Food, Fuel, and Facts: Distributional Effects of Global Price Shocks*

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Abstract

We show that global commodity price shocks lead to a significant decline over time in Indian household consumption. These negative effects are heterogeneous along the income distribution: households in lower income deciles experience more adverse consumption effects following an exogenous rise in food prices, whereas households in both the lower and the middle income deciles are affected similarly following an exogenous rise in oil prices. We investigate how income and relative price changes contribute to generating these heterogeneous consumption effects. Global food price shocks lead to significant negative real earnings effects that mirror the pattern of negative consumption effects along the income distribution. Both global oil and food price shocks pass-through to local consumer prices in India, increasing the relative prices of fuel and food respectively. Consumption expenditure shares of food and fuel however, increase for certain income groups with such a rise in relative prices, thereby providing evidence for non-homothetic preferences. Specifically, we show that food, and particularly, pulses and sugar, is an essential consumption good for the lower income groups, whereas fuel is an essential consumption good for the rich.

JEL classification: F41, F62, O11

Keywords: Global Price shocks; Food prices; Oil prices; Inequality; Household heterogeneity; Household consumption; Essential consumption good; Non-homotheticity; India

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*We thank Girish Bahal, Vimal Balasubramaniam, Jim Bullard, Oscar Jorda, Dilip Mookherjee, Chris Waller, Daniel Xu, and seminar and conference participants at the Econometric Society Australasian Meeting, University of Western Australia, Annual IJCB Conference, HKU, Annual SERI Conference, UNSW, IIM-Bangalore, Midwest Macro Conference, ISI-Delhi, Ashoka University, Shiv Nadar University, and ANU Crawford School for very helpful comments. We thank Sowmya Ganesh and Suraj Kumar for outstanding research assistance. First version: July 2022. This version: September 2023.

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1 Introduction

There has been a rapid increase in *global* oil and food prices recently. These large external shocks have raised major concerns worldwide, but especially so in emerging markets, whose economies tend to be more vulnerable to global shocks. For emerging markets, food and fuel price shocks affect livelihoods of a very large part of the population, which further increases their salience. Strong effects on inflation and cost-of-living are expected to hit these countries as a result of these external price increases, thereby exacerbating existing inequality.

Effects of such global price shocks driven inflation on macroeconomic outcomes and inequality have therefore been at the forefront of policy makers' agenda. For instance, in the April 2022 issue of the World Economic Outlook (WEO), the International Monetary Fund (IMF) states: *Fuel and food prices have increased rapidly, with vulnerable populations–particularly in low-income countries–most affected. ... Higher food prices will hurt consumers' purchasing power–particularly among low-income households–and weigh on domestic demand.* Moreover, with deteriorating conditions in food and energy markets, the IMF's stance is more grave in the July 2022 issue of the WEO: *Rising food and energy prices cause widespread hardship, famine, and unrest. Because energy and food are essential goods with few substitutes, higher prices are particularly painful for households. When the price of other items, such as electronics, furniture, or entertainment, increases, families can simply reduce or even eliminate spending on them. For food, heating, and transportation–often essential to earn a living, this is much harder.*

Despite previous research on the impact of such global shocks, particularly oil prices, on the overall macroeconomy, there exists limited rigorous evidence on the *distributional* consequences of such shocks, especially in emerging markets.[1] This paper seeks to address this gap by examining the causal connection between rises in global food and fuel prices and consumption inequality in India, a major emerging economy that has experienced significant inflationary pressures in these sectors recently. To this end, we begin by presenting motivating evidence that shows a positive correlation between global food and oil price fluctuations and aggregate measures of consumption inequality in India. While this correlation is intriguing and suggestive, it alone does not establish causality or demonstrate that the effects of external price price shocks are sustained over time. Moreover, it cannot help identify which segments of the population are more sensitive to food and fuel price shocks, which components of consumption constitute essential consumption goods for different income groups, or elucidate the economic mechanisms through which such global price shocks lead to consumption inequality in India.

To make headway on these questions, we utilize a comprehensive monthly household panel

[1] In fact, for emerging economies, even the aggregate effects, such as those on consumption and income, of global food and fuel price shocks has not been investigated rigorously.

dataset from India that spans 2014-2019. Leveraging the panel dimension of the data, in a local projection framework at the household level, we investigate whether the dynamic effects on consumption of global oil and food price fluctuations differ along the income distribution. Our analysis involves categorizing households into five income brackets and estimating interaction effects between these groups and the global price shocks. This allows us to discern whether the consumption effects of these shocks differ among the poor, the middle class, and the rich.

Furthermore, to ensure a more accurate and causal interpretation of our findings, we devise an instrumental variable (IV) strategy. Since we assume India to be a small open economy, we can regard changes in global oil and food prices as an external shock in our panel local projection exercise. However, as the literature on the macroeconomic impact of oil shocks suggests, separating out the effects of global demand (and commodity-specific demand) from those of global supply shocks is essential for a clear interpretation of the results. Using changes in world oil and food prices as a measure of shock would thus produce OLS estimates that conflate the effects of both types of shocks. To tackle this challenge, we employ an IV approach, using supply-side instruments for the global change in oil and food prices. For the global oil price change, we use the oil supply shock estimated in Baumeister and Hamilton (2019) as an instrument, while for the global food price change, we construct our own instrument. The latter is based on residuals of food commodity prices, after extracting two common factors, a food-specific and an aggregate common factor. These factors are estimated by imposing sign restrictions in a dynamic factor model that uses data on a panel of commodity prices.

Our principal finding follows. Effects on consumption of the global price shocks are clearly heterogeneous along the income distribution. Households in the lower income deciles bear a greater burden from an exogenous rise in food prices. Exogenous rise in fuel prices, in contrast, affects consumption of both the lower and the middle income deciles similarly. Finally, the consumption of the top income decile is minimally, if at all, affected by these exogenous price fluctuations.

Our IV estimates reveal substantive differences from the corresponding OLS estimates in some cases. There are discernible differences in the consumption responses of the highest income group when comparing the OLS and IV findings. While OLS results indicate an increase in consumption for this income group following an oil price increase, IV results exhibit a decrease instead. This finding aligns with economic intuition, as positive global demand shocks, which are a part of the OLS results, and which increase oil prices, are likely to benefit high-income households in India.[2]

We utilize the IV framework to further investigate the mechanisms that cause heterogeneous effects in consumption. First, state-level panel local projection IV results show that both global

[2]We show direct evidence of this phenomenon by examining the effects on income/earnings across the income distribution. We observe positive impacts on income/earnings for the high-income group following an oil price increase in OLS estimates, which are absent in IV estimates. This is reminiscent of the key conclusion in Kilian (2009).

shocks do exhibit a “pass-through" effect on local prices in India. The impacts are however, more widespread for oil price shocks. Specifically, while global food price shocks have a substantial impact on the food component of the CPI, global oil price shocks exert a stronger and more enduring effect on the core CPI, along with affecting domestic fuel inflation. Both these shocks, nevertheless affect relative prices strongly. Global food prices elevate the relative price of food, while global oil prices drive up the relative price of fuel in India. Recognising the composite nature of the food price index, we go deeper in our analysis to uncover particularly pronounced relative price effects resulting from an increase in global food prices on local relative prices of pulses, sugar, oils and fats, and vegetables.

Conventional homothetic demand functions would predict strong expenditure-switching effects due to such relative price effects. We, however, find strong evidence to the contrary. Specifically, we show that in response to the global food price shock, the food expenditure ratio increases for the lower income groups, whereas in response to the global oil price shock, the fuel expenditure ratio increases for the rich. Given that the relative price of food increases with the global food price shock and that the relative price of fuel increases with the global oil price shock, these consumption share responses suggest a role for income effects in relative demand. In particular, we infer that food is a necessity for lower income households while fuel is a necessity for the rich. Moreover, these results pertaining to the food expenditure ratio are particularly pronounced for expenditure ratios of pulses and sugar, underscoring the essential nature of these food components in the consumption basket of lower income households. In sum, we show evidence consistent with non-homothetic preferences, with variation between the rich and the poor regarding what constitutes an essential consumption good.[3]

Finally, in the household panel local projection IV framework, we estimate heterogeneous income and wage earnings effects of the global price shocks. Our analysis reveals that food price shocks lead to a negative effect on real income and earnings of the poorest households. Moreover, this shock also affects the income/earnings of low income households, with the effects monotonically decreasing as we move up the income distribution. This suggests that food price shocks affect consumption heterogeneously through their differential effects on wage income. In contrast, oil price shocks do not exhibit any significant effect on income/earnings, except for some transient effects on earnings of the poorest households.

Our paper is related to several strands of the literature. The two-way relationship between global oil prices and the U.S. macroeconomy, as well as the implications for US monetary policy, has been studied extensively in Hamilton (1983), Hamilton (2003), Barsky and Kilian (2004),

[3]As we discuss later, the class of preferences that align well with our results are iso-elastic non-homothetic constant elasticity of substitution preferences between food and fuel. See Matsuyama (2022) for a discussion of such utility functions and preferences.

and Kilian (2009). We extend this body of work by estimating the distributional effects of global oil prices, an area that has only recently garnered empirical attention (see, for example, Gelman, Gorodnichenko, Kariv, Koustas, Shapiro, Silverman, and Tadelis (2023), Peersman and Wauters (2022), and Känzig (2021)). Moreover, we use the oil supply shock estimated in Baumeister and Hamilton (2019) as an instrument in our panel IV specifications.

Although there has been some recent research on global food price shocks, such as De Winne and Peersman (2016) and Peersman (2022), this area of study is less developed than the oil shock literature. Previous studies have mainly examined the aggregate or sectoral effects of food price shocks, such as their impact on sectoral inflation. We contribute to this literature by estimating the distributional effects, at the household level, of global food prices. In our IV specification, the instrument we develop is novel as we use a statistical factor-based method with data from a broad cross-section of commodity prices to isolate food-specific and aggregate demand factors from global food price dynamics.

Our paper also contributes to two other strands of the literature that have examined the distributional effects of domestic monetary policy shocks. On the theoretical front, Auclert (2019) develops a general model that encompasses various redistribution based channels for monetary policy transmission. On the empirical front, Coibion, Gorodnichenko, Kueng, and Silvia (2017) study the effects of US monetary policy shocks on inequality, while Holm, Paul, and Tischbirek (2021) estimate the heterogeneous household effects of Norwegian monetary policy shocks along the liquid asset distribution. In building on this body of work, our paper focuses on the distributional implications of an external shock in the context of an emerging market. Additionally, we use detailed household panel consumption and income data at a monthly frequency to investigate these implications and transmission mechanisms.

Our paper shares a common theme with the literature that highlights the significant impact of external shocks on emerging market economies and their role in driving business cycle dynamics. For example, Neumeyer and Perri (2005) and Uribe and Yue (2006) have emphasized the role of global interest rate or spread shocks, while Fernandez-Villaverde, Guerron-Quintana, Rubio-Ramirez, and Uribe (2011) and Bhattarai, Chatterjee, and Park (2020) have highlighted the importance of global volatility or uncertainty shocks. Our paper focuses on a different type of external shock, namely global food and oil price shocks, and estimates their distributional implications in India. Specifically, we explore how the transmission of these shocks to consumption in India varies across the income distribution of households.

Furthermore, our findings regarding distributional effects on consumption imply that monetary policy in emerging markets might need to respond to such external shocks, even though they arise in sectors with flexible prices, in order to decrease consumption dispersion in the economy. The sticky price monetary policy literature highlights that optimal policy should not put any weight on inflation of flexible price sectors as they do not cause relative price distortions. In canonical open economy sticky price models, optimal monetary policy only targets domestic price inflation if import prices are determined flexibly (Clarida, Galı, and Gertler (2002)). Such insights do not account for effects of such shocks on consumption inequality. If such effects are present, optimal policy will need to respond to mitigate consumption disparities in the economy because with incomplete markets, consumption dispersion appears in the objective of the benevolent central bank (Bhattarai, Lee, and Park (2015), Benigno, Eggertsson, and Romei (2020), and Acharya, Challe, and Dogra (2020)). Our empirical results imply that disregarding shocks that only affect headline inflation directly, without affecting core inflation immediately, would be unwise as such shocks can significantly and persistently affect consumption inequality.

2 Data, Stylized Facts, and Instrumental Variables

2.1 Data Description

Our household data is from the Consumer Pyramid Household Survey (CPHS) dataset, a survey conducted by the Centre for Monitoring the Indian Economy (CMIE). CPHS has surveyed over 236,000 unique households since 2014 and is the most comprehensive longitudinal consumption data available for India. CPHS is unique in including both income data and detailed information about consumption in a single longitudinal dataset. Moreover, it is available at the monthly frequency, which allows an analysis of the dynamic effects of global food and oil prices in a straightforward way, without having to impute data due to frequency mismatch between the shock series and the consumption/income data. The time period of our analysis is Jan 2014-Dec 2019.

We construct consumption, income, and earnings measures following closely the method of Coibion, Gorodnichenko, Kueng, and Silvia (2017). Consumption expenditure comprises of 153 categories. Total consumption measure we construct is the sum of non-durable consumption (food, cooking fuel, electricity and transport, intoxicants), durable consumption (appliances, furniture, jewelry, clothing, electronics, toys, cosmetics), and service consumption (entertainment, beauty services, fitness services, restaurants, etc). We present results on total consumption and non-durable consumption separately in all our analysis.[4] We also present results on food, fuel (including cooking fuel and electricity and transport fuel), and detailed food sub-components consumption in further analysis.

Total consumption is deflated using monthly state-region level Consumer Price Index (CPI) - Combined series (2012 base) available from the Ministry of Statistics and Program Implementation

[4]The average share of non-durable consumption in total consumption is 75.1% in our dataset.

(MoSPI), Government of India.[5] The remaining consumption categories are deflated using their respective CPIs as follows. Food consumption is deflated by the index available from the MoSPI. Fuel consumption, where we include not just the cooking fuel expenditure given directly by the MoSPI but also fuel expenditure on transportation, is deflated using a weighted average of the two categories with the weights provided from the MoSPI. Non-durable consumption is deflated using a weighted average of food, cooking fuel, and transport price indices with the weights provided from the MoSPI. For detailed analysis of various food sub-components, we use the corresponding monthly state-region level deflators from the MoSPI directly.

We construct income as the sum of household income from rent, wages, self-production, private transfers, government transfers, business profits, sale of assets, lotteries and gambling, pension, dividends, interest and deposit provident fund and insurance. These categories are an exhaustive list of all income sources collected in the CPHS. Our earnings measure is constructed using income from wages and overtime bonus. To construct real values of these nominal income and earnings variables we use the state-region level CPI - Combined series (2012 base). Using these data, measures of inequality we construct for stylized facts are: Gini coefficients, cross-sectional standard deviations, and differences between individual percentiles (90th-10th and 75th-25th) on log levels.

Finally, we use the Food and Agriculture Organizations's Food Price Index (FPI, Nominal) and the West Texas Intermediate crude oil prices (WTI, US Dollar per barrel) as our measure of global food and oil prices.

2.2 Summary Statistics Along the Income Distribution

Several summary statistics from our household panel data, along the income distribution, are in the Appendix in Section 7.2. Most importantly, we present in Table A1 summary statistics on average (across households and months) monthly income, monthly consumption, share of non-durable consumption, and share of food consumption by various income deciles, where the deciles are on the basis of the initial period (2014) real household income. The poorest income group is definitely below poverty line and are net borrowers with a high share of non-durable and food in consumption. Savings rate rises while non-durable and food shares decline with income. The top income decile has nearly a 75% savings rate and a relatively low share of food in total consumption.[6]

[5] We use the most detailed state and region (urban or rural) level monthly deflator available for India at a monthly frequency for our time period, following the suggestions in Deaton (2019). There are 35 states and union territories (regions administered by the central government) in our dataset. While headline and food CPI is available for each state-region, core CPI (which excludes food and energy) and nondurable CPI has to be constructed. We overcome this challenge by constructing state-region (urban and rural) level core and non-durable CPI using state-region level headline CPI as well as state-region level food and energy consumption shares in the CPI basket. We provide further details on the data in the Appendix in Section 7.1.

[6] We also show in Tables A3 and A7 that earnings constitute the most important category of income for lower income groups, and most of them work in informal occupations. For higher income groups, capital income constitute

These statistics motivate us to divide households in five broad income groups when we estimate heterogeneous consumption effects of global commodity price shocks. In these regressions where we estimate interaction effects, we consider five income groups: very low income (decile 1), low income (deciles 2 and 3), lower middle income (deciles 4, 5 and 6), upper middle income (deciles 7, 8 and 9), and high income (decile 10). We determine the cut-offs for deciles based on real income in 2014, and assign each household to a group based on those cutoffs.[7]

2.3 Global Commodity Prices and Aggregate Inequality

We now present some stylized facts on global commodity prices and aggregate inequality in India.

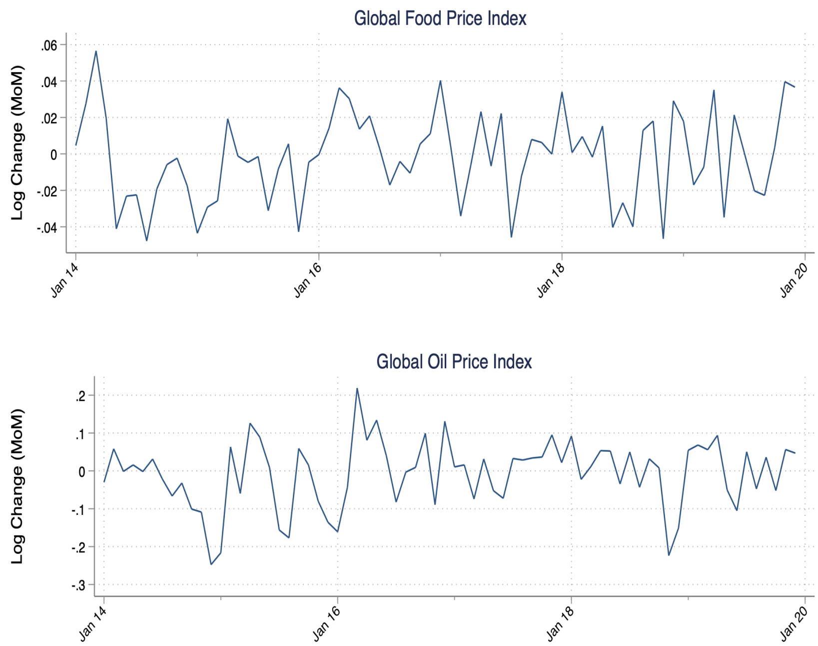

Figure 1: Changes in Global Food and Fuel Prices

Notes: This figure plots the log change in Food and Agriculture Organization's Food Price Index (FPI, Nominal) and West Texas Intermediate Crude Oil Prices (US Dollar per barrel).

We first plot the log changes in global food and oil prices in Figure 1. As expected, average of the changes is close to zero while the standard deviation is approximately 3% for food price and nearly 10% for oil price, confirming a higher oil price volatility. AR(1) coefficients of the estimated processes for these change in prices are very low, indicating that the changes are largely

a significant fraction of total income whereas for lower income groups transfers is an important component.

[7] Note that the same household may belong to different income groups at different points in time depending on their current real income. This is an issue we address in the sensitivity analysis in Section 5.

transitory in nature. Finally, changes in the two series are positively correlated but not very highly so, hence implying independent sources of variation.[8]

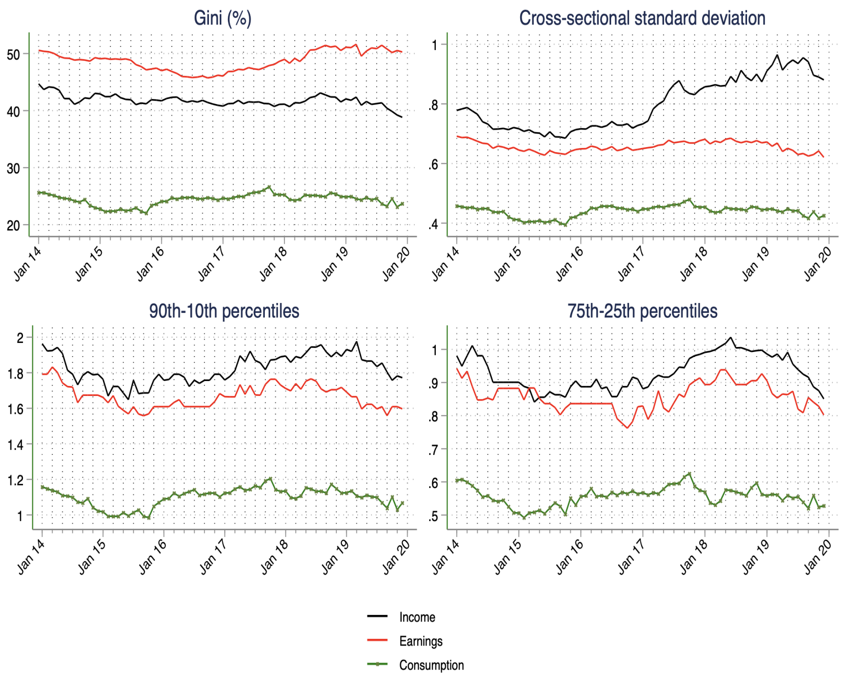

Figure 2: Changes in Aggregate Inequality in India

Notes: This figure plots the time series of various measures of inequality for income, earnings, and consumption that are constructed using the micro household panel data.

Figure 2 shows the dynamics of inequality for income, earnings and consumption in India. Income and earnings show higher inequality than consumption, as is commonly established in the literature.[9] We present summary statistics for these different measures of inequality in Table 1. As expected, broadly, income and earnings are more unequal than consumption in India, as panel A of Table 1 reveals. Moreover, overall, the unconditional volatility of these various measures of inequality is relatively low, as panel B of Table 1 reveals. The conditional correlation of various measures of inequality with one period lagged values of global food and oil price changes however, are mostly positive and much larger in magnitude, as shown in Table 2. The largest positive correlations are observed between consumption inequality and the two commodity price changes.

Response of consumption to global price shocks is the most relevant metric to evaluate welfare effects of such shocks. Our raw data reveals a strong correlation between aggregate consumption

[8]Correlation between the two series is 0.2. Some co-movement such as this to be expected given the role of energy as input in production of food as well as the possible role of global demand in driving both commodity prices. See, for example, Peersman, Rüth, and Van der Veken (2021).

[9]See, for example, Coibion et al. (2017) for the U.S.

inequality and the external commodity price changes. Does this “smell test" pass an econometric examination? This is the key focus of our paper.

Table 1: Summary Statistics on Indian Aggregate Inequality Measures

Panel A: Levels of Inequality Measures				
	Gini	SD	90th-10th	75th-25th
Income Inequality	0.519	0.799	1.824	0.930
Earnings Inequality	0.575	0.657	1.667	0.859
Consumption Inequality	0.375	0.440	1.100	0.556
Panel B: Volatility of Inequality Measures				
	Gini	SD	90th-10th	75th-25th
Income Inequality	0.004	0.007	0.007	0.003
Earnings Inequality	0.003	0.000	0.004	0.002
Consumption Inequality	0.006	0.000	0.003	0.001

Notes: This table shows mean and variance of various inequality measures for income, earnings, and consumption that are constructed using the micro household panel data.

Table 2: Correlations of Aggregate Inequality with Global Food and Oil Price Changes

Panel A: Correlations With Global Food Price Change				
	Gini	SD	90th-10th	75th-25th
Income Inequality	0.108	0.097	0.153	0.063
Earnings Inequality	0.058	0.098	0.077	-0.062
Consumption Inequality	**0.234**	**0.232**	**0.215**	**0.229**
Panel B: Correlations With WTI Crude Oil Price Change				
	Gini	SD	90th-10th	75th-25th
Income Inequality	0.137	0.134	0.118	0.134
Earnings Inequality	0.047	0.098	0.090	-0.023
Consumption Inequality	**0.285**	**0.296**	**0.269**	**0.230**

Notes: This table shows correlations of one-period lag of global food and oil price changes with various inequality measures for income, earnings, and consumption that are constructed using the micro household panel data.

2.4 Instrumental Variables for Global Commodity Prices

In our stylized facts above, and in some of our analysis below, we use changes in world oil and food prices (in logs) as an external shock, motivated by the small open economy assumption for India. These results can be considered as OLS versions of our estimation framework as they conflate the effects of various underlying shocks that lead to changes in world oil and food prices. As has been shown in the oil shock literature however, for a cleaner interpretation of these results, it is instructive to separate out such global oil/food price changes as coming from global demand or commodity-specific demand or supply shocks. To address this issue, we take an Instrumental Variable (IV) approach where we use instruments for the change in global oil and food prices in all our panel local projection regressions.

For the oil price change, our IV is the oil supply shock estimated in Baumeister and Hamilton (2019). For the food price change, we construct an IV based on residuals of food commodity prices after extracting two common factors from a cross-section of commodity prices. In particular, we residualize the global food price index with a common factor and a food specific factor estimated using sign restrictions on a panel of 37 non-energy commodity prices (13 industrial metals and 24 food prices, available from FRED and Bloomberg in the time period 1990-2022) in a dynamic factor model. Our estimation method for this dynamic factor model is outlined in Appendix 7.4.[10]

3 Distributional Effects of Global Commodity Price Shocks

To econometrically estimate the distributional effects of global shocks in a dynamic setting, we use a household panel regression framework where we estimate heterogeneous dynamic effects on consumption of global oil and food price shocks. In particular, these consumption effects will be allowed to differ along the income distribution.

3.1 Panel Local Projection Framework

To capture such dynamic heterogeneous effects, we estimate a household level panel local projection model with interaction effects. Our estimation equation is:

[10] It is challenging to estimate a supply shock for the food sector in a way analogous to the oil supply shock due to two main reasons. Unlike oil, food is not a single commodity–it is a composite of several commodities. Also, while monthly price data is available for various components of food, monthly production data is generally not available. There are two approaches that one can take to circumvent these problems: the first is to use a large cross-section of non-energy commodity prices and a combination of statistical and theory based identification to disentangle supply and demand shocks (for example, Alquist, Bhattarai, and Coibion (2020)) and this is the approach we take. The second is to use a limited cross-section of price and a proxy for monthly production data, as outlined in De Winne and Peersman (2016). However, the major crops of India are subject to various price regulations both on the supply and demand side in the domestic market due to minimum support prices for farmers and public distribution system of basis cereals for consumers. Hence, we prefer to rely on an approach that uses a broad cross-section of prices.

$$c_{i,t+h} - c_{i,t-1} = c^{g(t),h} + \beta_0^{g(t),h} ext_t + \sum_{k=1}^{K} \beta_k^{g(t),h} ext_{t-k} + \sum_{d=0}^{D} \delta^{g(t),h} D_{t-k}$$
$$+ \sum_{j=1}^{J} \alpha^{g(t),h}(c_{i,t-j} - c_{i,t-j-1}) + \gamma^{g(t),h} X_t + \epsilon_{i,t+h} \qquad (3.1)$$

Here, c_i is the log of consumption for household i for various measures of consumption; ext stands for different measures of the global price shock; and D is the dummy for the Indian government's demonetization policy, which is allowed to have lagged effects up-to three lags. For the AR and MA coefficients, we choose $J = 3, K = 3$. All regressions coefficients vary by whether a household i belongs to the income group g, $1_{i \in g}$.

The most important aspect of this specification is that we allow the consumption effects to differ by income of the household. That is, $g(t)$ denotes income group of household i at time t constructed using cutoffs from 2014 real income data. The effects of external shocks are thus, allowed to vary by income groups. We consider five income groups: very low income (decile 1), low income (deciles 2 and 3), low middle income (deciles 4, 5 and 6), upper middle income (deciles 7, 8 and 9), and high income (decile 10).[11]

X denotes controls for aggregate world conditions: world industrial production as a proxy for aggregate demand (Kilian (2009)); US monetary policy stance as captured by the federal funds rate; and global financial volatility as captured by the VIX index. These aggregate global controls are interacted with household income group dummies. Moreover, we include additional fixed effects such as state by calendar month fixed effects, state by calendar year fixed effects, fixed effects for different socioeconomic groups (caste, religion, education group, big city), and fixed effects for different age groups to control for demographics.[12]

As we discussed above, in addition to OLS results, based on using changes in global food and oil prices as the shock measure ext, we will also present IV results where we instrument the changes in global food and oil prices. These IV results will isolate variation coming from supply shocks to global food and oil prices as we discussed previously.

The standard errors are clustered at the state level. We report cumulative impulse responses below, for both our OLS and IV specifications. Table 3 lists all the control and instrumental

[11] As we mentioned before, summary statistics for these various income groups are presented in Appendix 7.2.

[12] There are a total of eleven age groups defined based on the age of the household head. The youngest and the oldest groups consist of households below twenty years and above 65 years respectively. Households between these two ages, which roughly corresponds to working age, are classified in to groups of five years each. Education groups are defined similarly based on the education level of the household head. We consider three groups – below high school, high school educated but less than college educated, and college graduate and above. Summary statistics for different household characteristics are presented in Table A2 in Appendix 7.2.

variables in our household panel local projection estimation.

Table 3: Instrumental and Control Variables in Household Panel Local Projection

Panel A. Instrumental Variables

- Oil supply shock estimated in Baumeister and Hamilton (2019)
- Food supply shock estimated using a dynamic factor model of non-energy commodity prices

Panel B. Control Variables

- Lags of outcome variables
  - 3 lags
- Lags of global oil and food price changes
  - 3 lags
- State-by-time-fixed effects
  - State-by-calendar month-fixed effects
  - State-by-calendar year-fixed effects
- Socio economic status-fixed effects
  - Caste
  - Religion
  - Education groups
  - Big city
- Demographic controls
  - Age fixed effects for 5-year age bins over working life
- Aggregate world condition controls (interacted with household income group dummies)
  - World Industrial Production
  - US Federal Funds Rate
  - Change in global VIX
- Demonetization policy dummy

Notes: This table shows our instrumental variables and a set of control variables in our baseline panel household local projection regressions.

3.2 OLS Results

Based on household data and estimation of equation (3.1), Figures 3 and 4 present the OLS results to the key question of the paper: How does the dynamic response of consumption to global food and oil price shocks vary by ex-ante income quintiles? We show results for total and non-durable consumtion for both shocks. Additionally, we show results for food consumption for the food shock and fuel consumption for the oil shock.

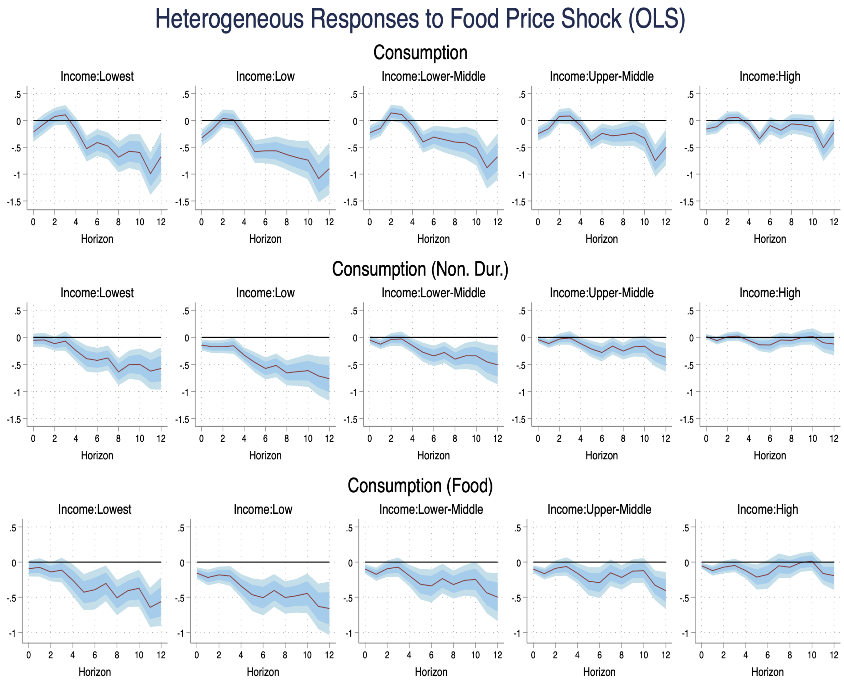

Figure 3: Response of Consumption to External Food Price Shocks by Income Quintiles

Notes: Cumulative IRFs on the basis of equation (3.1) where external shock is log changes in global food price and the dependent variable is log changes in household consumption. The light blue region refers to the 90% confidence interval and the dark blue region is the 68 % confidence interval.

Broadly speaking, in Figure 3, we observe a monotonically larger negative impact of food price shock on total and non-durable consumption as we move to lower levels of income, whereas in Figure 4, we see that the lower and middle-income groups seem to suffer an equivalent degree of total and non-durable consumption loss with rising oil prices. In both Figures 3 and 4, however, the effects on the top income deciles are both small and transitory. In addition, effects of the food shock on food consumption are negative across the income distribution and the effects are increasing as we move to lower levels of income. In contrast, effects of the oil shock on fuel consumption are not negative for any income group.[13]

These observations lead us to conclude that lower income deciles are hit harder by a rise in food prices, whereas a rise in fuel prices hurts both the lower and the middle income deciles. For both shocks, consumption of the top income decile is affected to a much less, if any, extent.

[13] We discuss and interpret the positive effect of the oil price shock on consumption of the top income group later in this section where we discuss the differences in our IV results.

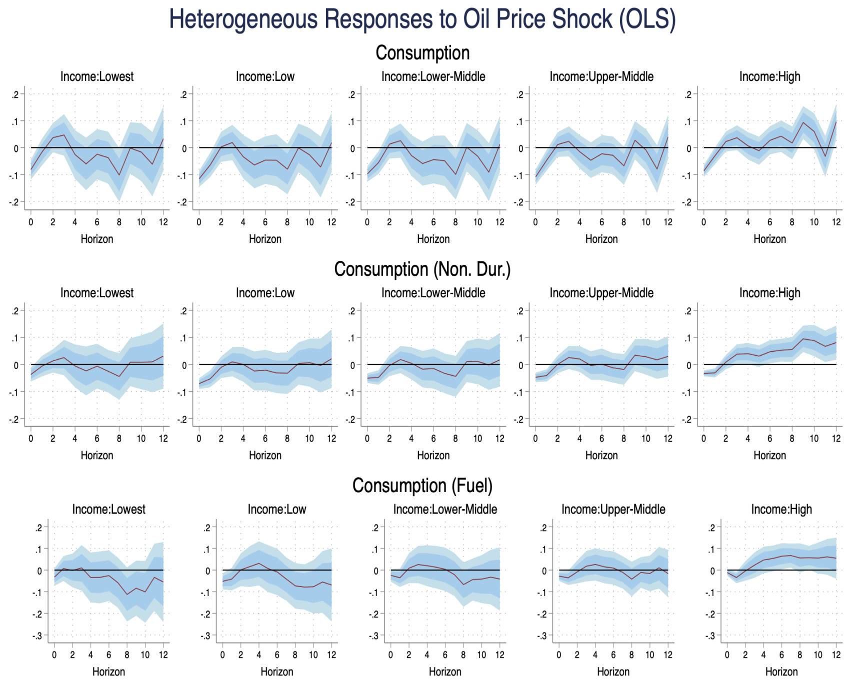

Figure 4: Response of Consumption to External Oil Price Shocks by Income Quintiles

Notes: Cumulative IRFs on the basis of equation (3.1) where external shock is log changes in global oil price and the dependent variable is log changes in household consumption. The light blue region refers to the 90% confidence interval and the dark blue region is the 68 % confidence interval.

To illustrate these empirical patterns more succinctly, we present a set of summary statistics on the basis of the estimated impulse responses presented in Figures 3 and 4 for non-durable consumption. A box and whisker plot is presented in Figure 5 to illustrate that the monotonic impact of increase in food price and the non-monotonic impact of increase in oil price on consumption is not specific to any horizon.[14] Over the entire horizon of the estimated impulse responses, poorer income groups suffer a larger consumption loss due to rise in food prices, whereas middle-income groups tend to suffer comparatively more from an increase in oil prices.[15]

[14] A box and whisker plot displays the five-number summary of a set of data. Here, the data is the median impulse response estimates over 12 month horizon for a dependent variable and an external shock. The five-number summary is the minimum, first quartile, median, third quartile, and maximum.

[15] Our poorest income group is below the official poverty line and households in that group potentially have access to social insurance in the form of public distribution of basic food grains. This is reflected in Figures 3 and 5 where the poor group suffers almost equally in terms of non-durable consumption as the poorest due to rising food prices. This point will be more clearer when we compare with the income and earnings results in the discussion section.

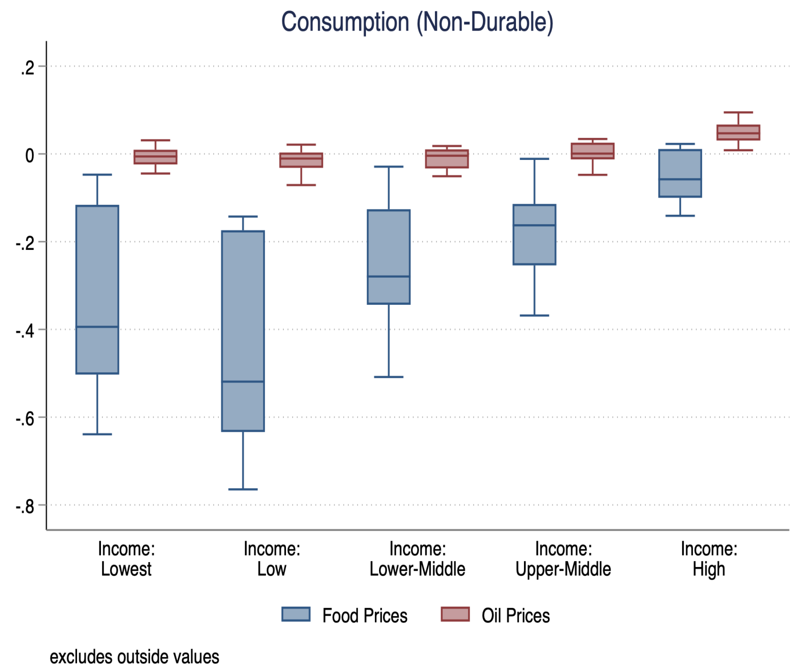

Figure 5: Summary Statistics of Response of Non-durable Consumption to External Food and Fuel Price Shocks by Income Quintiles

Notes: This figures is a box and whisker plot that summarizes the responses of non-durable consumption to the two external shocks that are presented in Figures 3 and 4.

3.3 IV Results

Next, for this local projection household panel exercise where the effects on consumption are allowed to vary along the income distributions, the IV estimates are in Figures 6 and 7 for oil price shocks and food price shocks respectively. Like our baseline OLS results, these IV effects also paint a picture of heterogeneous effects on consumption along the income distribution, for both total consumption and nondurable consumption. In particular, lower income deciles are hit harder by an exogenous increase in food prices while both lower and middle income deciles are equally hit by an exogenous increase in oil prices. Finally, the effects on the rich, which are now negative consistently for both shocks, are the smallest.

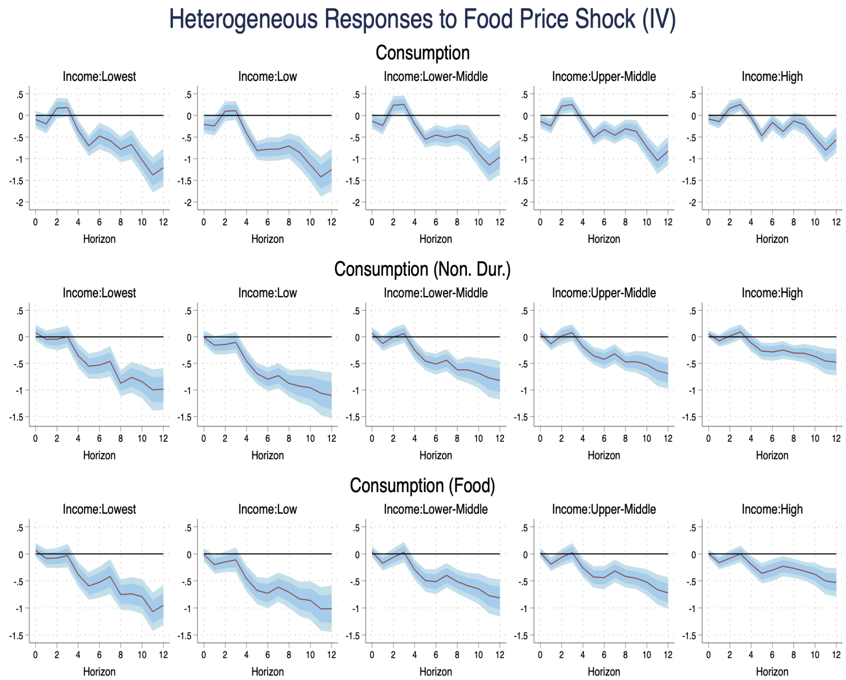

Figure 6: Response of Consumption to External Food Price Shocks by Income Quintiles (IV)

Notes: Cumulative IRFs on the basis of equation (3.1) where external shock is log changes in global food price, which is instrumented by a global food supply shock and the dependent variable is log changes in household consumption. The light blue region refers to the 90% confidence interval and the dark blue region is the 68% confidence interval.

Compared to the OLS results in Figures 3 and 4, the IV counterparts here in Figures 6 and 7 have broadly the same insight.[16] One distinction however, which comes about from isolating global supply side variation with our IV strategy, is that the effects on the rich are now consistently negative, even if less negative than other income groups. This is particularly important for oil price shocks, where global demand is well known to play an important role in driving oil price changes. Thus, we expect the richer Indian households to benefit with relatively higher income/earnings if higher oil prices are caused by an increase in global demand, which in turn affects the Indian economy positively.[17] This effect is not present in our IV estimates. In fact, for fuel consumption to decline in response to the oil shock, the IV framework is critical for all income groups, as can be seen by comparing the third row of Figures 4 and 7. Figure 7 then shows that fuel consumption declines very similarly for the poor and middle-income groups in response to the oil price shock, while the effects are muted for the rich. In addition, even for the food shocks, the IV effects are more negative and more precisely estimated for the higher income groups.

[16] First stage F stats are reported in Table A4.

[17] We later show direct evidence consistent with this interpretation by looking at effects on income and earnings.

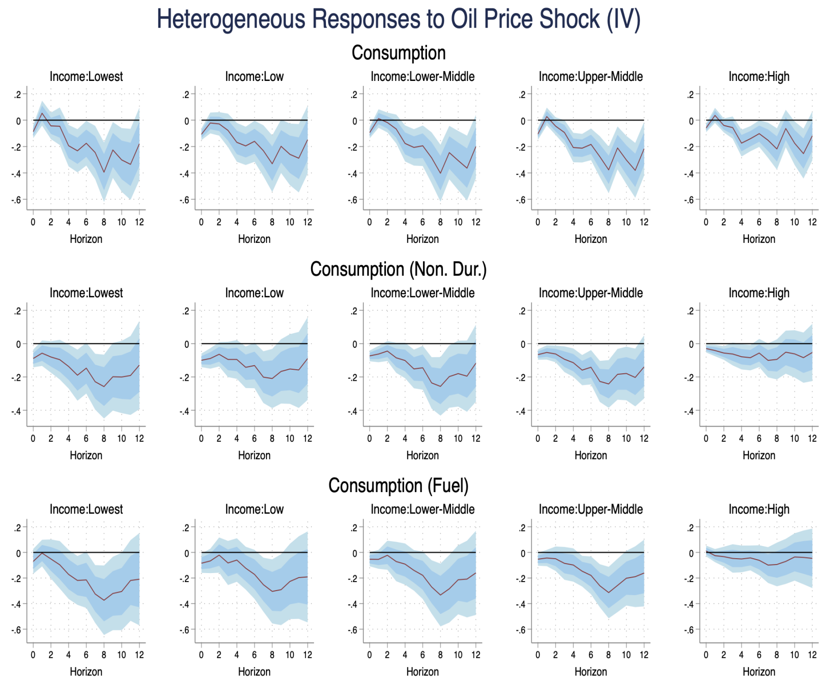

Figure 7: Response of Consumption to External Oil Price Shocks by Income Quintiles (IV)

Notes: Cumulative IRFs on the basis of equation (3.1) where external shock is log changes in global oil price, which is instrumented by a global oil supply shock and the dependent variable is log changes in household consumption. The light blue region refers to the 90% confidence interval and the dark blue region is the 68 % confidence interval.

To conclude this section, Figure 8 provides summary statistics for these results for non-durable consumption that are easier to see visually. As before, we observe that poorer income groups suffer a substantially larger consumption loss across all horizons following an exogenous rise in global food prices, whereas poor and middle-income groups are equally vulnerable to an exogenous rise in oil prices.[18]

[18] Also, as in Figure 5, the poor (deciles 2 and 3) group is as vulnerable as the poorest to rising food prices, possibly due to the public distribution system shielding some of the consumption loss of the very poor.

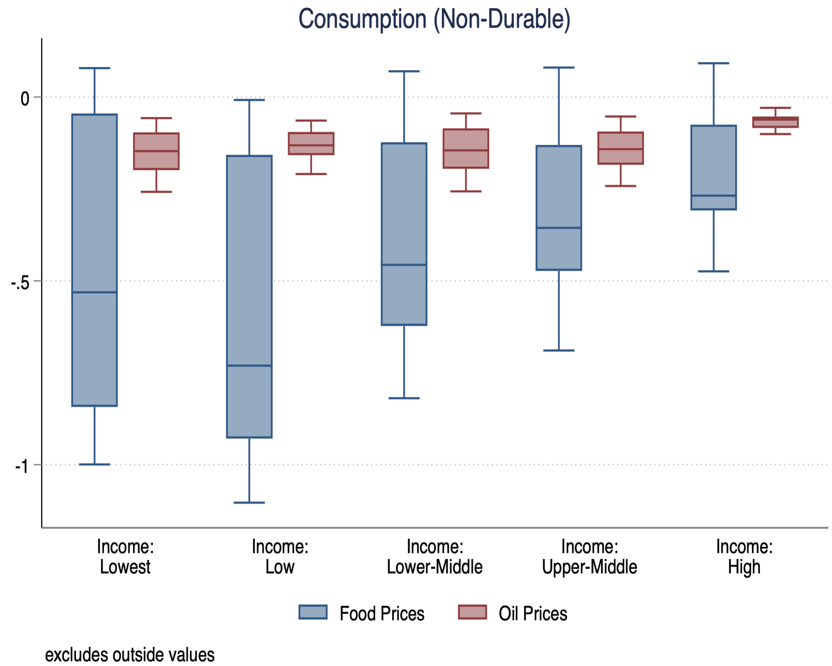

Figure 8: Summary Statistics of Response of Non-durable Consumption to Food and Fuel Price Shocks by Income Quintiles (IV)

Notes: This figures is a box and whisker plot that summarizes the responses of non-durable consumption to the two external shocks that are presented in Figures 6 and 7.

Table 4: Magnitude of Real Non-durable Consumption Loss (in %)

	1 SD Price Shock		**2022 External Price Shock**	
Income Group	Max Impact 1 sd food shock	Max Impact 1 sd oil shock	Max Impact 2022 food shock (8% in Aug 2022)	Max Impact 2022 oil shock (26% in Aug 2022)
Lowest	-3.00	-2.56	-8.00	-6.70
Low	-3.31	-2.09	-8.83	-5.44
Lower middle	-2.46	-2.56	-6.55	-6.70
Upper middle	-2.07	-2.42	-5.51	-6.29
High	-1.42	-1.00	-3.79	-2.62

Notes: This table shows the loss in real non-durable consumption (in % terms) for the five income groups based on the estimates of elasticities presented in Figure 8. Columns (2)-(3) refer to a 1 standard deviation shock to food prices (3%) and oil prices (10%). Columns (4)-(5) refer to the August 2022 massive rise in food prices (8 %) and oil prices (26 %).

To appreciate the magnitude of consumption loss due to the external shocks and the pattern of heterogeneity along the income distribution, in Table 4, we translate the elasticity estimates presented in Figure 8 to consumption loss in % terms. The first two columns of Table 4 capture the maximum negative impact of a 1 standard deviation shock in global food and oil prices (3 % rise in the food price index and 10 % rise in the WTI crude oil price index, respectively, as presented earlier in Figure 1). This clearly shows the pattern of heterogeneity we have emphasized: for an exogenous food price increase, the poorest two groups clearly suffer the most in consumption loss in % terms and there is a clear pattern of monotonicity along the income distribution, while for an exogenous oil price increase, the low and middle income groups suffer equally.

To make this analysis salient for recent events, a similar pattern is observed when we evaluate the consumption loss for the massive rise in food and oil prices in 2022 in the last two columns of Table 4. In August 2022, the FAO Food Price Index was higher by 8 percent while the WTI Crude Oil Prices was higher by 26 percent, compared to a year ago. For such a large rise in external food prices, the poorest two groups suffer more than 8 % loss in non-durable consumption and the effect declines monotonically with income. The oil price increase leads to a smaller, but nearly uniform along the income distribution, consumption loss for all groups except the rich.

4 Channels for Heterogeneous Consumption Effects

After establishing these baseline results on heterogeneous effects on consumption, we delve further into interpretation and possible transmission mechanisms. In particular, we aim to assess the channels that work via relative price effects (say across sectors), those that work via real income, and those that reflect non-homotheticity in preferences.

4.1 Transmission Mechanisms in Theory

We start by developing a theoretical framework that will inform how we explore and test for various transmission mechanisms in the data.

4.1.1 Dynamic Consumption-Saving Problem

As in Auclert (2019), we consider a infinite horizon consumption-savings problem in a perfect foresight environment with unexpected shocks, where the household can trade various nominal and real assets of different maturities. The household chooses $\left\{C_t, \frac{B_t}{P_t}, \frac{B_{2,t}}{P_t}, E_t, L_t\right\}$ to maximize lifetime utility

$$\sum_{t=0}^{\infty}\beta^t\left[\frac{C_t^{1-\sigma}}{1-\sigma}-\frac{L_t^{1+\phi}}{1+\phi}\right]$$

subject to a sequence of flow budget constraints

$$C_t + Q_t b_t + Q_{2,t} b_{2,t} + S_t E_t = b_{t-1}\frac{1}{\Pi_t} + Q_t b_{2,t-1}\frac{1}{\Pi_t} + (S_t + D_t)\, E_{t-1} + w_t L_t + T_t, \tag{4.1}$$

where C_t is aggregate consumption, L_t is labor, B_t is holdings of one-period risk-free nominal bonds, $B_{2,t}$ is holdings of two-period risk-free nominal bonds, and E_t is holdings of stocks.[19] Q_t, $Q_{2,t}$, and S_t are prices of the one-period bond, the two-period bond, and the stock respectively. The stock yields dividends D_t, P_t is the aggregate nominal price level, $\Pi_t = \frac{P_t}{P_{t-1}}$ is gross inflation, w_t is real wages, and T_t is lump-sum transfers. Thus, $b_t = \frac{B_t}{P_t}$ is the real holdings of the one-period nominal bonds and $b_{2,t} = \frac{B_{2,t}}{P_t}$ is the real holdings of the two-period nominal bonds. Finally, $\beta \in (0,1)$ is the discount factor, σ^{-1} is the intertemporal elasticity of substitution, and ϕ^{-1} is the Frisch elasticity of labor supply.

The flow budget constraint, equation (4.1), makes clear how shocks in period t affect consumption-savings decisions through their effects not only on labor earnings $w_t L_t$, but also through revaluations of financial positions by affecting inflation and asset prices Π_t, Q_t, and S_t. In this perfect foresight environment, the asset pricing conditions imply equal interest rates across the various assets. Using these no-arbitrage conditions and the Transversality condition together with the flow budget constraints yields the intertemporal budget constraint

$$\sum_{s=0}^{\infty} \rho_{t,t+s} C_{t+s} = \left[\frac{1}{\Pi_t}\left(b_{t-1} + Q_t b_{2,t-1}\right) + (S_t + D_t)\, E_{t-1}\right] + \sum_{s=0}^{\infty} \rho_{t,t+s}\left(w_{t+s} L_{t+s} + T_{t+s}\right) \tag{4.2}$$

where

$$\rho_{t,t} = 1;\, \rho_{t,t+s+1} = \prod_{j=0}^{s} R_{t+j+1}^{-1};\, R_{t+j+1} = \frac{1}{Q_{t+j}\Pi_{t+j+1}}.$$

The intertemporal budget constraint, equation (4.2), states that the present discounted value of consumption, using time-varying interest rates for discounting, equals the present discounted value of labor income and transfers as well as the real value of payoffs from ex-ante financial positions. It also shows that unexpected shocks can affect consumption through (a) wage earnings by affecting current or future wages or labor supply; (b) discount factors by affecting current or future real interest rates; and (c) real value of payoffs on ex-ante financial holdings by affecting current inflation, short-term nominal interest rate, or stock prices. Heterogeneity in how such unexpected shocks affect wage earnings or heterogeneity in ex-ante financial positions in terms of nominal bonds, maturity of nominal bonds, and stocks in turn can then generate heterogeneity in consumption effects.

[19]The household also faces an appropriate no-Ponzi game constraint.

Going further, if we impose a unit intertemporal elasticity of substitution (σ^{-1}=1), since

$$\rho_{t,t+s+1} = \prod_{j=0}^{s} \frac{\beta C_{t+j}}{C_{t+j+1}},$$

by manipulating equation (4.2) we get the solution for current consumption as

$$C_t = (1-\beta)\left[\frac{1}{\Pi_t}\left(b_{t-1} + Q_t b_{2,t-1}\right) + \left(S_t + D_t\right) E_{t-1} + \sum_{s=0}^{\infty} \rho_{t,t+s}\left(w_{t+s} L_{t+s} + T_{t+s}\right)\right]. \quad (4.3)$$

Equation (4.3) makes clear how the various transmission mechanisms discussed above, (a)-(c), govern the effect of unexpected shocks on current consumption. Perhaps even more importantly, it shows that heterogeneity in the response of wage income (including transfers) as well heterogeneity in ex-ante positions in nominal bonds,maturity of nominal bonds, and stocks will lead to heterogeneity in consumption.

4.1.2 Static Expenditure Allocation Problems

Given the dynamic consumption-saving problem and solution in the previous section that determines the level of aggregate consumption, we now present the static expenditure allocation problem across various consumption categories, given a level of total consumption, C_t.

C_t is a standard constant elasticity of substitution (CES) aggregator of non-durable consumption goods and the rest of consumption goods, for example, durable and services, denoted by $C_{N,t}$ and $C_{S,t}$ respectively:

$$C_t = \left[(1-\alpha)^{\frac{1}{\eta}} C_{N,t}^{\frac{\eta-1}{\eta}} + \alpha^{\frac{1}{\eta}} C_{S,t}^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}. \quad (4.4)$$

Here, $\eta > 0$ is the elasticity of substitution and $\alpha > 0$ governs the share of the two types of consumption goods. Standard expenditure minimization problem gives the corresponding optimal price indices and relative expenditure shares as:

$$P_t = \left[(1-\alpha) P_{N,t}^{1-\eta} + \alpha P_{S,t}^{1-\eta}\right]^{\frac{1}{1-\eta}},$$

$$\frac{P_{N,t} C_{N,t}}{P_t C_t} = (1-\alpha)\left(\frac{P_{N,t}}{P_t}\right)^{1-\eta}; \frac{P_{N,t} C_{N,t}}{P_{S,t} C_{S,t}} = \frac{1-\alpha}{\alpha}\left(\frac{P_{N,t}}{P_{S,t}}\right)^{1-\eta},$$

where $P_{N,t}$ and $P_{S,t}$ are prices of the non-durable and rest of consumption goods respectively. Hence, relative expenditure shares between non-durable and total consumption are completely governed by relative prices. In particular, expenditure share of non-durable consumption ($M_i, i =$

N) in total consumption is given in logs as

$$\log M_{N,t} = \log(1-\alpha) - (\eta - 1)\log\left(\frac{P_{N,t}}{P_t}\right). \tag{4.5}$$

Next, we model non-durable consumption as an iso-elastic non-homothetic CES aggregator of food and fuel.[20] Hence, expenditure shares of food and fuel ($M_i, i = F, O$ for food and fuel respectively) in non-durable consumption are given by

$$M_{it} \equiv \frac{P_{it}C_{it}}{P_{N,t}C_{N,t}} = \beta_i \frac{E_{Nt}}{P_{Nt}}^{\epsilon_i - 1} \frac{P_{it}}{P_{Nt}}^{1-\sigma_\epsilon}, \tag{4.6}$$

where $P_{i,t}$ are prices of the food and fuel ($i = F, O$ for food and fuel respectively), $E_{Nt} = P_{N,t}C_{N,t}$ is nominal expenditure on non-durable goods, ϵ_i is the slope of the Engel curve, $\sigma_\epsilon > 1$ is the price elasticity and β_i is the expenditure share in non-durable.

In the presence of such non-homotheticity, the expenditure shares depend on the level of real non-durable consumption. Accordingly, relative expenditure shares are

$$\log\left(\frac{M_{it}}{M_{jt}}\right) = \log\left(\frac{\beta_i}{\beta_j}\right) - (\sigma_\epsilon - 1)\log\left(\frac{P_{it}}{P_{jt}}\right) + (\epsilon_i - \epsilon_j)\log\left(\frac{E_{Nt}}{P_{Nt}}\right). \tag{4.7}$$

A good i is a necessity if and only if $\epsilon_i < \bar{\epsilon}$ and a luxury if and only $\epsilon_i > \bar{\epsilon}$, where $\bar{\epsilon}$ is the budget-share weighted average of ϵ_i. This means that iso-elastic non-homothetic CES can allow the same good to be luxury or necessity depending on the level of real expenditure.[21]

4.2 Empirical Evidence on Transmission Mechanisms

We now present empirical evidence on the various transmission mechanisms we developed theoretically above.

[20]For this class of utility function, for a consumption bundle **x**, $U(\mathbf{x})$ is given implicitly as:

$$[\sum_{i=1}^{n} \beta_i^{\frac{1}{\sigma}} U(\mathbf{x})^{\frac{\epsilon_i - \sigma_\epsilon}{\sigma_\epsilon}} x_i^{1-\frac{1}{\sigma_\epsilon}}]^{\frac{\sigma_\epsilon}{\sigma_\epsilon - 1}} \equiv 1,$$

where $\sigma_\epsilon > 0$ ensures global quasi-concavity, and $\frac{\epsilon_i - \sigma_\epsilon}{1-\sigma_\epsilon} > 0$ ensures global monotonicity. Given total expenditure on this bundle of consumption, E, the cost of living index (P) is implicitly given by:

$$[\sum_{i=1}^{n} \beta_i (\frac{E}{P})^{\epsilon_i - 1} (\frac{p_i}{P})^{1-\sigma_\epsilon}]^{\frac{1}{1-\sigma_\epsilon}} \equiv 1.$$

See Matsuyama (2022) for further details and references.

[21]This will be important to interpret some of our empirical results where we find food to be a necessity only for low income households and fuel to be a necessity only for high income households.

4.2.1 Earnings and Income Channel

We start by assessing heterogeneous real income/labor earnings effects of these shocks in the household panel IV local projection framework. That is, we estimate equation (3.1), but with real income/labor earnings as the dependent variable. In our theoretical framework, the intertemporal budget constraint, equation (4.2), and the solution for consumption, equation (4.3), have shown how heterogeneity in effects on labor income (including transfers) can lead to heterogeneity in effects on consumption.

Figures 9 and 10 show the results for food price and oil price shocks respectively. A clear distinction emerges between the two shocks: while oil price shocks do not lead to significant effects on income/earnings, except for some periods for the poorest, food price shocks have a significant and persistent effect on real income and earnings of the poorest.

Moreover, food price shocks also have a significant effect on other lower income groups, especially on their earnings. These negative earnings effects of food price shocks are monotonically decreasing along the income distribution, analogous to their negative consumption effects that we showed in Figure 6.

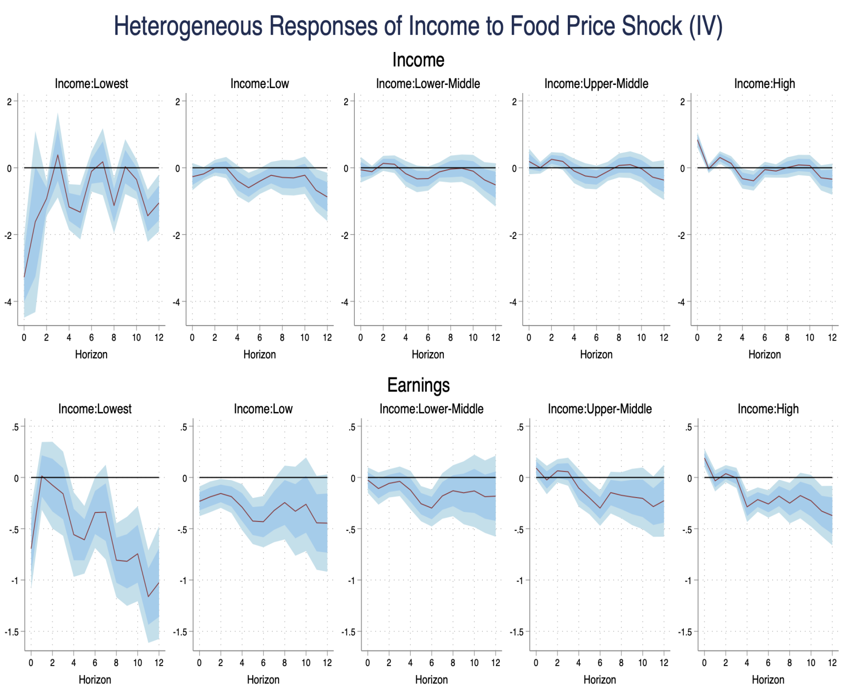

Figure 9: Response of Income to External Food Price Shocks by Income Quintiles (IV)

Notes: Cumulative IRFs on the basis of equation (3.1) where external shock is log changes in global food price, which is instrumented by a global food supply shock and the dependent variable is log changes in household income/ earnings. The light blue region refers to the 90% confidence interval and the dark blue region is the 68 % confidence interval.

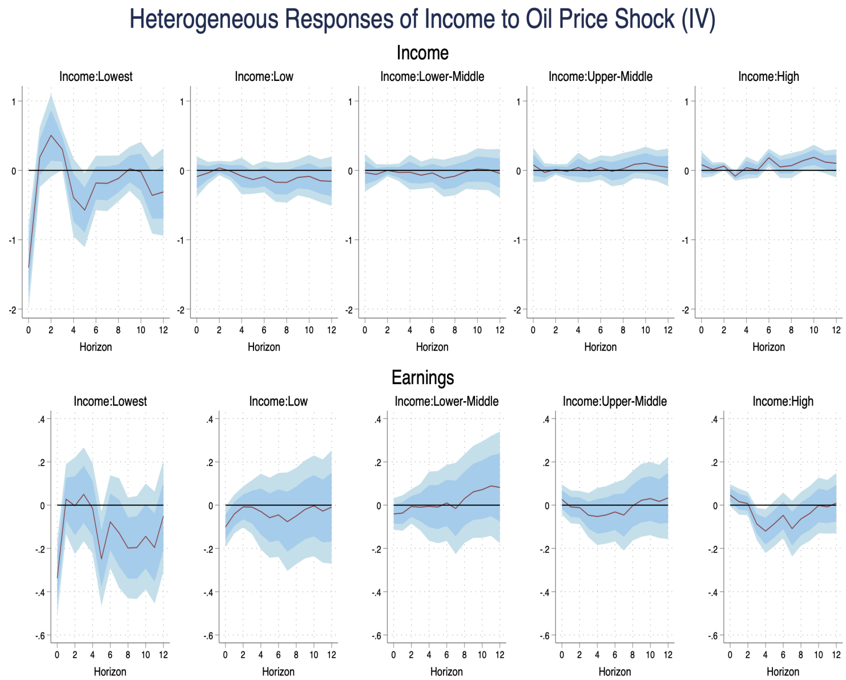

Figure 10: Response of Income to External Oil Price Shocks by Income Quintiles (IV)

Notes: Cumulative IRFs on the basis of equation (3.1) where external shock is log changes in global oil price, which is instrumented by a global oil supply shock and the dependent variable is log changes in household income/ earnings. The light blue region refers to the 90% confidence interval and the dark blue region is the 68 % confidence interval

We want to emphasize the importance of IV estimation for these results. The OLS counterparts to Figures 9 and 10 are in Figures A1 and A2 in the Appendix. As is clear, in OLS estimates, the negative effects of these external price changes on income/earnings are much less pronounced and moreover, the higher income group get affected positively. For global food price shocks, the monotonicity across the income distribution that we see in Figure 9 is less prominent, even while ignoring the sign of the effects. As we have mentioned before, our IV estimation, by isolating global supply side variation, allows us to separate out the effects of global demand that are present in the OLS estimation. Not surprisingly, with positive global demand shocks influencing the OLS estimates, income/earnings are not affected negatively consistently and effects are, on net, in fact positive for the high income group.

4.2.2 Aggregate Price and Relative Price Channel

We now assess the various price channels through which external commodity price shocks can affect consumption inequality. To do so, we investigate whether external price shocks pass-through to domestic prices that Indian consumers face, which is an important channel of transmission. We use state level monthly CPI data, for various components, from MoSPI as measures of domestic prices. We then estimate the dynamic responses of domestic prices, that is, these various components of state level monthly CPI, to global price shocks in a panel local projection framework.

In our theoretical framework, the intertemporal budget constraint, equation (4.2), and the solution for consumption, equation (4.3), have shown how aggregate inflation can affect consumption by affecting the real value of pay-offs of nominal assets and how heterogeneity in ex-ante positions on such assets can lead to heterogeneous effects on consumption. Moreover, assessing the effects of these external shocks on relative prices is critical to understanding relative consumption responses across various categories, as given in equations (4.5) and (4.7).

In addition, while not incorporated in our modelling framework, in standard sticky-price models, if external commodity price shocks lead to aggregate inflation, then by acting like "cost-push" shocks, they can cause a recession and lead to a fall in real income and wage earnings. Empirically, there is evidence for such effects as well. For instance, the oil supply shock of Baumeister and Hamilton (2019) that we use as an IV for global oil prices is shown to contract global industrial production, after a delay and with some imprecision in the estimates, in Baumeister and Hamilton (2019).[22]

The specification for the state-level panel local projection regression to estimate dynamic effects on regional prices (and relative prices) of the external commodity price shocks is:

$$
\begin{aligned}
P_{s,t+h} - P_{s,t-1} = c + \sum_{j=1}^{J} \alpha_j^h (P_{s,t-j} - P_{s,t-j-1}) + \sum_{k=0}^{K} \beta_k^h ext_{t-k} \\
+ \sum_{d=0}^{D} \delta^h D_{t-k} + \gamma_h X_t + \theta_s + \delta_t + \epsilon_{s,t+h} \qquad (4.8)
\end{aligned}
$$

where $P_{s,t}$ denotes various measures of prices or relative prices in period t for state s, h denotes the projection horizon, ext denotes different measures of the external commodity price shock, and $J = 1, K = 1$ are respectively the AR and MA coefficients in the specification.

Moreover, D is the dummy for the Indian government's demonetization policy. X denotes controls for aggregate world conditions: world industrial production as a proxy for aggregate demand (Kilian (2009)); US monetary policy stance as captured by changes in the federal funds rate; and global financial volatility as captured by the US VIX index. Finally, our specification includes state and time fixed-effects. Standard errors are clustered at the state level.

As we discussed before, in addition to OLS results, based on using changes in global food and oil prices as the shock measure ext, we will also present IV results where we instrument the changes in global food and oil prices. These IV results will isolate variation coming from

[22] Relatedly, Kanzig (2021) identifies an oil supply news shock using a different identification strategy and shows that such a shock increases oil prices, increases U.S. inflation, and decreases U.S. economic activity.

supply shocks to global food and oil prices as we discussed previously. We report cumulative impulse responses below, for both our OLS and IV specifications. Table A10 lists our control and instrumental variables.

Table 5: Instrumental and Control Variables in Regional Panel Local Projection

Panel A. Instrumental Variables

- Oil supply shock estimated in Baumeister and Hamilton (2019)
- Food supply shock estimated using a dynamic factor model of non-energy commodity prices

Panel B. Control Variables

- Lags of outcome variables
  - 1 lag
- Lags of global oil and food price changes
  - 1 lag
- State-fixed effects
- Time-fixed effects
  - Calendar month
  - Calendar year
- Aggregate world condition controls
  - World Industrial Production
  - US federal funds rate
  - Change in global VIX
- Demonetization policy dummy

Notes: This table shows our instrumental variables and a set of control variables in our baseline panel regional local projection regressions.

We present results based on the IV specification.[23] Figure 11 shows that there is pass-through into prices: exogenous changes in global oil price affect all sub-components of CPI including core while exogenous global food price changes affect mainly domestic food prices. Dynamic effects of global food price change on overall CPI very closely follows its impact on the food component of CPI.[24] Finally, global oil price shock passes through strongly to domestic energy prices (comprising of fuel, light and transportation cost) in India, but as can be gauged from the response of headline CPI, it also affects core inflation significantly, especially in urban areas. These results show that while increases in food prices can be expected to hurt the poor more because food features more prominently in their consumption basket, oil prices have a more broad based impact through a wider range of sectoral prices.

[23]The OLS results for comparison are in Figure A3.

[24]This is to be expected given that on average, food constitutes around 45 percent of the CPI index share in India.

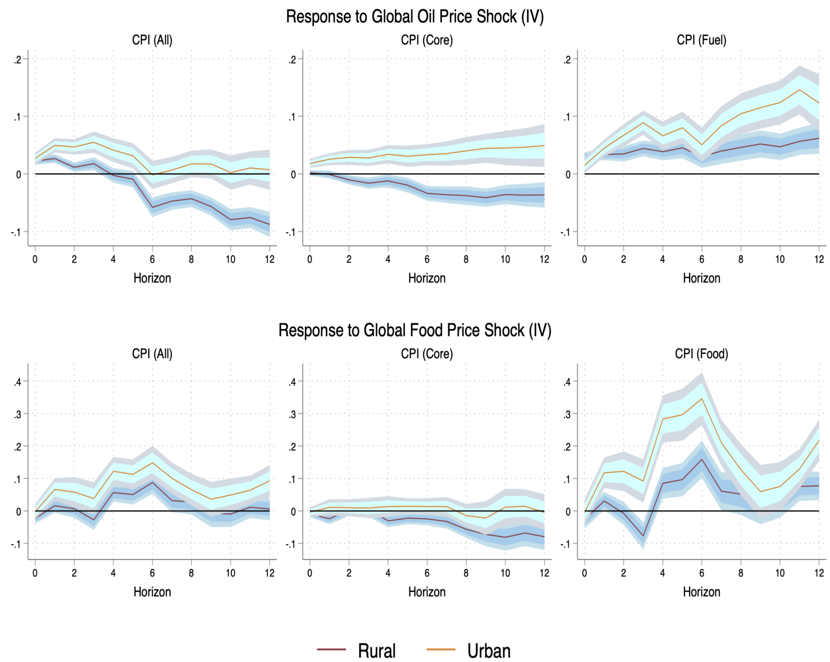

Figure 11: Response of State Level Prices to External Oil and Food Price Shocks (IV)

Notes: Cumulative IRFs on the basis of equation (5.2) where external shock is log changes in global food price in the top panel and log changes in global oil price in the bottom panel. These external price changes are instrumented by global supply shocks. The dependent variable is log changes in state level prices. The light blue region refers to the 90% confidence interval and the dark blue region is the 68 % confidence interval.

In addition, to illustrate clearly the effects of these shocks on relative prices, in Figure 12 we show the responses of three relative prices: ratio of non-durables consumption price to total consumption price (left column), ratio of food price to fuel price (middle column), and the ratio of food or fuel price to the non-durables consumption price (right column).[25] As is clear, global food price shocks increase the relative price of non-durables in India while global oil price shocks, after a delay, decrease the relative price of non-durables in India (primarily because of its impact on core inflation). Moreover, global food price shocks clearly increase the relative price of food in India while global oil price shocks increase the relative price of fuel in India.

[25]Note that the sum of food and fuel prices cover most of non-durable prices in our data.

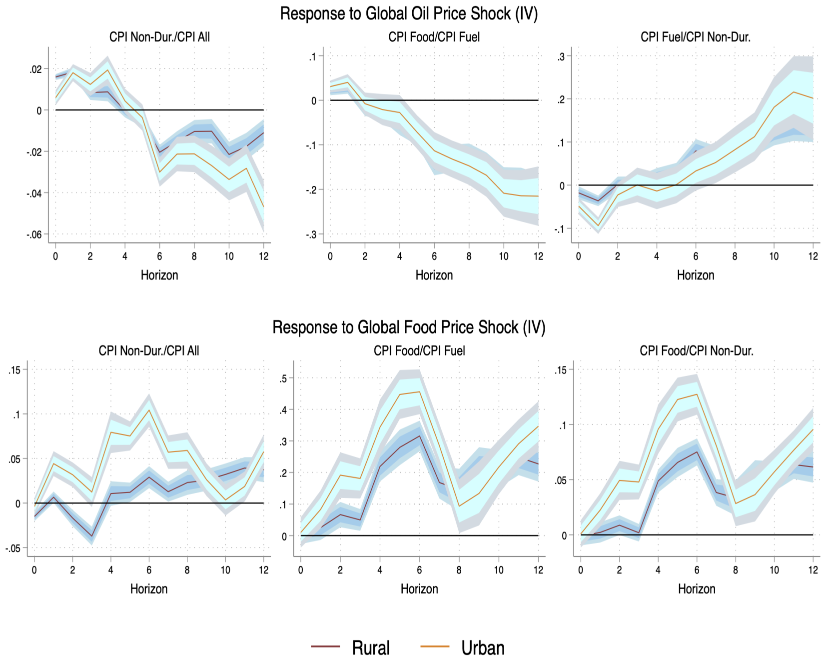

Figure 12: Response of State Level Relative Prices to External Oil and Food Price Shocks (IV)

Notes: Cumulative IRFs on the basis of equation (5.2) where external shock is log changes in global oil price in the top panel and log changes in global food price in the bottom panel. These external price changes are instrumented by global supply shocks. The dependent variable is log changes in state level relative prices. The light blue region refers to the 90% confidence interval and the dark blue region is the 68 % confidence interval.

Overall, these results confirm that external commodity price shocks have a strong impact on different components of regional inflation in India, changing both the general cost of living (for example, as captured by overall CPI or core CPI) as well as relative prices (for example, as captured by food and fuel CPI ratios). This, certainly, has implications for consumer behaviour. In particular, the effects on both headline and core inflation of the global oil price shock suggest that this relative price channel could be important for the transmission of this shock to consumption. Moreover, the effects on relative prices of both shocks suggests that relative consumption expenditures will be affected non-trivially by them.

4.2.3 Expenditure Switching: Non-Durable Goods Consumption Share Effects

We now investigate the effects on nominal consumption expenditure ratio of non-durable to total consumption. Note that in Figure 12 we showed that global food price shocks increase the relative price of non-durables in India while global oil price shocks, after a delay, decrease the relative price of non-durables in India. Estimating effects on ratios of nominal consumption expenditures on non-durables to total consumption now allows us to assess if these share responses are consistent with expenditure switching due to relative price movements, as suggested by the theoretical framework in equation (4.5). Thus, in the household panel IV local projection framework we estimate equation (3.1), but with the nominal expenditure share of non-durable consumption to total consumption as the dependent variable.

Figure 13 presents results for the response of non-durable to total consumption expenditure ratio for both external price shocks. The results show that consistent with expenditure switching that comes about due to relative price changes as given in equation 4.5, this ratio increases for the global oil shock, while it decreases for the global food shock.[26] In addition, response of the non-durable consumption shares are very similar across various income groups, suggesting that relative price movements are the main determinant, as appropriately captured by a homothetic CES aggregatorin equation (4.5).

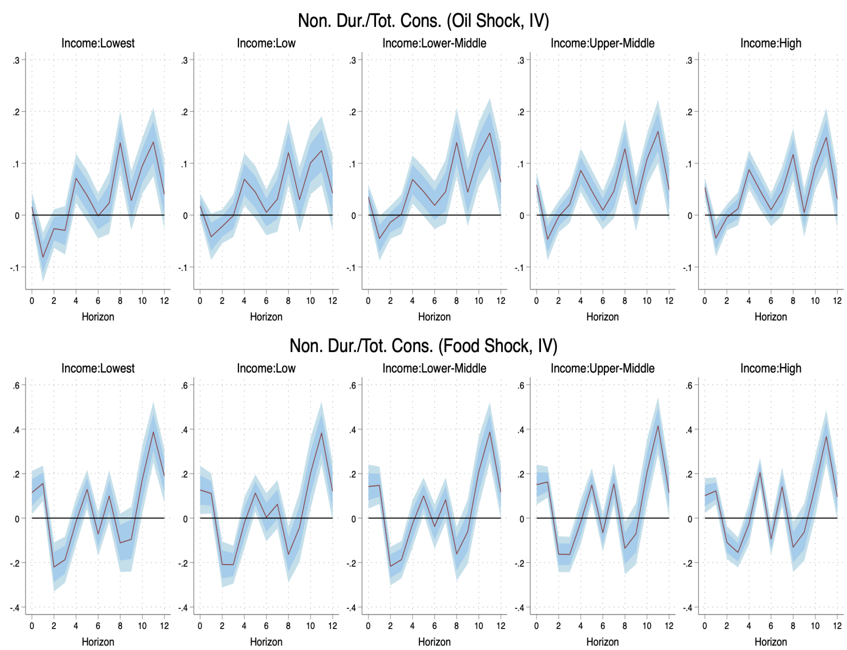

Figure 13: Response of Non-durable to Total Consumption Share to External Oil and Food Price Shocks (IV)

Notes: Cumulative IRFs on the basis of equation (3.1) where external shock is log changes in global food price (top panel), which is instrumented by a global food supply shock and log changes in global oil price (bottom panel), which is instrumented by a global oil supply shock.

4.2.4 Non-Homotheticity: Consumption Share Effects Across Non-durable Categories

We next investigate the effects on nominal consumption expenditure ratios across the two main non-durable categories, food and fuel. Note that in Figure 12 we showed that relative food and fuel prices increase in response to global food and fuel price shocks respectively while in Figures 6 and

[26]The results for the food price shock are comparatively noisier, especially towards the end of the impulse response horizon.

7 we showed that real non-durable consumption expenditure falls in response to both global food and fuel price shocks. Estimating effects on ratios of nominal consumption expenditures of food and fuel now allows us to assess if there are any effects that suggest non-homotheticity or if these share responses are simply consistent with expenditure switching due to relative price movements. Our theoretical framework showed how both of these channels can be captured by equations (4.6) and (4.7).

Figure 14 presents results for food and fuel expenditure ratios with respect to non-durable consumption expenditure while Figure 15 presents results for food to fuel expenditure ratios. As is clear, in response to the global food price shock, food expenditure ratio increases for the poor while in response to the global oil price shock, fuel expenditure ratio increases for the rich. Given the relative price responses in Figure 12, these consumption share responses suggest a role for income effects in relative demand and in particular, we infer that food is a necessity for the poor while fuel is a necessity for the rich. We also note that the responses of the two low income groups are very similar. In other words, this is evidence for non-homotheticity in preferences with variation across the rich and poor in terms of essential goods.

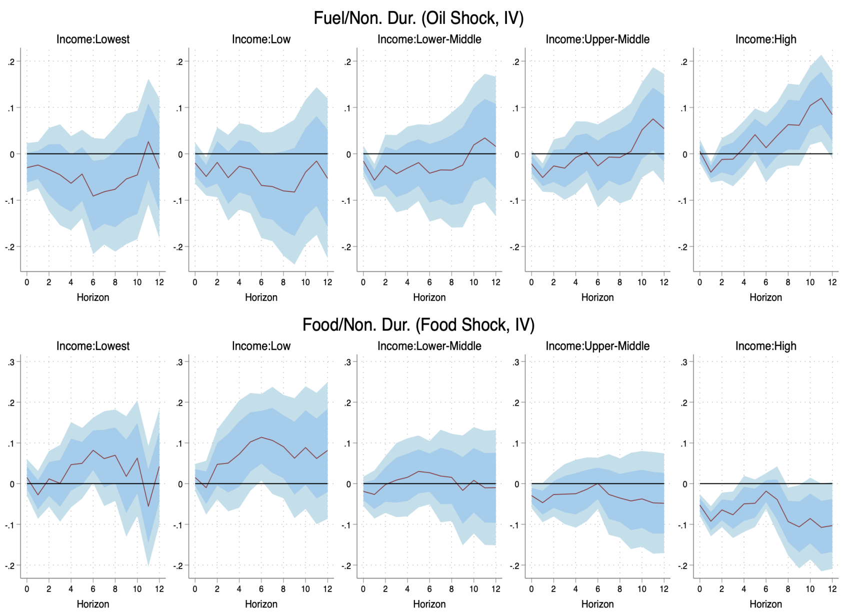

Figure 14: Response of Food and Fuel to Non-durable Consumption Shares to External Oil and Food Price Shocks (IV)

Notes: Cumulative IRFs on the basis of equation (3.1) where external shock is log changes in global oil price (top panel), which is instrumented by a global oil supply shock and log changes in global food price (bottom panel), which is instrumented by a global food supply shock.

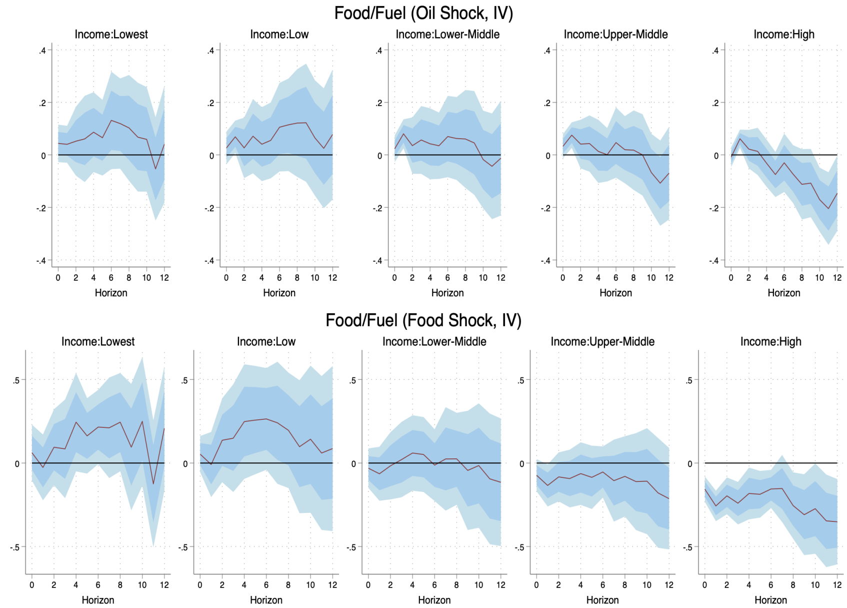

Figure 15: Response of Food to Fuel Consumption Shares to External Oil and Food Price Shocks (IV)

Notes: Cumulative IRFs on the basis of equation (3.1) where external shock is log changes in global oil price (top panel), which is instrumented by a global oil supply shock and log changes in global food price (bottom panel), which is instrumented by a global food supply shock.

By looking at detailed food sub-categories, we next delve into these results that suggest non-homothetic preferences for food for the poor. This is warranted as food is a composite category and as such, there might be worries that our results so far mask a lot of interesting heterogeneity. We focus on the food price shock as it is likely to be most informative about the mechanisms and lead to sharper results.

First, in Figure 16 we present results for relative price responses of various food components, as ratio to fuel prices, using state level CPI data. That is, Figure 16 presents in a more dis-aggregated form the results that we presented in Figure 12. It shows that in response to an exogenous increase in global food prices, relative prices of many food categories (compared to fuel prices) increase. While the increase in relative price of food categories is broad-based, quantitatively, they appear particularly salient for certain food types, such as pulses, sugar, oil and fats, and vegetables. In addition, we can see that the increase in relative prices of food categories is a common phenomenon across rural and urban India.

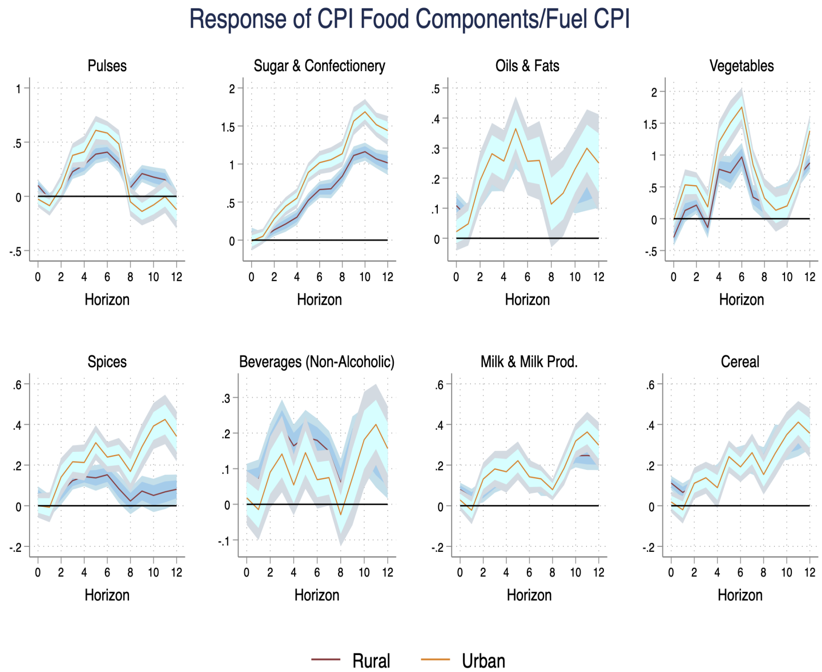

Figure 16: Response of State Level Relative Prices to External Food Price Shocks (IV)

Notes: Cumulative IRFs on the basis of equation (5.2) where external shock is log changes in global food price. The external food price changes are instrumented by global supply shocks. The dependent variable is log changes in state level relative prices, the ratio of various food category CPI to fuel CPI. The light blue region refers to the 90% confidence interval and the dark blue region is the 68 % confidence interval.

Next, in Figures 17 and 18 we present results for responses of various food components to fuel expenditure ratios, when global food prices increase. That is, Figures 17 and 18 present in a more dis-aggregated form the results that we presented in Figure 15. They show that evidence for non-homotheticity in preferences of the poor (including the two low income groups) with respect to various food categories is quite clear for pulses and sugar. In addition, in these two food categories, the rich clearly engage in expenditure switching. In other words, pulses and sugar are essentials for the poor but not for the rich.

Moreover, Figures 17 and 18 show that the pattern of lack of expenditure switching by the poor (again including both the low income groups) for various food categories is quite prominent. For several food categories, such as oil and fats, vegetables, spices, and beverages, the results, while noisier than for pulses and sugar, are still consistent with non-homothetic preferences of the poor combined with standard expenditure switching behavior by the rich. Finally, we note that milk and cereals show nuanced results. In particular, milk consumption behavior depicts standard expenditure switching for all income groups while for cereals, we do not observe evidence consistent with it being an essential good for the poor, even while focusing only on point estimates.[27]

[27] Of course, as we noted before, the public distribution system of the government is mainly focused on cereals, which might have affected our results.

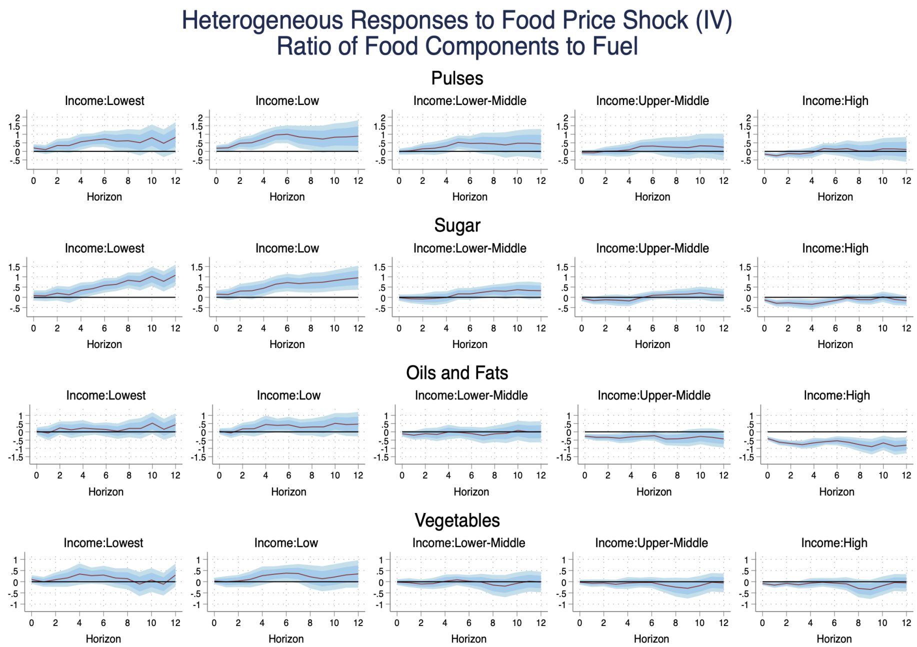

Figure 17: Response of Detailed Food Categories to Fuel Consumption Shares to External Food Price Shocks (IV)

Notes: Cumulative IRFs on the basis of equation (3.1) where external shock is log changes in global food price (bottom panel), which is instrumented by a global food supply shock.

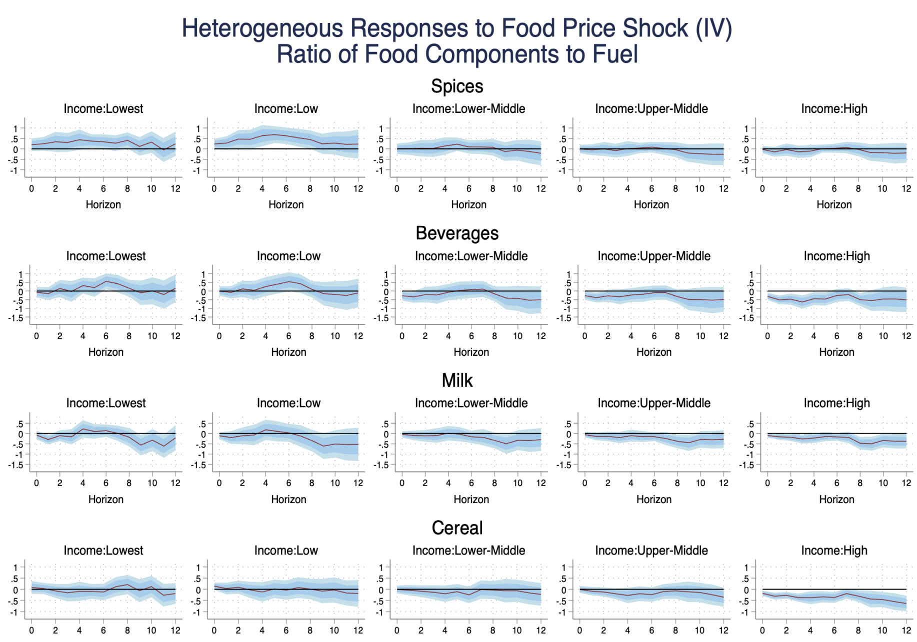

Figure 18: Response of Detailed Food Categories to Fuel Consumption Shares to External Food Price Shocks (IV)

Notes: Cumulative IRFs on the basis of equation (3.1) where external shock is log changes in global food price (bottom panel), which is instrumented by a global food supply shock.

5 Discussion, Sensitivity Analyses, and Extensions

In this section, we discuss some features of the empirical results that we have presented so far that demand further attention and context. We also discuss some key sensitivity analyses to show that our key conclusions regarding heterogeneous consumption impact of global price shocks is robust. Finally, we discuss some extensions that provide complementary evidence.

5.1 Discussion

We start by discussing some aspects of our results that need further elaboration and also put them in context with related literature. First, in Figure A4 we compute summary statistics to compare earnings and non-durable consumption responses from Figures 6, 7, 9, and 10. For all income groups other than the poorest, effects on consumption are larger in magnitude than that on labor earnings. What can explain such a large consumption response? From the point of view of the theoretical model presented in Section 4.1.1, and in particular, the solution for consumption in equation (4.3), a relatively larger response of consumption (compared to the present discounted value of labor earnings using a constant discount factor) may arise either due to time-varying interest rates and wealth effects or due to asset price changes that alter the real value of payoffs from ex-ante asset positions. We, in fact, do find evidence of such effects in Indian macro data, as presented in Figure A5. A rise in global food and oil prices, instrumented by corresponding supply shocks in an aggregate time series local projection framework, leads to a rise in India's short term interest rate spread (compared to the U.S. benchmark) and lowers stock prices. Such an effect on interest rates is further confirmed using detailed annual bank-branch level (weighted) average lending rate data in a panel regression in Table A6.[28]

We also note that our results showing a strong response of consumption to these shocks (even non-durable consumption), compared to wage income and overall income, connect to the unconditional stylized facts from the emerging market business cycle literature. For instance, for a large sample of countries, Uribe and Schmitt-Grohe (2017) documents that consumption growth is clearly more volatile than income growth for emerging market economies and that consumption-smoothing in this sense appears to be limited. Using Indian annual data (1965-2010), Uribe and Schmitt-Grohe (2017) finds that relative volatility of consumption is higher than income (relative volatility $\frac{\sigma_c}{\sigma_y}$: 1.07) in India, while we reach the same conclusion using first-differenced (relative volatility $\frac{\sigma_c}{\sigma_y}$: 1.94) or HP filtered (relative volatility $\frac{\sigma_c}{\sigma_y}$: 1.35) quarterly national income accounts data (1996:Q2 to 2019:Q4).

Another important insight emerges from Figure A4 while comparing the effects on earnings with the effects on non-durable consumption for food price shocks. Earnings effects of the exoge-

[28] Data source of the detailed interest rate data is Basic Statistical Return of Reserve Bank of India, 1998-2016.

nous rise in food price are clearly much larger for the poorest than for the poor (Figure 9), but non-durable consumption effects are comparable (Figure 8). This suggests a role for the public distribution system as an insurance mechanism for those below the poverty line.

Second, in Figure A6 we compute summary statistics to compare the income and earnings responses presented in Figures 9 and 10. Here, we observe that while food shocks have persistent negative impact on wage earnings of the poorest three groups, income effects appear either to be more transitory as they recover within a year or not always statistically significant. This points towards role of government transfers and possibly, capital income, in cushioning the earnings loss.[29] While less dramatic for higher income groups, even for them, income loss is less persistently negative than earnings loss, which again suggests financial income as a source of a hedge against persistent labor income risk. Moreover, the richer income groups might be able to invest in inflation-protected securities or in real assets, which can hedge them against inflation that arises due to the food price shocks. This makes their real (total) income less cyclical than real wage income.

Third, as seen in Figure 9, what might be an economic mechanism at work that gives a clear role for the income/earnings channel for food price shocks? This can be rationalized based on the fact that most of the poorest work in the informal sector in India, as documented in Table A7, where there is no inflation adjustment in nominal wage income.[30] In other words, inflation is very likely to outstrip nominal wage growth for the poor. With a rise in oil prices and its broad-based price impact, there is more likely an immediate impact on the cost of living of the middle class, a large fraction of whom work in the more organized, formal sector. Consequently, there is a nominal wage adjustment of the middle class which then percolates to the nominal income of the poor.[31] However, with a rise in global food price and its direct effect on domestic food prices, cost of living of the poor rises disproportionately due to the higher share of food in the consumption basket of the poor.[32] This however, does not set off the same nominal wage adjustment process in the informal sector and as a result, we observe a decline in the real earnings of the poor.[33]

Fourth, in a summary statistics format, in Figure A7 we compare the non-durable and total consumption responses to global food and oil price shocks from the IV panel results presented

[29]Note that labor earnings and transfers is the major component of income for the poorer group as described in Table A3, similar to the observation in Lee, Macaluso, and Schwartzman (2021) comparing Black and White households in the US.

[30]Note that the classification of formal and informal occupations for CMIE data is from IIM Bangalore doctoral student Shweta Shogani's ongoing PhD thesis work. We are extremely grateful to her for sharing this classification.

[31]We do observe a temporary decline in the real income and earnings of the poor immediately after the oil supply shock as well.

[32]Summary statistics for these various income groups, including share of food consumption, are presented in Appendix 7.2, which show this pattern.

[33]This impact on real income of the poor is consistent with an order magnitude larger impact of inflation on household income as observed in Cardoso, Ferreira, Leiva, Nuño, Ortiz, Rodrigo, and Vazquez (2022).

in Figures 6 and 7. Remarkably, the elasticity of total consumption is uniformly larger than that of non-durable consumption, pointing towards larger response of durable consumption to external price shocks.[34]

5.2 Sensitivity Analyses

The answer to our key research question: does household consumption response in India to global price shocks differ by income levels, is a clear yes. Moreover, different global shocks lead to different patterns of consumption heterogeneity: global food prices have a monotonically larger impact on poorer segments of the population, whereas global oil prices affect low- and middle-income groups similarly.

Naturally, our answer may be sensitive to how we assign individuals to different income groups. In our baseline results summarized in Figures 5 and 8, households are grouped according to cut-offs based on total household real income in the initial period, 2014. Moreover, while the definition of the groups is on the basis of the initial income distribution, depending on current income, households can and do transition to a different income group over time. In this section, we report two important sensitivity analyses of our baseline results where we change the definition of income groups.

In the first exercise, instead of total household real income, we group households according to *per capita* household real income in the initial period. Because average household sizes differ by income groups, per capita household income may more accurately capture the resources available to household members, as argued in Deaton (2019). Indeed, characteristics of households by per capita income deciles, as reflected in Table A8, are somewhat different from those reported in our baseline summary statistics in Table A1. In order to account for this, we group households into five income groups according to per capita income deciles and estimate the heterogeneous consumption responses according to equation 3.1. Summary statistics of non-durable consumption response, estimated using panel IV regressions, are in Figure A8. The results in Figure A8 reflect the same pattern of heterogeneous consumption response as in Figure 8.

In the second exercise, we retain the grouping according to total household real income in the initial period, but we restrict the transition matrix. The baseline transition matrix across income groups is presented in Table A9. While more than 80% of households remain in the same income group over time (as captured by the diagonal entries of Table A9), there are some households who transition from the highest to lowest income groups. Such a transition can potentially reflect measurement error. In order to restrict such unusual movements, we estimate the baseline panel

[34] Note that total consumption includes non-durable, durable, and some service consumption. The excess volatility of durable consumption is a well-known empirical fact in other contexts (see, for example, Alvarez-Parra, Brandao-Marques, and Toledo (2013)) and can be rationalized in canonical models of consumption smoothing.

IV local projection framework of equation 3.1 while restricting the transition matrix such that no household are allowed to move more than two (absolute) steps in the transition matrix. The resulting summary statistics of non-durable consumer response is in Figure A9. These results again are similar in nature to the baseline results of Figure 8.

Thus, alternate definitions of income groups leave our key conclusions regarding heterogeneous household consumption response to global price shocks unchanged. While everyone suffers consumption losses due to rising food prices, poorer income groups are far more vulnerable to such food price shocks. In contrast, low and middle income groups suffer equally from an increase in global oil prices.

5.3 Extensions

In this section, motivated by the vast regional heterogeneity of India, we conduct two extensions of our baseline empirical framework.

In the first exercise, in our baseline household regression as given in equation (3.1), we allow the impact of global price shocks to differ not just by income groups, but also by the location (rural or urban) of the household. We may reasonably expect these responses to differ by location because, among other stark differences, households who work in agriculture primarily reside in rural areas and may be differentially impacted by food price shocks. Our extended specification is as follows:

$$c_{i,t+h} - c_{i,t-1} = c^{g(t),h} + \beta_0^{g(t),h} ext_t \times \mathbb{1}_{i\in g} \times \mathbb{1}_{i\in r} + \sum_{k=1}^{K} \beta_k^{g(t),h} ext_{t-k} \times \mathbb{1}_{i\in g} \times \mathbb{1}_{i\in r}$$
$$+ \sum_{d=0}^{D} \delta^{g(t),h} D_{t-k} + \sum_{j=1}^{J} \alpha^{g(t),h}(c_{i,t-j} - c_{i,t-j-1}) + \gamma^{g(t),h} X_t + \epsilon_{i,t+h} \tag{5.1}$$

where $\mathbb{1}_{i\in r}$ captures whether household i resides in an urban or a rural area, $r =$ rural, urban.

Results for consumption responses are presented in Figures A10 and A11, and the corresponding income results are in Figures A12 and A13. Low income groups in rural areas seem to be suffer a larger (compared to their urban counterparts) non-durable consumption loss due to a global food price shock, while the high income households in rural areas suffer a larger (again, compared to their urban counterparts) consumption loss due to a global oil price shock. On the earnings/income side, the sharp drop in earnings for the lowest income households due to an increase in global food prices seems to be driven by urban households. Apart from these differences, the broad pattern of responses are largely similar across urban and rural India.

In the second exercise, we assess the effects on regional inequality of the global commodity price shocks, which we make operational by constructing several measures of regional inequality.

The specification for the state-level panel local projection regression to estimate dynamic effects on regional consumption inequality of the external commodity price shocks is:

$$Cineq_{s,t+h} - Cineq_{s,t-1} = c + \sum_{j=1}^{J} \alpha_j^h (Cineq_{s,t-j} - Cineq_{s,t-j-1}) + \sum_{k=0}^{K} \beta_k^h ext_{t-k} + \sum_{d=0}^{D} \delta^h D_{t-k} + \gamma_h X_t + \theta_s + \delta_t + \epsilon_{s,t+h} \tag{5.2}$$

where $Cineq_{s,t}$ denotes various measures of state-level inequality (in log) for total consumption and non durable consumption in period t, h denotes the projection horizon, ext denotes different measures of the external commodity price shock, and $J = 1, K = 1$ are respectively the AR and MA coefficients in the specification. Finally, our specification includes state and time fixed-effects. Standard errors are clustered at the state level. This specification is similar to the state price regression specification outlined in 4.8.

For the food price shock, Figure A14 presents the OLS results while Figure A16 presents the IV results. Figure A16 shows that consumption inequality increases robustly following an exogenous change in global food prices, when we use our estimated food IV to instrument for global food price changes. For the oil price shock, Figure A15 presents the OLS results while Figure A17 presents the IV results. We see that an increase in global oil prices does not have as clear of an effect on consumption inequality as does global food prices, suggesting that inequality measures might not capture the subtle ways in which household get differentially affected along the income distribution by exogenous oil price shocks.

6 Conclusion

In this paper, we explore the distributional implications of the increasing global food and oil prices by utilizing rich consumption and income panel data from India. Our research findings indicate that regional (state-level) consumption inequality persistently rises after a positive shock to global food prices. To estimate heterogeneous consumption effects along the income distribution, we employ a household panel local projection IV method. Our results show robust evidence that lower income deciles are more affected by an exogenous increase in food prices, while both lower and middle income deciles are hit by an exogenous increase in fuel prices. We also evaluate whether these effects on consumption operate through the income/earnings or relative price channels. Examining the relative expenditure responses in the light of the relative price effects allows us to uncover very interesting patterns of non-homotheticity in non-durable consumption where food, especially some categories such as pulses and sugar, are essential consumption goods for the poor while fuel is essential for the rich.

Our findings have significant implications for monetary policy. The substantial distributional effects on consumption that we have documented suggest that in emerging markets, monetary policy may need to react to external shocks in the food and oil sectors, despite the flexibility of prices in these sectors. This response would be advantageous in terms of reducing consumption inequality in the economy. In our future research, we intend to further investigate this matter by studying the optimal monetary policy in a heterogeneous agent open economy model.

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7 Appendix

7.1 Data Description

Survey Data

We use data from the Consumer Pyramid Household Survey (CPHS) dataset, a survey conducted by the Centre for Monitoring the Indian Economy (CMIE). The CPHS has surveyed over 236,000 unique households since it began in 2014, and is the most comprehensive longitudinal consumption data available for India. The CPHS is itself divided into 4 distinct datasets: Consumption Pyramids, Income Pyramids, People of India Survey and Aspirational India survey. We use the data from the Consumption and Income Pyramid surveys to construct our variables, and data from the People of India survey for our control variables about demographics. Our analysis spans data from January 2014 to December 2019.

Level variables

We construct income, earnings, and consumption categories closely following the definitions given by Coibion and Gorodnichenko (2017). We first construct income as the sum of household income from rent, wages, self-production, private transfers, government transfers, business profits, sale of assets, lotteries and gambling, pension, dividends, interest and deposit provident fund and insurance. These categories are an exhaustive list of all income sources collected in the CPHS survey.

Additionally, we construct narrow and broad measures of capital income. The narrow measure of capital income includes income accrued from dividends, interest and business, whereas the broad measure includes the income sources from the narrow measure as well as income accrued from sale of assets and rent.

Our (labor) earnings measure is constructed using only the category of income from wages and overtime bonus.

We construct consumption closely matching the categories constructed by Coibion and Gorodnichenko (2017). The consumption variable we construct is the sum of non-durable consumption (food, fuel, intoxicants), durable consumption (appliances, furniture, jewelry, clothing, electronics, toys, cosmetics), and service consumption (electricity, entertainment, public transport, airfare, highway tolls, beauty services, fitness services, restaurants etc). We then deflate all our income and earnings measures by the Consumer Price Index (CPI) - Combined series (2012 base). We also winsorize our constructed variables at the 1 percent level.

Inequality variables

The measures of inequality we construct using these variables are: Gini coefficients, cross-sectional standard deviations and differences between individual percentiles (90th-10th and 75th-25th) on log levels.

External shock measure

We use FAO's Food Price Index (FPI) and WTI crude oil prices for our food and oil prices. We construct shocks by taking differences of the logs of both food and oil prices.

Data on Prices

The Ministry of Statistics and Programme Implementation (MoSPI), Government of India, releases detailed data on prices at the monthly frequency. The series has 2012 as the base year and data is available from January 2011. The data is dis-aggregated by geography as well as by products. Geographically, data is available by urban and rural areas within each state. There is some missing data at the state-geography level, but it is not a major concern (97% of India's consumption is covered in the state-geography data).

On the product side, aggregate CPI is broken down into six broad sub-classifications (national level weights are in parenthesis): i) food and beverages (45.86%); ii) pan, tobacco, and intoxicants (2.38%); iii) clothing and footwear (6.53%); iv) housing (10.07%); v) fuel and light (6.84%); and vi) miscellaneous (28.32%). The coverage (in terms of sub-products) varies across the sub-classifications. The most detailed data is available only for food categories. It comprises of i) cereals and products; ii) meat and fish; iii) egg; iv) milk and milk products; v) oils and fats; vi) fruits; vii) vegetables; viii) pulses and products; ix) sugar and confectionery; x) spices; xi) non-alcoholic beverages; and xii) prepared meals, snacks, sweets, etc.

We construct price indexes for fuel, non-durables, and "core" categories. Although the MoSPI provides an index for fuel, it only includes fuel used for cooking and excludes the fuel used in transportation; the index for transportation is available under the "miscellaneous (transportation and communication)" category. While this category has several missing values at the state-geography level, the missing values are concentrated among smaller states (such as Andaman and Nicobar islands) that contribute to under 3% of India's consumption. We use the state-geography level weights of fuel and light (FL) and miscellaneous (transportation and communication, or TC) categories to construct a new composite index:

$$CPI(FL+TC)_{sgt} = \frac{W(FL)_{sg}CPI(FL)_{sgt} + W(TC)_{sg}CPI(TC)_{sgt}}{W(FL)_{sg} + W(TC)_{sg}}$$

where subscript s represents state, $g \in \{Urban, Rural\}$ represents geography, and t represents month. This provides a closer measure of energy consumption.

Next, the "core" index is constructed to capture prices of non-food and non-fuel components of the consumption basket. It excludes not just the traditional food and fuel price indices available directly from MoSPI, but also the transportation and communication price index (which are part of the composite fuel index as described above) as well as the prices of pan, tobacco, and intoxicants, which are best thought of as food. This is calculated as

$$CPI(Core)_{sgt} = \frac{100*CPI(All) - W(Food)_{sg}CPI(Food)_{sgt} - W(FL)_{sg}CPI(FL)_{sgt} - W(TC)_{sg}CPI(TC)_{sgt} - W(Pan)_{sg}CPI(Pan)_{sgt}}{100 - W(Food)_{sg} - W(FL)_{sg} - W(TC)_{sg} - W(Pan)_{sg}}$$

The non-durable price index is the complement of the core index – it includes food and the composite fuel prices. It is calculated as

$$CPI(NonDur.)_{sgt} = \frac{W(Food)_{sg}CPI(Food)_{sgt} + W(FL)_{sg}CPI(FL)_{sgt} + W(TC)_{sg}CPI(TC)_{sgt} + W(Pan)_{sg}CPI(Pan)_{sgt}}{W(Food)_{sg} + W(FL)_{sg} + W(TC)_{sg} + W(Pan)_{sg}}$$

7.2 Summary Statistics of Income, Consumption and Household Characteristics

Table A1: Summary Statistics by Income Decile

	No. of Hhs	Income	Consumption	Non-durable Share	Food Share
1st Decile	43,210.66	476.65	1,221.19	0.78	0.62
2nd Decile	8,034.27	4,365.17	4,168.35	0.78	0.64
3rd Decile	10,832.47	5,579.25	4,708.03	0.77	0.63
4th Decile	12,049.10	6,720.92	5,190.72	0.77	0.61
5th Decile	12,673.92	7,972.92	5,669.16	0.76	0.60
6th Decile	14,400.27	9,613.48	6,093.47	0.76	0.59
7th Decile	15,089.84	11,736.90	6,655.97	0.75	0.58
8th Decile	15,101.95	14,850.60	7,345.38	0.74	0.56
9th Decile	15,345.27	20,166.59	8,302.80	0.73	0.55
10th Decile	19,239.84	37,353.66	10,447.05	0.72	0.51

Notes: This table presents some summary statistics by income deciles. Income and consumption are in real terms where they are deflated by the CPI (all, 2012=100) Non-durable and food share refer to consumption shares of non-durable and food consumption.

Table A2: Socio-Economic Variables by Income Quintiles

	Q_1	Q_2	Q_3	Q_4	Q_5
	Quintile Shares (%)				
Panel A: Religion					
Buddhist	26	13	16	20	25
Christian	30	10	14	20	26
Hindu	30	14	16	18	21
Jain	21	4	10	17	47
Khasi	32	5	6	20	36
Muslim	30	16	19	19	15
Not Applicable	25	1	5	8	62
Other Religion	33	11	14	17	25
Religion not stated	50	9	9	11	20
Sikh	24	7	12	19	38
Panel B: Caste Category					
Intermediate Caste	32	10	14	17	27
Not Applicable	25	1	5	8	62
Not Stated	35	7	11	18	29
OBC	30	15	18	19	18
SC	29	19	19	19	14
ST	41	17	16	14	12
Upper Caste	27	10	14	19	31
Panel C: Education Category					
Upto 7th Std	34	18	19	18	12
Upto 12th Std	28	13	17	20	22
$\geq$ College Graduate	24	5	9	17	44
Panel D: Region					
Urban	25	13	17	20	25
Rural	39	16	16	15	13

Notes: This table presents summary statistics on some socio-economic variables by income deciles.

Table A3: Income Composition by Income Groups

Income Group	Earnings	Transfers	Capital Income (Broad)	Pensions
Lowest	.63	.16	.03	.03
Low	.88	.04	.05	.02
Lower middle	.84	.02	.09	.04
Upper middle	.75	.02	.15	.08
High	.67	.01	.21	.10

Notes: This table presents some summary statistics by income groups, where it shows shares of various sources of income.

7.3 Additional Results

7.3.1 OLS Results on Income/Earnings

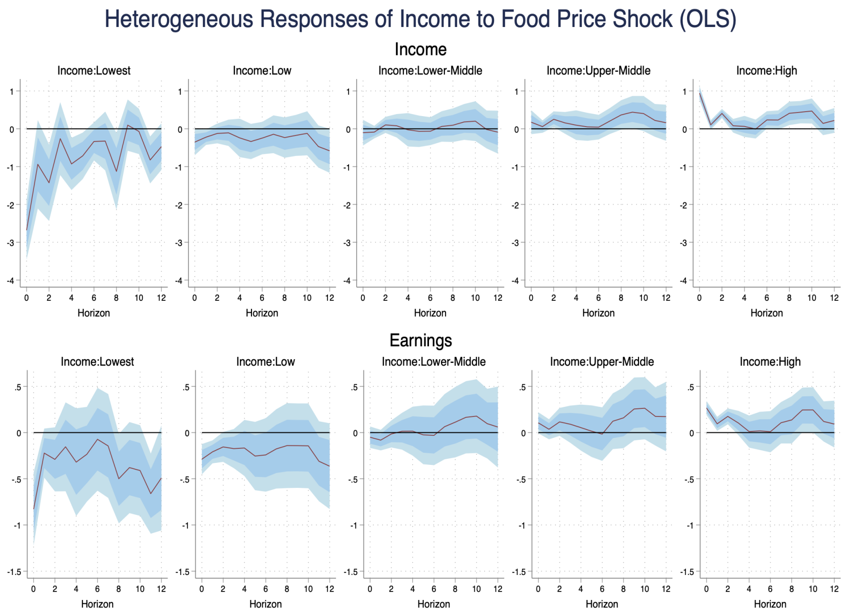

Figure A1: Response of Income to External Food Price Shocks by Income Quintiles

Notes: Cumulative IRFs on the basis of equation (3.1) where external shock is log changes in global food price.

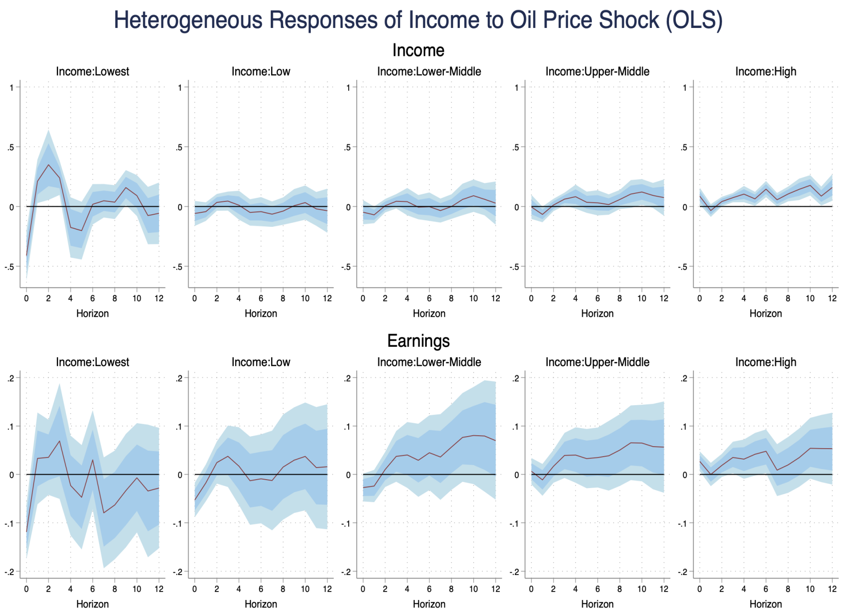

Figure A2: Response of Income to External Oil Price Shocks by Income Quintiles

Notes: Cumulative IRFs on the basis of equation (3.1) where external shock is log changes in global oil price.

7.3.2 OLS Results on Regional Inflation

The estimation framework is:

$$p_{s,t+h} - p_{s,t-1} = c + \sum_{j=1}^{J} \alpha_j^h (p_{s,t+h-j} - p_{s,t-1}) + \sum_{k=0}^{K} \beta_k^h ext_{t-k} + \sum_{d=0}^{D} \delta^h D_{t-k} + \gamma_h X_t + \epsilon_{t+h}. \quad (7.1)$$

Here, $p_{s,t+h}$ is the log CPI (overall and various sub components) for state s at horizon h after the shock to external prices at time t; ext denotes different measures of the external commodity price shock, and $J = 3, K = 3$ are respectively the AR and MA coefficients in the specification. Note that we include lagged values of the dependent variable as controls. Moreover, D is the dummy for the Indian government's demonetization policy. X denotes controls for aggregate world conditions: world industrial production as a proxy for aggregate demand (Kilian (2009)); US monetary policy stance as captured by changes in the federal funds rate; and global financial volatility as captured by the US VIX index. Finally, our specification includes state and time fixed-effects.

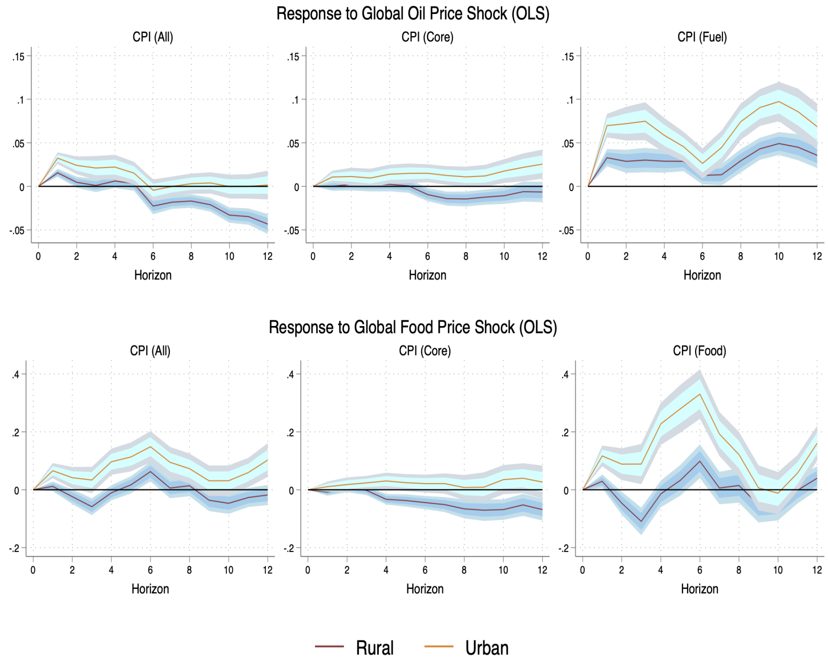

Figure A3: Response of Domestic Inflation to Global Price Shocks

Notes: This figure plots the responses of state-level prices to changes in global food and oil prices. The responses are based on estimates from equation (7.1).

We present the cumulative impulse responses on the basis of equation (7.1) in Figure A3, where the top panel captures the effect of an increase in global food price and the bottom panel captures the effect of an increase in global oil price. Clearly, general CPI and food prices in India respond positively and significantly to an increase a global food price. Relative to general CPI, food becomes more expensive domestically with a positive shock to global food prices. Moreover, this effect on domestic food prices persists over nearly 10 moths following the initial shock to global food prices, which is transitory in nature as we emphasized above. Response of domestic inflation to global oil price shock shows that energy prices rises, as expected, significantly.

7.3.3 First-Stage F-stats for IV Specifications

Table A4: F-statistics for Panel Local Projection IV Regressions of Household Consumption

	(1)	(2)
	Consumption	Non-durable Consumption
	Panel A : Global Food Price Shock & Food Supply IV	
First stage F-stats	5644.9	5684.6
	Panel B : Global Oil Price Shock & Oil Supply IV	
First stage F-stats	810.3	799.3

Notes: This table shows F-statistics from first-stage regressions for our panel IV local projection estimation of effects on household consumption (Column(1)) and non-durable consumption (Column (2)).

Table A5: F-statistics for Panel Local Projection IV Regressions of State-Geography-Level Prices

	(1)	(2)	(3)	(4)
	CPI (All)	CPI (Core)	CPI (Food)	CPI (Fuel)
	Panel A : Global Food Price Shock & Food Supply IV			
First stage F-stats	37,203,407.5	4,981,602.9	2,627,434.5	666,072.5
	Panel B : Global Oil Price Shock & Oil Supply IV			
First stage F-stats	326,462.8	178,680.8	722,970.6	1,667,164.9

Notes: This table shows F-statistics from first-stage regressions for our panel IV local projection estimation of effects on regional prices. Columns (1) through (4) show the F-statistics for estimation of effect on CPI (headline), CPI (Core), CPI (Food), and CPI (Fuel) respectively.

7.3.4 Discussion Results

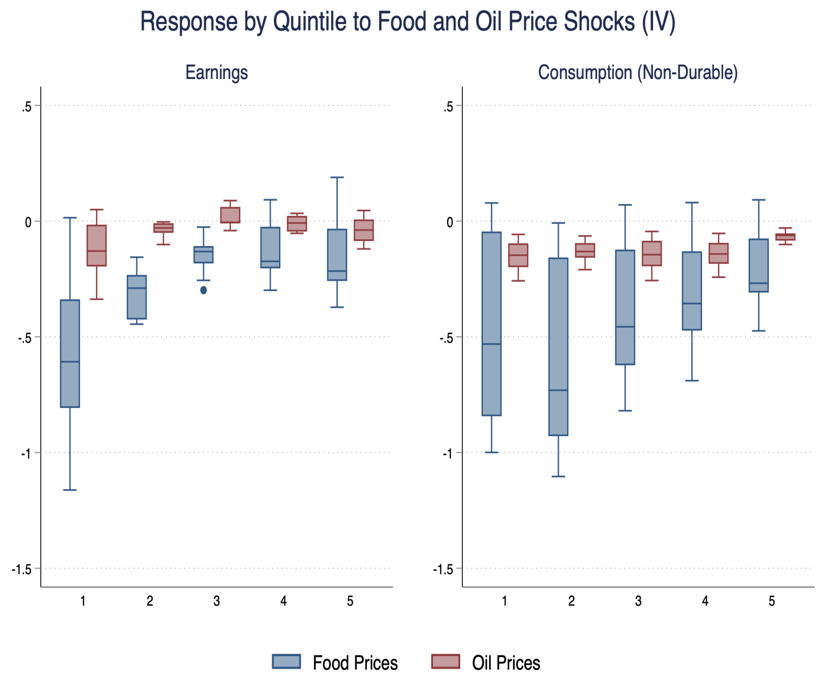

Figure A4: Summary Statistics of Response of Earnings and Non-durable Consumption to Food and Fuel Price Shocks by Income Quintiles (IV)

Notes: This figures is a box and whisker plot that summarizes the responses of income and earnings to the two external shocks that is presented in Figures 6, 7, 9 and 10.

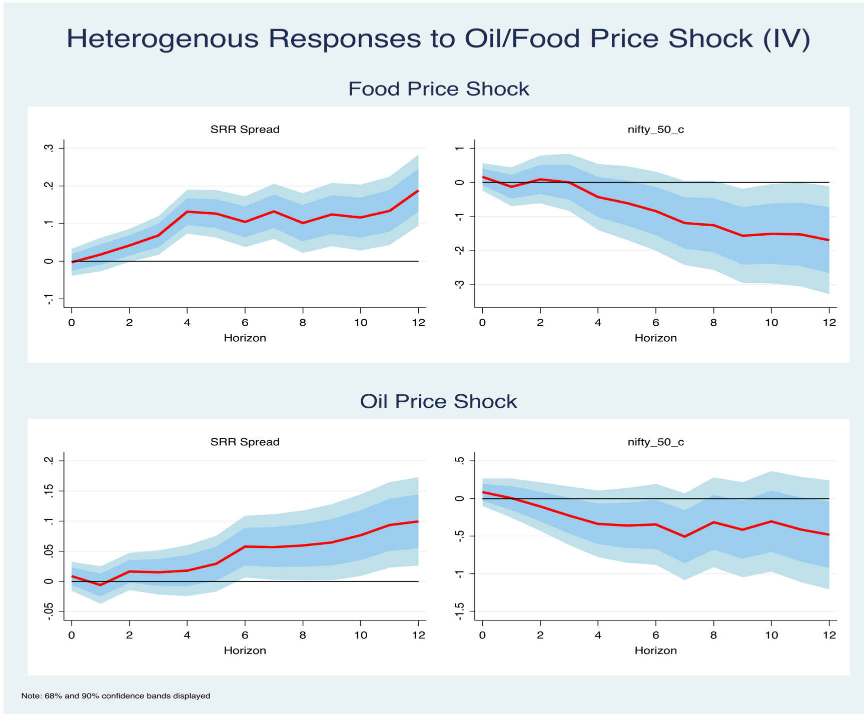

Figure A5: Response of Short Term Interest Rate Spread and Stock Prices to Food and Fuel Price Shocks (IV)

Notes: This figures is the impulse response estimated on the basis of a time series local projection framework.

In Figure A5, in the left columns, we use monthly time series data on short-run (3 month) interest rate spread (relative to the U.S.) as the dependent variable, Y, and Indian industrial production and CPI as well as dummies for global financial crisis, taper tantrum and demonetization as controls, X, in a local projection framework:

$$Y_{t+h} - = c + \sum_{j=1}^{J} \alpha_j^h (Y_{t-j}) + \sum_{k=0}^{K} \beta_k^h ext_{t-k} + \gamma_h X_t + \epsilon_{t+h}.$$

Here, ext is our measure of global food and oil price changes instrumented by the corresponding supply shocks, and $J = 3; K = 3$. In the right two columns, our dependent variables are month-to-month changes in the Indian stock price index, Nifty 50, and the estimated impulse responses are cumulative. Our monthly time series data is obtained from Datastream and CEIC, and covers the period January, 2000 to March, 2018.

Table A6: Impact of Global Food and Oil Price on Branch Level Lending Rate (IV)

	(1) Lending Rate (t)	(2) Lending Rate (t)	(3) Lending Rate (t+1)	(4) Lending Rate (t+1)
Global Food Price Change	0.019***		0.026***	
	(0.0001)		(0.0001)	
Global Oil Price Change		0.009***		0.016***
		(0.0000)		(0.0001)
Lending Rate (t-1)	0.540***	0.536***	0.309***	0.307***
	(0.0023)	(0.0023)	(0.0022)	(0.0022)
Observations	1,161,401	1,161,401	1,014,277	1,014,277
R-squared	0.34	0.33	0.17	0.10
Bank FE	Y	Y	Y	Y
District FE	Y	Y	Y	Y

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Table A6, we use the administrative lending rate data at bank-branch level obtained from the Basic Statistical Returns reported to the Reserve Bank of India. Because the data is annual (1998-2016), we need to aggregate our monthly global price changes to the annual level. Because of the short time series, we use a dynamic panel regression to estimate the impact of global price rises on lending rates contemporaneously and one period ahead (instead of a local projection to estimate the entire horizon of dynamic effects as impulse response functions). Our regression specification is:

$$lr_{b,t+1} = c + \alpha(lr_{b,t-1}) + \beta ext_t + \gamma X_t + \delta_{bank} + \delta^*_{district} + \epsilon_{t+h}$$

As before, ext is our measure of global food and oil price changes instrumented by the corresponding supply shocks and the standard errors are clustered at the district level.

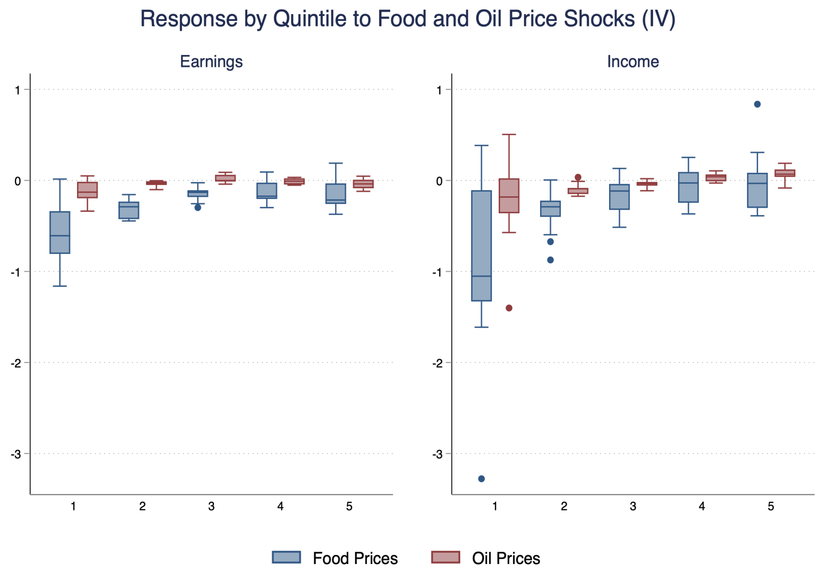

Figure A6: Summary Statistics of Response of Earnings and Income to Food and Fuel Price Shocks by Income Quintiles (IV)

Notes: This figures is a box and whisker plot that summarizes the responses of income and earnings to the two external shocks that is presented in Figures 9 and 10.

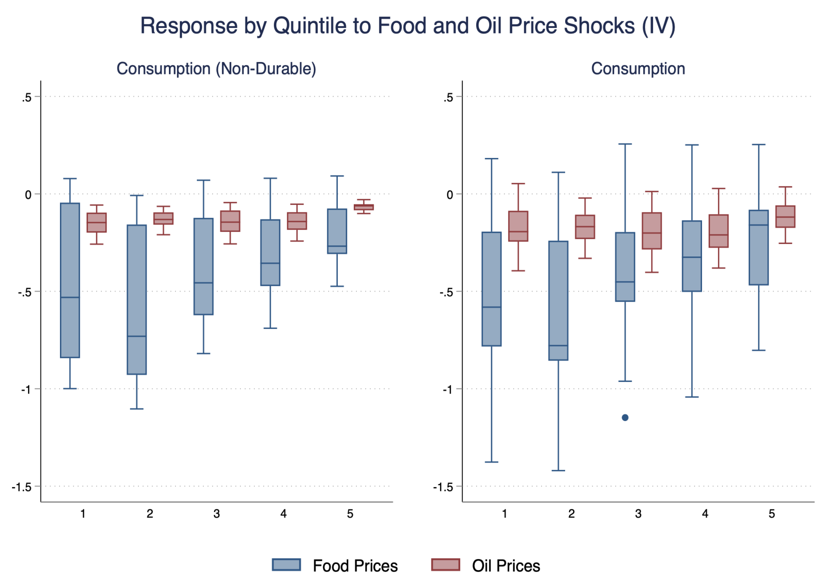

Figure A7: Summary Statistics of Response of Total and Non-durable Consumption to Food and Fuel Price Shocks by Income Quintiles (IV)

Notes: This figures is a box and whisker plot that summarizes the responses of total and non-durable consumption to the two external shocks that is presented in Figures 6 and 7.

Table A7: Share of Formal and Informal Occupations by Income Groups (in %)

Income Groups	Share of Formal Occupation	Share of Informal Occupation
Lowest	34	66
Low	24	76
Low middle	32	68
Upper middle	46	54
High	75	25

Notes: This table presents the average share of formal and informal occupations among people in labor force for corresponding income groups. Informal occupations include agricultural laborers, home-based worker, small farmer, small trader/ hawker/ businessman without fixed premises, self employed entrepreneurs, legislator/ social workers/ activists and wage laborer. Formal occupations include businessman, industrial workers, managers, non-industrial technical employee, organised farmer, qualified self employed professionals, support staff, white collar clerical employees and White-Collar Professional Employees and Other Employees. The share is calculated on the basis of people who report occupations. While for the top four income groups roughly 8 % do not report an occupation, in the lowest income group, nearly 40 % do not report an occupation.

7.3.5 Sensitivity Analysis: Groups on the basis of per capita household income

Table A8: Summary Statistics by Income Decile (Based on Per Capita Household Income)

	No. of Hhs	Income		Consumption		Non-durable Share	Food Share
		Household	Per Capita	Household	Per Capita	Household	Household
1st Decile	43,223.65	728.16	111.33	1,413.53	274.08	0.78	0.62
2nd Decile	6,959.47	5,596.87	916.17	4,888.35	855.09	0.78	0.64
3rd Decile	8,060.78	6,453.36	1,148.40	5,138.74	966.81	0.78	0.63
4th Decile	9,017.66	7,319.30	1,373.23	5,400.72	1,068.39	0.77	0.62
5th Decile	10,436.45	8,173.62	1,621.02	5,646.06	1,183.47	0.77	0.61
6th Decile	12,116.28	9,287.45	1,923.05	5,950.28	1,304.91	0.76	0.60
7th Decile	13,258.50	10,657.55	2,315.70	6,255.31	1,445.09	0.75	0.59
8th Decile	14,910.67	12,704.20	2,869.67	6,713.44	1,619.70	0.75	0.58
9th Decile	18,170.81	16,230.00	3,852.63	7,367.53	1,885.03	0.74	0.56
10th Decile	29,823.33	28,500.95	8,177.00	8,928.43	2,665.15	0.72	0.52

Notes: This table presents some summary statistics by income deciles, where the deciles were calculated based on per-capita household income. Income and consumption are in real terms where they are deflated by the CPI (all, 2012=100) Non-durable and food share refer to consumption shares of non-durable and food consumption.

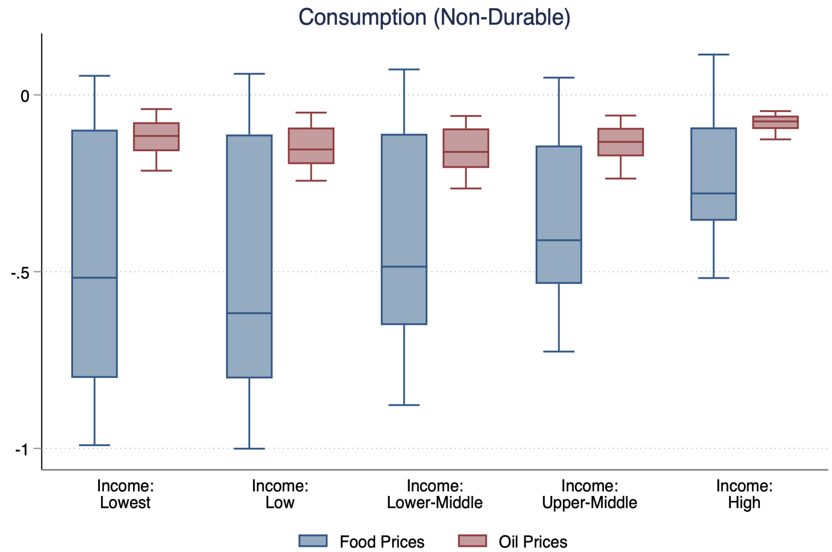

Figure A8: Summary Statistics of Response of Non-durable Consumption to Food and Fuel Price Shocks by Per Capita Income Quintiles (IV)

Notes: This figures is a box and whisker plot that summarizes the responses of non-durable consumption to the two external shocks when households are grouped on the basis of real per capita income in 2014.

7.3.6 Sensitivity analysis: Restricting the income transition matrix

Table A9: Transition Matrix of Real Income

	Q_1	Q_2	Q_3	Q_4	Q_5	Total
Q_1	80.98	4.15	4.40	6.16	4.31	100.00
Q_2	7.26	76.07	13.70	2.21	0.75	100.00
Q_3	4.17	6.35	80.13	8.60	0.75	100.00
Q_4	4.89	0.89	6.87	83.71	3.65	100.00
Q_5	7.70	0.76	1.59	8.15	81.80	100.00

Notes: This table presents the average transition probabilities (in % terms) between different income groups in our sample.

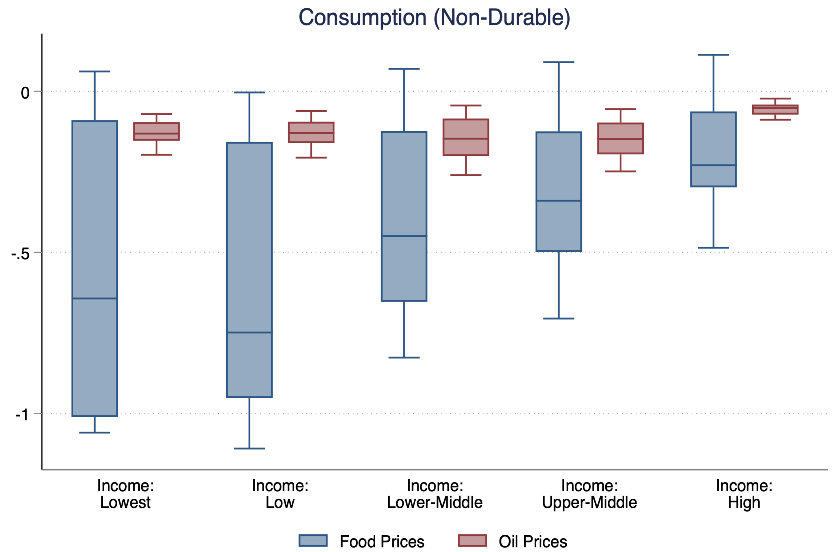

Figure A9: Summary Statistics of Response of Non-durable Consumption to Food and Fuel Price Shocks by Income Quintiles with restricted transition matrix(IV)

Notes: This figures is a box and whisker plot that summarizes the responses of non-durable consumption to the two external shocks while restricting the income transition matrix.

7.3.7 Rural Urban Comparison

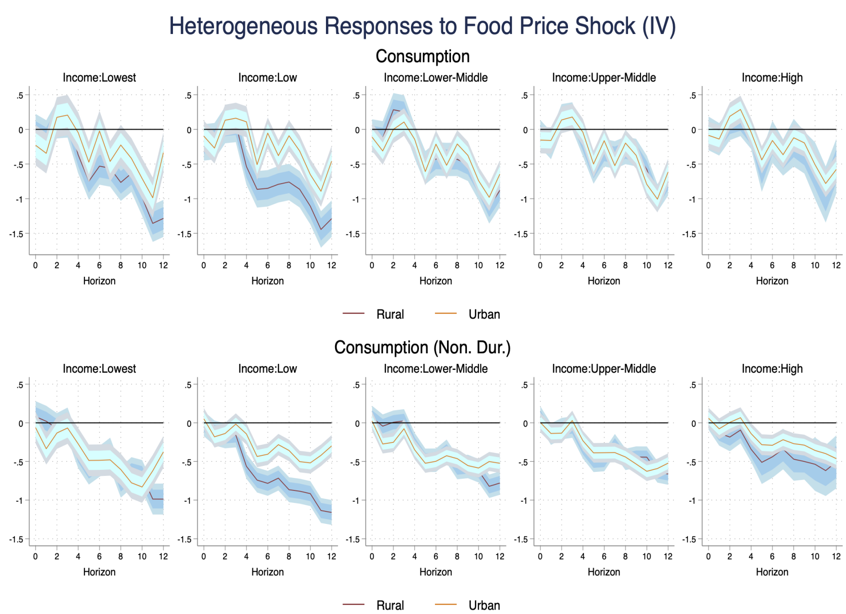

Figure A10: Response of Consumption to External Food Price Shocks by Income Quintiles

Notes: Cumulative IRFs on the basis of equation (5.1) where external shock is log changes in global food price.

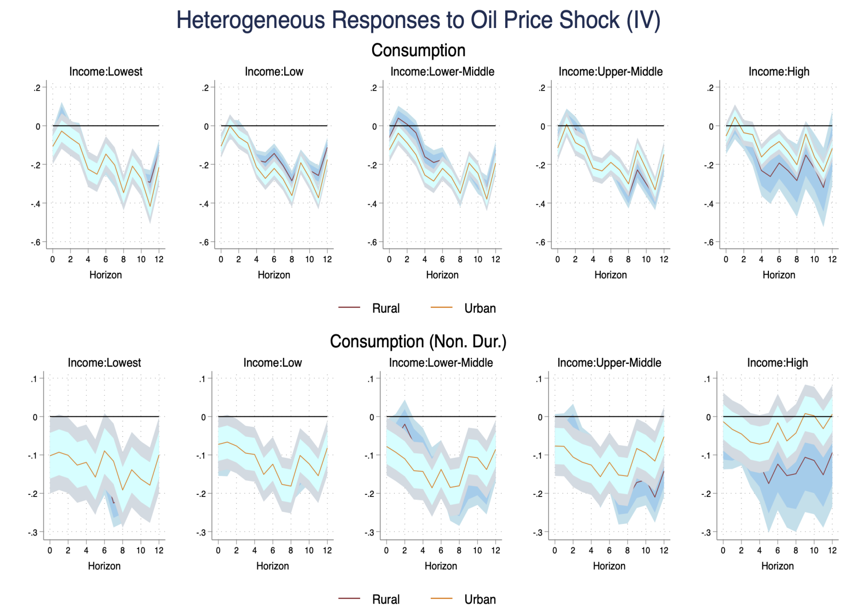

Figure A11: Response of Consumption to External Oil Price Shocks by Income Quintiles

Notes: Cumulative IRFs on the basis of equation (5.1) where external shock is log changes in global food price.

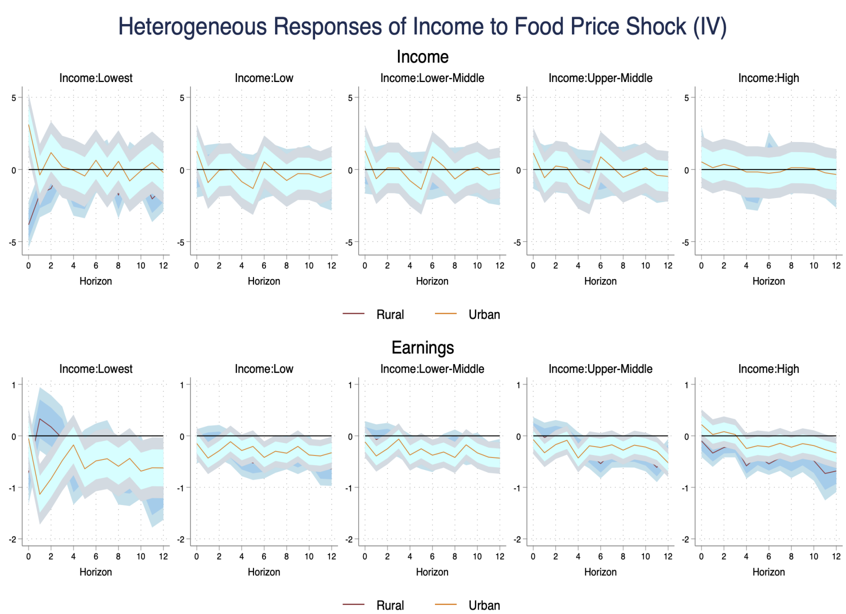

Figure A12: Response of Income to External Food Price Shocks by Income Quintiles

Notes: Cumulative IRFs on the basis of equation (5.1) where external shock is log changes in global food price.

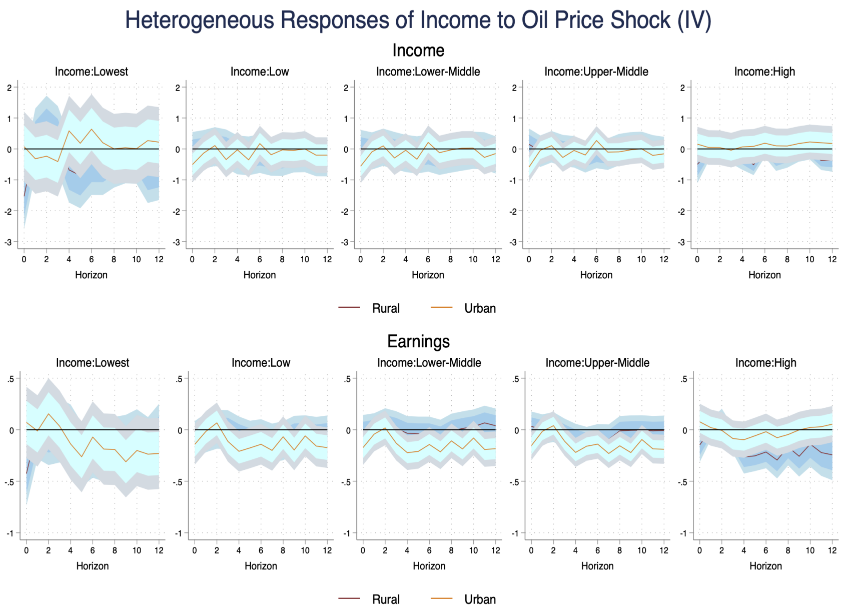

Figure A13: Response of Income to External Oil Price Shocks by Income Quintiles

Notes: Cumulative IRFs on the basis of equation (5.1) where external shock is log changes in global food price.

7.3.8 Effects on Regional Inequality

In addition to OLS results, based on using changes in global food and oil prices as the shock measure ext, we will also present IV results where we instrument the changes in global food and oil prices. These IV results will isolate variation coming from supply shocks to global food and oil prices as we discussed previously. We report cumulative impulse responses below, for both our OLS and IV specifications. Table A10 lists our control and instrumental variables.

Figures A14 and A15 present answers to the key question of this section based on an OLS specification of equation 5.2: How does regional consumption inequality evolve dynamically in response to external food and oil price changes? Broadly speaking, in Figure A14, we observe that an increase in global food prices increases consumption inequality within a state over time, with effects on both total and non-durable consumption inequality statistically significant and persistent.

Table A10: Instrumental and Control Variables in Regional Panel Local Projection

Panel A. Instrumental Variables

◦ Oil supply shock estimated in Baumeister and Hamilton (2019)

◦ Food supply shock estimated using a dynamic factor model of food commodity prices

Panel B. Control Variables

◦ Lags of outcome variables

– 1 lag

◦ Lags of global oil and food price changes

– 1 lag

◦ State-fixed effects

◦ Time-fixed effects

– Calendar month

– Calendar year

◦ Aggregate world condition controls

– World Industrial Production

– US federal funds rate

– Change in global VIX

◦ Demonetization policy dummy

Notes: This table shows our instrumental variables and a set of control variables in our baseline panel regional local projection regressions.

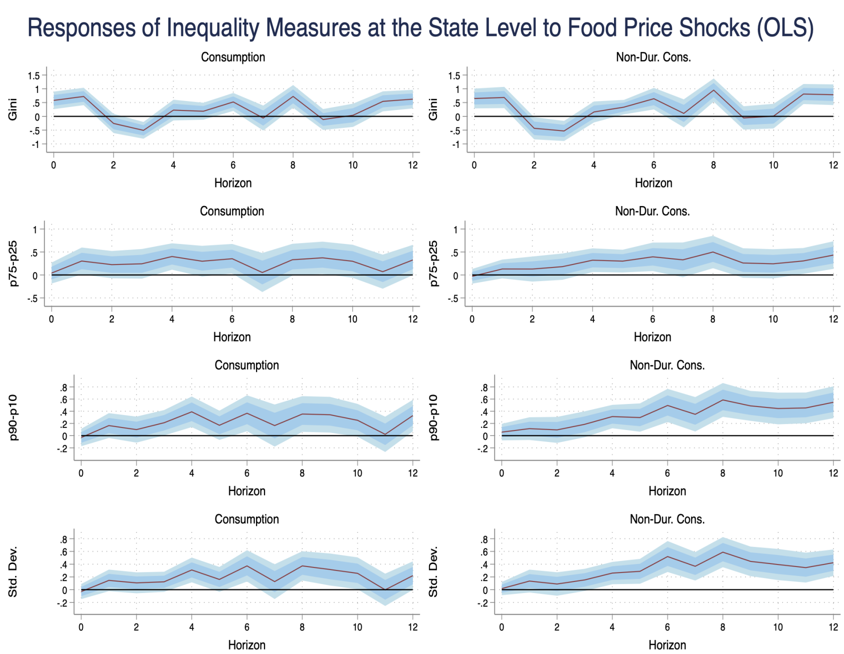

Figure A14: Response of Regional Consumption Inequality to External Food Price Shocks

Notes: Cumulative IRFs on the basis of equation (5.2) where external shock is log changes in global food price and the dependent variable is log changes in inequality. The light blue region refers to the 90% confidence interval and the dark blue region is the 68 % confidence interval.

In Figure A15, we see that an increase in global oil prices does not have as clear of an effect on consumption inequality. In fact, consumption inequality for most of these measures seems to decrease over time. This finding raises some questions on the effects of the oil price changes on regional consumption inequality that we explore further below, where we will show that it is important to decompose oil price changes into demand vs. supply disturbances to get a more accurate picture on how oil shocks affect regional inequality.

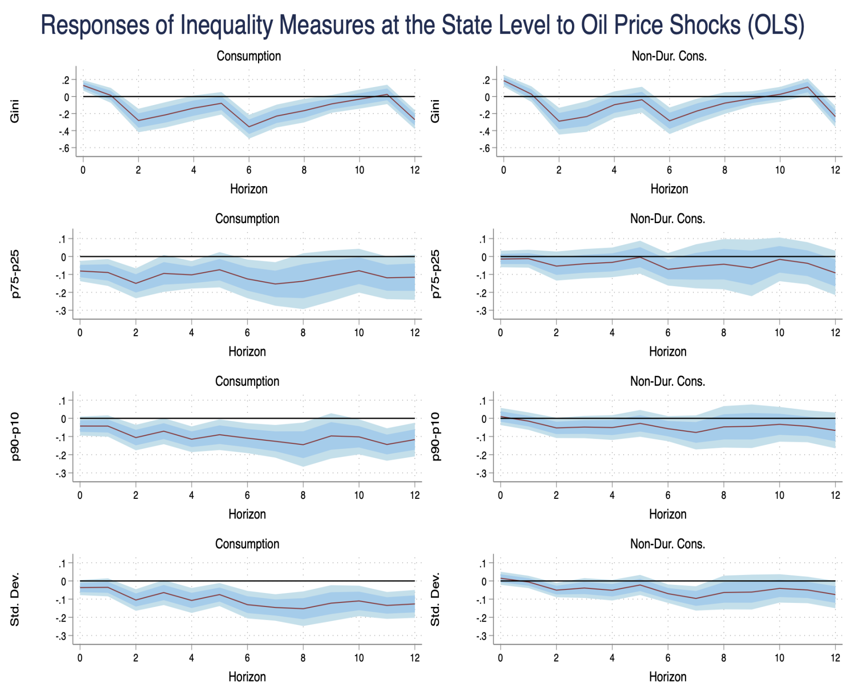

Figure A15: Response of Regional Consumption Inequality to External Oil Price Shocks

Notes: Cumulative IRFs on the basis of equation (5.2) where external shock is log changes in global oil price and the dependent variable is log changes in inequality. The light blue region refers to the 90% confidence interval and the dark blue region is the 68 % confidence interval.

Next, we present the IV results. Figure A16 shows that consumption inequality increases robustly following an exogenous change in global food prices, when we use our estimated food IV to instrument for global food price changes in the panel local projection framework in equation 5.2. Compared to the corresponding OLS results in Figure A14, the IV results are very similar and for the Gini coefficient and total consumption, they show more robustly an increase in inequality over time.

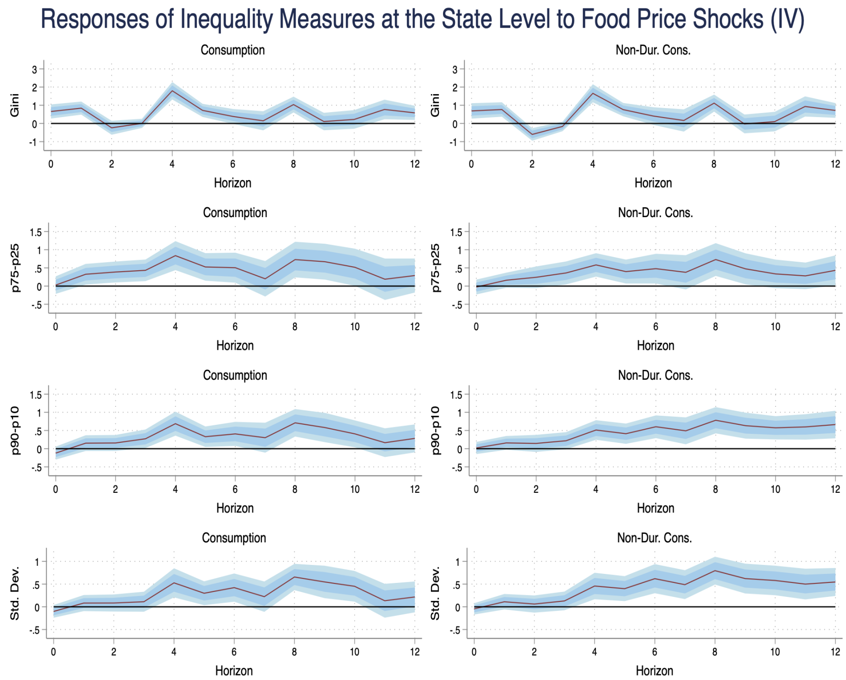

Figure A16: Response of Regional Consumption Inequality to External Food Price Shocks (IV)

Notes: Cumulative IRFs on the basis of equation (5.2) where external shock is log changes in global food price, which is instrumented by a global food supply shock and the dependent variable is log changes in inequality. The light blue region refers to the 90% confidence interval and the dark blue region is the 68 % confidence interval.

Figure A17 depicts the dynamic effects of global oil price change on state-level consumption inequality, where global oil price change is instrumented by the oil supply shock of Baumeister and Hamilton (2019). Compared to Figure A15, the corresponding OLS results, the IV results in Figure A17 show less of a clearer negative effect of oil price increase on inequality, especially on inequality in non-durable consumption. This exercise demonstrates the importance of separating out demand and supply side factors in understanding consequences of oil price changes, as was emphasized in Kilian (2009) for assessing aggregate macroeconomic effects. Still, the effects of oil shocks on regional inequality are not clear and appear to be more nuanced, consistent with what we uncover from detailed household level data in the next section.

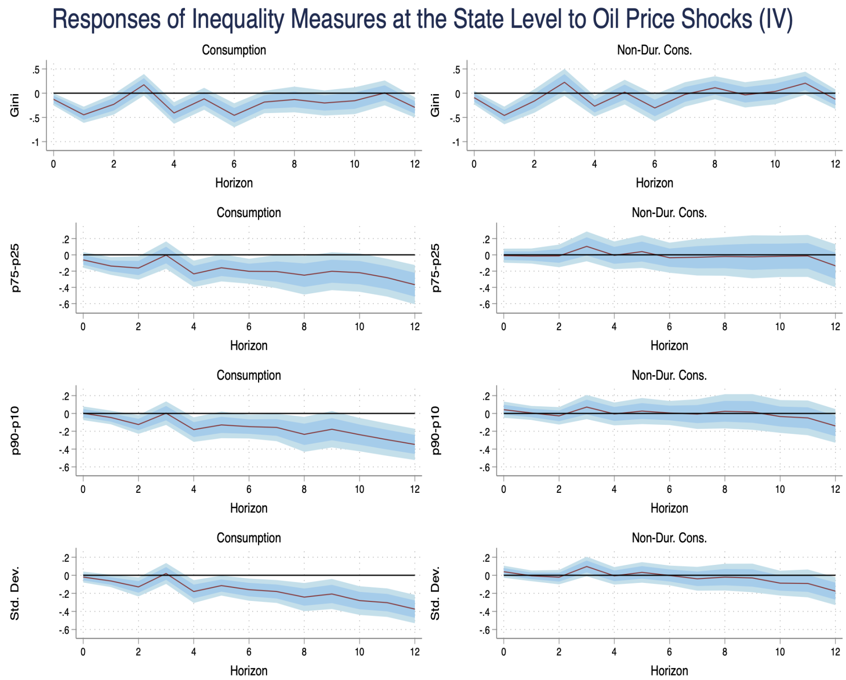

Figure A17: Response of Regional Consumption Inequality to External Oil Price Shocks (IV)

Notes: Cumulative IRFs on the basis of equation (5.2) where external shock is log changes in global oil price, which is instrumented by a global oil supply shock and the dependent variable is log changes in inequality. The light blue region refers to the 90% confidence interval and the dark blue region is the 68 % confidence interval.

Overall, Figure A16 shows clear evidence of adverse effects on regional inequality of global food price shocks while Figure A17 shows that the effects of global oil price shocks on regional inequality are not as clear cut. To further understand these effects, we now turn to leveraging household level data, which can help us affirm how different parts of the income distribution are differentially sensitive to these external shocks. In particular, while doing so, we will be able to explain why the effects of oil prices on regional inequality are more nuanced.

7.4 Estimation of the Food Commodity IV

Table A11: Non-energy Prices used in estimating the Dynamic Factor Model

Food	Food	Industrial Metals
Rice	Wheat	Iron ore
Bananas	Barley	Aluminium
Beef	Cocoa	Copper
Coffee Arabica	Coffee Robust	Cotton
Fishmeal	Corn	Lead
Poultry	Fish	Soft logs
Shrimp	Sugar	Hard logs
Orange	Tobaco	Nickel
Tea	Olive Oil	Rubber
Palm Oil	Rapseed Oil	Tin
Soybean Oil	Sunflower Oil	Wool coarse
Groundnut oil	Coconut oil	Wool fine
		Zinc

Notes: Commodity prices data are collected from FRED and Bloomberg and are quoted in US Dollar per unit. The units differ by commodity, but in the estimation we only use the log difference in price levels, i.e., returns.

In order to estimate the food shock, we first estimate a dynamic factor model with one common factor and two sector specific factors in a panel of 37 non-energy commodity prices (see, Table A11) which comprise of 13 industrial metals and 24 food prices. Following Ma, Vivian, and Wohar (2020), the dynamic factor model can be described as:

$$r_{i,t} = B^i f_t + C^i S_{j,t} + \eta_{i,t}$$

where $r_{i,t}$ is the log difference in commodity price, f_t is the common factor and $S_{j,t}, j = 1, 2$ is the sector-specific factor, and $\eta_{i,t}$ is the idiosyncratic component. Both the common factor and the sector-specific factors follow an AR(1) process. In order to identify the common factor as an aggregate demand factor, following the interpretation of Alquist et al. (2020), we impose the sign restriction that the factor loadings of the common factor, $B^i \geq 0$. Similarly, we interpret the food specific factor as the common demand factor for the food sector. Along with identification restriction, we also need to impose a normalization restriction, in order to overcome the well-known problem of unidentified models resulting from rotational indeterminacies of factors and loadings. Following Justiniano (2004) and Kose, Otrok, and Whiteman (2008), we normalize the contemporaneous factor loading of the iron ore for the common factor, and the contemporaneous factor loading of poultry for the food factor, to unity.[35]

We cast the dynamic factor model in the state space form and estimate it using Bayesian methods using Markov Chain Monte Carlo (MCMC). Two approaches have become popular for the estimation and identification of factor models: the analysis of principal components and Bayesian methods. Due to its simplicity and the availability of high speed computers, principal component analysis is extensively used for both static and dynamic factor models, extending to models using hundreds of series. As Justiniano (2004) and Kose et al. (2008) explain, principal component method is, however, not well suited for estimating models under exclusion restrictions. Model estimation using principal component requires deriving factors from the variance or spectrum of all series simultaneously, and therefore, it becomes inappropriate when a subset of variables is assumed to relate to the factors in a different manner than the rest of the variables. In other words, factors cannot be derived in one step. Therefore, we follow Justiniano (2004) and Kose et al. (2008) and use the Bayesian method which easily accommodates restrictions on how the factors affect subsets of series. The following paragraph outlines our estimation technique.

We need to use special techniques to estimate the model as the factors are unobservable. Following Chatterjee (2016), we apply the Bayesian posterior simulation method to estimate the dynamic latent factor model. The estimation procedure is based on the following vital observation: if the factors were observable, under a conjugate prior, the models would be a simple set of regressions with Gaussian autoregressive errors; that simple structure can, in turn, be used to determine the conditional normal distribution of the factors given the data and the parameters of the model. This conditional distribution can, then, easily be used to generate random samples, which can serve as proxy series for the unobserved factors. As the full set of conditional distribution is known − parameters given data and factors and factors given data and parameters − it is possible to generate samples from the joint posterior distribution for the unknown parameters and the unobserved factors using sequential sampling of the full set of conditional distributions in a Gibbs sampling. The process is iterated a large number of times. Under the regularity conditions satisfied here, the Markov chain so produced converges, and yields a sample from the joint posterior distribution of the parameters and the unobserved factors, conditioned on the data.

Once we estimate the common demand factor and the food specific factor from the dynamic factor model, we residualize the log changes in global food price index to construct our food commodity shock that we used as an instrument. .

[35] We have tried alternative normalizations of the food factor setting factor loadings for rice, or wheat or beef, to unity. The results are remarkably similar.