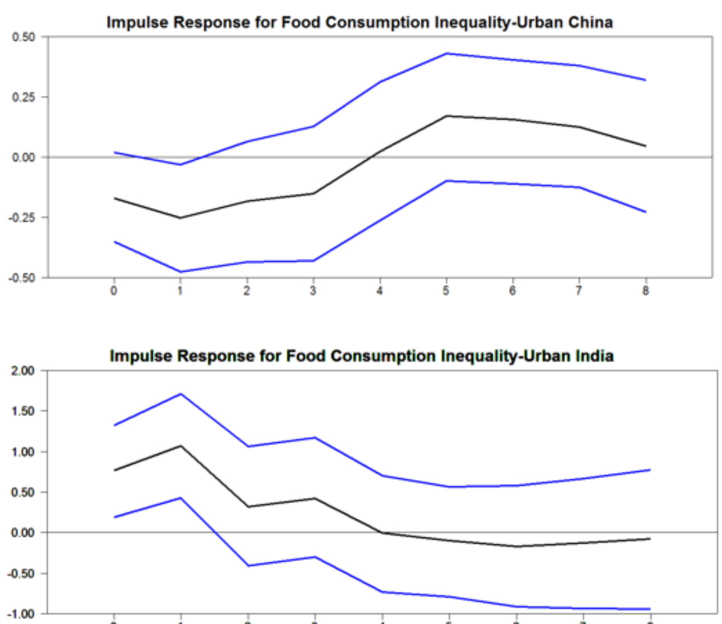

Figure 17: Food Consumption Inequality, Urban China vs. Urban India

Notes: Impulse response of food consumption inequality to an expansionary monetary policy shock, urban China vs. urban India.

Table 1: Average Annual Growth Rate, China, 1996-2013

Variable	Growth Rate (%)
GDP	9.10
CPI	1.99
Nominal Money	17.10
Food Price	3.50
Real PFCE, Bottom Quintile, Rural China	4.06
Real PFCE, Bottom Quintile, Urban China	6.92
Real PFCE, Top Quintile, Rural China	3.63
Real PFCE, Top Quintile, Urban China	6.61

Source: Federal Reserve Bank of St. Louis Data Base (FRED); National Bureau of Statistics (NBS), China.
Notes: Real PFCE, Bottom Quintile indicates the real per capita food consumption expenditure of households who fall in the 0-20% of income distribution (20th percentile), and Real PFCE, Top Quintile indicates the real per capita food consumption expenditure of households who fall in the 80-100% of income distribution (80th percentile).

Table 2: Unit root tests, China, 1996-2013

Variable	Unit root test (PP Statistic)
GDP	-1.61
CPI	-1.40
Interest Rate	-2.23
Nominal Money	-1.87
Relative Food Price	-2.57
Real PFCE, Bottom Quintile, Rural China	-4.76
Real PFCE, Bottom Quintile, Urban China	-1.79
Real PFCE, Top Quintile, Rural China	-3.22
Real PFCE, Top Quintile, Urban China	-1.85
5% critical value	-3.47

Notes: PP stat = Phillips/Perron unit root test statistic (model includes deterministic trend). Real PFCE, Bottom Quintile indicates the real per capita food consumption expenditure of households who fall in the 0-20% of income distribution (20th percentile), and Real PFCE, Top Quintile indicates the real per capita food consumption expenditure of households who fall in the 80-100% of income distribution (80th percentile).

8 Appendix: Robustness Check

Likelihood Based Analysis of Cointegration
Variables: GDP CPI INR Nominal Money Relative Food Pr Real PFCE-BQ Real PFCE-TQ
Estimated from 1996:03 to 2013:04
Data Points 66 Lags 4 with Constant restricted to Cointegrating Vector

Unrestricted eigenvalues and -T log(1-lambda)

Rank	EigVal	Lambda-max	Trace	Trace-95%	LogL
0					-459.0681
1	0.7677	96.3551	272.8105	134.5400	-410.8905
2	0.5973	60.0264	176.4553	103.6800	-380.8773
3	0.4601	40.6778	116.4290	76.8100	-360.5384
4	0.3838	31.9590	75.7512	53.9400	-344.5589
5	0.3103	24.5157	43.7922	35.0700	-332.3011
6	0.1721	12.4637	19.2765	20.1600	-326.0693
7	0.0981	6.8129	6.8129	9.1400	-322.6628

Cointegrating Vector for Largest Eigenvalue

GDP	CPI	INR	Nominal Money	Relative Food Pr	Real PFCE-BQ	Real PFCE-TQ	Constant
-0.385618	0.124953	-1.457702	-0.010385	0.631951	-0.110718	0.552534	199.683002

Figure 18: Cointegration Test, Rural China

Notes: Real PFCE, BQ indicates the real per capita food consumption expenditure of the bottom quintile and Real PFCE, TQ indicates the real per capita food consumption expenditure of the top quintile.

Likelihood Based Analysis of Cointegration
Variables: GDP CPI INR Nominal Money Relative Food Pr Real PFCE-BQ Real PFCE-TQ
Estimated from 1996:03 to 2013:04
Data Points 66 Lags 4 with Constant restricted to Cointegrating Vector

Unrestricted eigenvalues and -T log(1-lambda)

Rank	EigVal	Lambda-max	Trace	Trace-95%	LogL
0					-450.3610
1	0.8081	108.9390	274.2082	134.5400	-395.8915
2	0.5474	52.3158	165.2693	103.6800	-369.7336
3	0.4947	45.0455	112.9534	76.8100	-347.2108
4	0.3238	25.8202	67.9079	53.9400	-334.3007
5	0.2882	22.4381	42.0877	35.0700	-323.0816
6	0.1650	11.8986	19.6495	20.1600	-317.1323
7	0.1108	7.7509	7.7509	9.1400	-313.2568

Cointegrating Vector for Largest Eigenvalue

GDP	CPI	INR	Nominal Money	Relative Food Pr	Real PFCE-BQ	Real PFCE-TQ	Constant
-0.372790	-0.128393	0.915093	0.228308	-0.031844	-0.371733	0.476619	70.176867

Figure 19: Cointegration Test, Urban China

Notes: Real PFCE, BQ indicates the real per capita food consumption expenditure of the bottom quintile and Real PFCE, TQ indicates the real per capita food consumption expenditure of the top quintile.

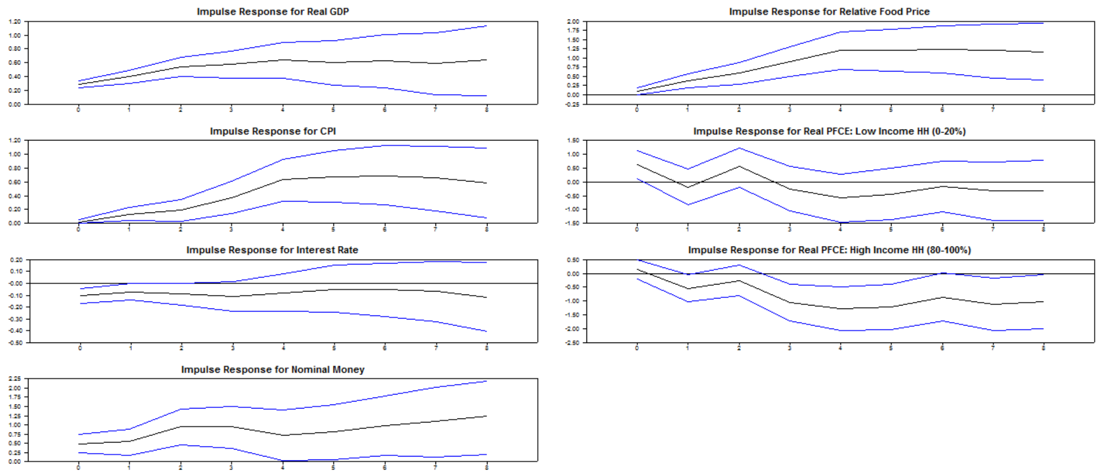

Figure 20: Impulse Responses from VAR in first differences, Rural China

Notes: Impulse responses to an expansionary monetary policy shock in rural China. All variables have been transformed to log first-differences except for interest rate which is just first differenced, to impose stationarity. The sign restrictions have been imposed on the accumulated IRF's.

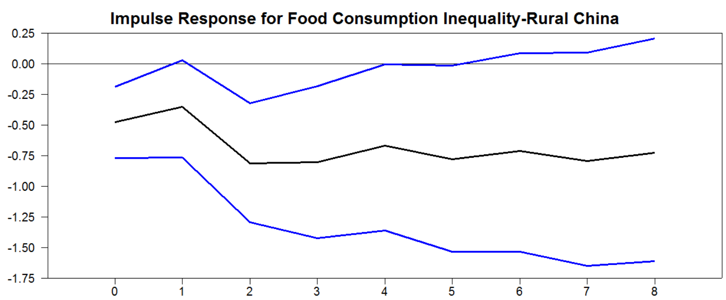

Figure 21: Food Consumption Inequality from VAR in first differences, Rural China

Notes: Impulse responses to an expansionary monetary policy shock in rural China. Food consumption inequality is measured by the difference between the top quintile (80th percentile) and the bottom quintile (20th percentile) of the log levels in food consumption distribution.

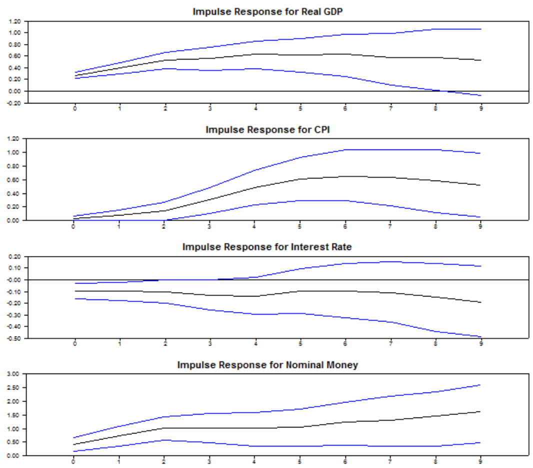

Figure 22: Impulse Responses from VAR in first differences, Urban China

Notes: Impulse responses to an expansionary monetary policy shock in urban China. All variables have been transformed to log first-differences except for interest rate which is just first differenced, to impose stationarity. The sign restrictions have been imposed on the accumulated IRF's.

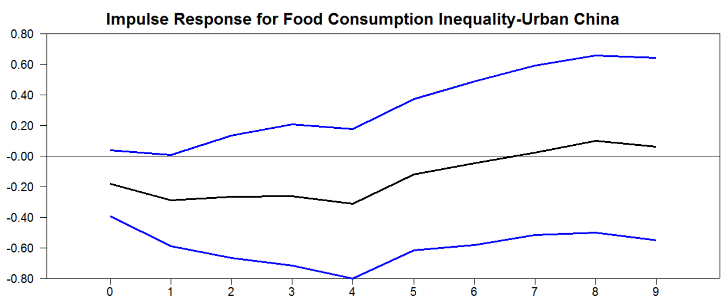

Figure 23: Food Consumption Inequality from VAR in first differences, Urban China

Notes: Impulse responses to an expansionary monetary policy shock in urban China. Food consumption inequality is measured by the difference between the top quintile (80th percentile) and the bottom quintile (20th percentile) of the log levels in food consumption distribution.

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