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

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Abstract

Exogenous 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 groups experience more adverse consumption effects following a rise in food prices, whereas households in the extremes of the income distribution are affected similarly following a rise in oil prices. Global food price shocks lead to significant negative wage income effects that mirror the pattern of negative consumption effects along the income distribution. Global price shocks pass-through to consumer prices in India and increase the relative prices of fuel and food. Expenditure share of food increases with such a rise in relative prices, which provides unambiguous evidence for non-homothetic preferences. Using the expenditure share responses together with theory, we show that food, compared to fuel, is a necessary consumption good for all income groups.

JEL classification: F41, F62, O11

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1 Introduction

There has been a sharp 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 the livelihoods of a very large part of the population, which further increases their salience. Strong effects on inflation and *increases in cost-of-living* are expected to hit poorer people in these countries more because of the necessary nature of food and/or fuel in consumption, thereby exacerbating existing inequality.

Effects of such global price shocks driven inflation on macroeconomic outcomes and inequality have therefore been at the forefront of policymakers' agenda. For instance, in the April 2022 issue of the World Economic Outlook ((IMF) (2022a)), 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 outlook ((IMF) (2022b)): *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 price shocks on the overall macroeconomy (Hamilton (1983), Hamilton (2003), Kilian (2009), Baumeister and Hamilton (2019), Kanzig (2021), De Winne and Peersman (2016), De Winne and Peersman (2021), Peersman (2022)), there exists limited rigorous evidence on the *distributional* consequences of such shocks, especially in emerging markets. Recent literature on distributional consequences of gas/oil prices or carbon pricing (Gelman, Gorodnichenko, Kariv, Koustas, Shapiro, Silverman, and Tadelis (2023), Kanzig (2023), Pallotti, Paz-Pardo, Slacalek, Tristani, and Violante (2023)) *focuses on advanced economies and (explicitly or implicitly) assumes fuel/energy to be essential in consumption* such that fluctuations in oil price can be treated as unexpected income shocks.

In this paper, we examine 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. Critically, we do not assume, ex-ante, that either food or fuel are necessary consumption goods, and rather use our empirical results and a non-homothetic demand structure to econometrically infer whether food and/or fuel are indeed necessities in the consumption basket.[1]

We find clear distributional consequences in India of a rise in global food prices. An exogenous increase in global food price leads to a statistically significant, and economically meaningful, increase in consumption inequality as we find monotonically larger adverse consumption effects on poorer income groups. While an exogenous rise in global fuel prices clearly has adverse effects on consumption, the pattern of heterogeneity, and consequently the impact on inequality, is less evident as the poorest and the two richest household groups are similarly affected. Analyzing empirical estimates of consumption expenditure shares and price responses through the lens of a non-homothetic demand structure, we then establish that food is indeed a necessary consumption good for all households in India.

We begin our analysis 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 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 necessary 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 house-

[1]We use the terms non-homothetic demand and a necessary consumption good in this paper as in classical consumer theory. Non-homothetic demand implies an income effect on expenditure shares and a necessary (luxury) consumption good has an *income elasticity of demand* that is less (greater) than one. With homothetic demand, there are no necessary or luxury goods. In common use, a good with a low *price elasticity of demand* is referred to as an essential good. Formally, an essential good is one such that zero consumption of that good implies a zero marginal utility of all other goods.

hold panel 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.[2]

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 emphasizes, separating the effects of global demand (and commodity-specific demand) shocks from those of global supply shocks is essential for a clear interpretation of the results. Using changes in global oil and food prices as a measure of shock would thus produce OLS estimates that conflate the effects of both types of shocks. Moreover, global demand shocks can lead to omitted variable bias if they directly affect Indian household consumption through the households' exposure to the global business cycle.

To tackle this challenge, we employ an IV approach, using supply-side instruments for the change in global oil and food prices.[3] For the global oil price change, we use the oil supply shock estimated in Baumeister and Hamilton (2019) as an IV, while for the global food price change, we construct our own IV. 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 panel data on commodity prices.

Our principal findings are as follows. Effects on consumption of the global price shocks are clearly adverse, and heterogeneously so, along the income distribution. Households in the lower income deciles bear a greater burden from an exogenous rise in food prices and the negative consumption effects become progressively less severe as we move up the income distribution. An exogenous rise in fuel prices, in contrast, affects consumption of both the lowest and the two highest income groups similarly. Moreover, consumption of the low-income group decreases the most for food price shocks while it

[2]We refer to these income groups as lowest, low, low-middle, upper-middle, and high-income groups.

[3]Using an IV helps address any reverse causality concerns as well since India is growing fast and may have an impact on global demand.

decreases the least for oil price shocks.

Our IV estimates reveal substantive differences from the corresponding OLS estimates in some cases. For instance, 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 is intuitive, 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.[4]

We utilize the IV framework to further investigate the mechanisms that cause heterogeneous effects in consumption. First, we estimate the heterogeneous wage earnings effects of the global price shocks. Our analysis reveals that food price shocks lead to a negative effect on the real wage incomes of the poorest households. Moreover, this shock also affects non-trivially the labor earnings of other 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 real wage income. For oil price shocks, there are consistently negative labor income effects on the lowest and highest income groups, which is aligned with the negative consumption effects for these groups.

Second, state-level panel local projection IV results show that both global shocks "pass-through" to local prices in India, affecting not just own-category prices but also overall (headline) prices. Both these shocks also affect relative prices: Global food price shocks elevate the relative price of food, while global oil price shocks drive up the relative price of fuel in India.

Conventional homothetic demand functions would predict expenditure-switching effects due to such relative price change. 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, which is not consistent with expenditure switching as the only channel determining expenditure shares. In fact, given that the relative price of food increases with the global food price shock, these consumption share responses unambiguously suggest a role for income effects in rel-

[4]We show direct evidence of this phenomenon by examining the effects on labor earnings. We observe positive impacts on labor income 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). Generally, in OLS estimates of the effects of oil price shocks, we find minor negative consumption effects irrespective of the income group.

ative demand and expenditure shares. Moreover, going further, using the responses of relative food prices, relative food expenditures, and real non-durable consumption expenditure together, we infer econometrically that food is a necessary consumption good (that is, food has an income elasticity of demand less than one), compared to fuel, for all income groups in India.[5]

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), and Kilian (2009).[6] 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 et al. (2023), Peersman and Wauters (2022), Kanzig (2023), and Pallotti et al. (2023)). Our findings that at least part of the heterogeneous response in consumption to oil shocks can be traced to heterogeneous response in wage income is similar to the results in Kanzig (2023) for carbon tax/energy price shocks. Moreover, like in Kanzig (2023), we show evidence consistent with "leaning-in" monetary policy as interest rates in the economy rise in response to such shocks.

In one important difference from this recent literature on distributional effects of oil/energy price changes, we do not assume ex-ante that fuel is a necessary good, and rather *infer statistically* whether food and fuel are necessities. Moreover, taking a leaf out of the rich literature that establishes that not all oil shocks are alike in terms of aggregate macroeconomic effects, we use the oil supply shock estimated in Baumeister and Hamilton (2019) as an instrument in our panel IV specifications to isolate the role of supply shocks. We indeed find that for distributional effects too, it is critical to distinguish between supply and demand shocks that jointly drive commodity prices.

There has been some recent research on the macroeconomic effects of global food price shocks, such as De Winne and Peersman (2016) and Peersman (2022). Previous

[5]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. Our econometric analysis uses this class of preferences. In these preferences, distinct parameters govern separately the price elasticity of demand (which will capture the standard expenditure switching channel) and the income elasticity of demand (which will capture the non-homotheticity channel). See Matsuyama (2022) for a discussion. For this class of preferences, an increase in relative price has non-trivial effects on the cost of living depending on the levels of real expenditure. We also do the econometric analysis at a dis-aggregated food category level and find evidence that many food categories constitute a necessary consumption good.

[6]Lakdawala and Singh (2019) study aggregate output and price effects in India of oil supply shocks using the Baumeister and Hamilton (2019) supply shocks directly as a measure of external shocks.

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.[7]

There is a large body of work in development economics that primarily studies the measurement of poverty, including the impact of food price rises on poverty and household consumption. This literature is deeply concerned with understanding the impact on household welfare using detailed consumption data along with the estimation of (food and more recently, broader) Engel curves. See for example, Deaton (2016), Deaton (2019), and Atkin, Faber, Fally, and Gonzalez-Navarro (2024) for work that uses Indian data.[8] Our key contribution is that we estimate dynamic causal effects, using an IV strategy to isolate exogenous supply-side variation in global food prices, and combine the estimated impulse responses of relative expenditure and a non-homothetic demand structure to infer the existence of necessary consumption goods.

Our empirical results that establish food as a necessity consumption good also place our work in the context of the rapidly growing macroeconomic literature on non - homothetic preferences. Jaravel (2021) is a recent survey of this work. One theme of this literature is how innovation, macroeconomic shocks, or policy changes can cause distributional effects by differentially affecting cost-of-living along the income distribution. That is, these changes lead to inflation inequality (Jaravel (2019)). Another theme is that such preferences can interact with features such as price stickiness or market size effects to generate non-trivial aggregate effects and novel policy implications. Jaravel and Olivi (2019), for example, show implications for optimal redistributive taxation.

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 house-

[7] In supplementary results in the Appendix, we also illustrate the aggregate macroeconomic effects of the global food supply shocks on the Indian macroeconomy.

[8] Atkin et al. (2024) estimate relative Engel curves, that is, the relationship between the relative expenditure of a good within a certain subset of goods and total outlays.

hold 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 findings regarding distributional effects on consumption imply that emerging markets' central banks 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 the 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 the 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) and Acharya, Challe, and Dogra (2023)). Moreover, given the clear evidence for non-homothetic preferences that we uncover, it will be interesting to assess how incorporating such preferences will lead to new insights on the effects of monetary policy compared to standard models (e.g., as in Clayton, Schaab, and Jaravel (2019)).

2 Data, Stylized Facts, and Instrumental Variables

We now discuss our data, present some stylized facts that serve as motivation for the econometric exercise, and describe in detail our 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 Indian Economy (CMIE). CPHS has surveyed over 236,000 unique households since 2014 and it uniquely provides both income data and detailed consumption data 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 and the consumption/income data. Our analysis uses data from January 2014 to December 2019.[9]

We construct consumption, income, and earnings measures following closely the method of Coibion, Gorodnichenko, Kueng, and Silvia (2017). Consumption expenditure comprises 153 categories. The 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 analyses.[10] We also present results on food, fuel (including cooking fuel, electricity, and transport fuel to be consistent with the price index), and detailed food sub-components consumption.

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 (MoSPI), Government of India. The remaining consumption categories are deflated using their respective CPIs as follows. Food consumption is deflated by the index available from MoSPI. Fuel consumption, where we include not just the cooking fuel expenditure given directly by MoSPI but also fuel expenditure on transportation, is deflated using a weighted average of the two categories with the weights provided by MoSPI. Non-durable consumption is deflated using a weighted average of food, cooking fuel, and transport price indices with the weights provided by MoSPI.[11] Using these data, measures of inequality we construct for stylized facts are: Gini co-

[9]To emphasize how uniquely positioned this dataset is for us to answer the key research questions, we note that administrative tax returns data, often used in the literature on effects of monetary policy on inequality, is annual and contains little information on consumption; datasets such as the Consumer Expenditure Survey are extraordinarily rich but have a rotating panel; and the longest running (since 1968) panel income dataset, the Panel Study of Income Dynamics, has consumption data available only from 1999 and only at a bi-annual frequency. See Sahasranaman and Kumar (2021) for a study of the dynamics of inequality using the CPHS data.

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

[11]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, nondurable CPI has to be constructed. We overcome this challenge by constructing state-region (urban and rural) level 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 in Appendix A.

efficients, cross-sectional standard deviations, and differences between individual percentiles (90^{th}-10^{th} and 75^{th}-25^{th}) on log levels.

Income is 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.Our earnings measure is constructed using income from wages and overtime bonuses. To construct real values of these nominal income and earnings variables we use the state-region level CPI - Combined series (2012 base).

Finally, we use IMF's Global Price of Food Index (Nominal, US Dollar) and the Brent crude oil prices (US Dollar per barrel) as our measure of global food and oil prices respectively.

2.2 Summary Statistics Along the Income Distribution

Several summary statistics from our household panel data, along the income distribution, are in Online Appendix A. 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 the poverty line and is composed of net borrowers with a high share of non-durable and food in consumption. The savings rate rises while non-durable and food shares decline with income. The top income decile has nearly a 70% savings rate and a relatively low share of food in total consumption.[12]

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

[12]Note that we do not include monthly expenditures on rent, EMIs, health, and education in our measure of total consumption. If we include these expenditures, the share of food in total consumption is even lower for the richer income groups. We also show in Table A2 that earnings constitute the most important category of income for lower income groups. For higher-income groups, capital income constitutes a significant fraction of total income whereas for lower income groups transfers are an important component.

to a group based on those cutoffs.[13]

2.3 Global Commodity Prices and Aggregate Consumption Inequality

We now present stylized facts on global commodity prices and aggregate inequality in India. We first plot the log changes in global food and oil prices in Figure 1. As expected, the average of the changes is close to zero while the standard deviation is approximately 2.4% for food prices and nearly 8.7% for oil prices, 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 transitory in nature. Finally, changes in the two series are positively correlated but not very highly so, hence implying independent sources of variation.[14]

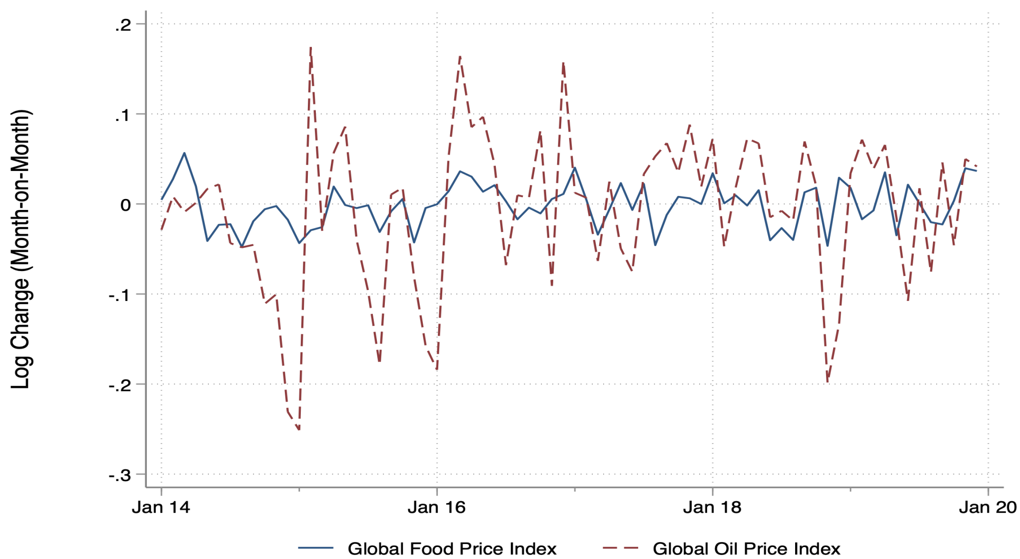

Figure 1: Changes in Global Food and Fuel Prices

Notes: This figure plots the log change in IMF's Global Price of Food Index (Nominal US Dollar) and Brent Crude Oil Prices (US Dollar per barrel).

We construct various aggregate measures of consumption inequality and compute correlations of them with one period lagged values of global food and oil price changes.

[13]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 sensitivity analysis in Section 5.

[14]Correlation between the two series is 0.34 in our sample. Some co-movement such as this is to be expected given the role of energy as input in the 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).

As shown in Table 1, the correlations are positive. Moreover, the correlations are higher for global food price changes compared to oil price changes. Our raw data thus reveals a positive correlation between aggregate consumption inequality and external commodity price changes. Does this "smell test" pass an econometric examination? This is the key focus of our paper.

Table 1: Correlations of Consumption Inequality with Global Food and Oil Price Changes

	Gini	SD	90th-10th	75th-25th
Food Price	0.111	0.051	0.049	0.052
Oil Price	0.044	0.046	0.044	0.032

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

2.4 Instrumental Variables for Global Commodity Price Changes

In our stylized facts above we use changes in world oil and food prices (in logs) as an external shock, motivated by the small open economy assumption for India. Such results can be considered as OLS versions of our estimation framework below 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 results, it is instructive to separate out such global oil/food price changes as coming from global demand or supply shocks. In addition to allowing a cleaner interpretation, isolating supply side variation also guards against omitted variable bias (OVB) problems. For instance, OVB can arise as Indian households could have *direct* exposure to the global business cycle, which is well-known to drive global commodity prices. To address this issue, we take an Instrumental Variable (IV) approach where we use supply side instruments for the change in global oil and food prices.

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 the residual of global food commodity prices after extracting two common factors from a cross-section of commodity prices. Specifically, 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) in a dynamic factor model. Our estimation method for this dynamic factor model is outlined in Online Appendix B.[15]

We provide several details about the IVs in the Appendix. Macroeconomic effects of a rise in global food price driven by supply shocks on the Indian economy are illustrated in Figure A1 in Online Appendix B, while similar macroeconomic effects are shown for supply-driven oil price shocks in Lakdawala and Singh (2019). We plot the changes in global commodity prices and their IVs, the respective supply shocks, in Figure A2 in Online Appendix C. Figure A3 in Online Appendix C shows the pass-through of respective adverse supply shocks to global food and fuel prices.

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 local projection framework where we estimate heterogeneous dynamic effects of global oil and food price shocks on household consumption. In particular, these consumption effects will be allowed to differ along the income distribution.

[15]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 (e.g., as in 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 the public distribution system for consumers. Hence, we prefer to rely on an approach that uses a broad cross-section of prices. We use data available from FRED and Bloomberg in the time period 1990-2022.

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:

$$
\begin{aligned}
c_{i,t+h} - c_{i,t-1} = \beta^{g,h}_{0,\text{food}} ext^{\text{food}}_{t} \times \mathbb{1}_{i\in g(t)} + \beta^{g,h}_{0,\text{oil}} ext^{\text{oil}}_{t} \times \mathbb{1}_{i\in g(t)} + \sum_{j=1}^{J} \alpha^{h} (c_{i,t-j} - c_{i,t-j-1}) \\
+ \sum_{k=1}^{K} \beta^{h}_{k,\text{food}} ext^{\text{food}}_{t-k} + \sum_{k=1}^{K} \beta^{h}_{k,\text{oil}} ext^{\text{oil}}_{t-k} + \sum_{d=0}^{D} \delta^{h} D_{t-d} + \gamma^{g,h} X_t \times \mathbb{1}_{i\in g(t)} \\
+ \delta_{\text{c},t} + \delta_{\text{l},t} + \delta_{\text{e},t} + \delta_{\text{city},t} + \delta_{\text{age},t} + \mathbb{1}_{i\in \text{s}} \times \mathbb{1}_{\text{year}} + \mathbb{1}_{i\in \text{s}} \times \mathbb{1}_{\text{month}} + \epsilon_{i,t+h} \qquad (3.1)
\end{aligned}
$$

Here, c_i is the log of consumption for household i for various measures of consumption; ext^{food} and ext^{oil} stand for measures of the global food and oil price shocks respectively[16]; $\delta_{\text{c},t}$, $\delta_{\text{l},t}$, $\delta_{\text{e},t}$, $\delta_{\text{city},t}$, and $\delta_{\text{age},t}$ are respectively the fixed effects for household's caste, religion, education, residence in a big city, and age; $\mathbb{1}_{i\in \text{s}} \times \mathbb{1}_{\text{year}}$ and $\mathbb{1}_{i\in \text{s}} \times \mathbb{1}_{\text{month}}$ are a set of household i's residence state by calendar year and residence state by calendar month fixed effects to account for state-specific trends and seasonality respectively; and D is the dummy for the Indian government's demonetization policy, which is allowed to have lagged effects for up-to three periods.[17] For the AR and MA coefficients, we choose $J = 3, K = 3$.

We estimate the above specification separately for each horizon ranging from $h = 0$ to $h = 12$. In all the regressions, the observations are weighted using sampling weights provided by CMIE which takes into account the non-response factor. The standard errors are clustered at the state-region level where region denotes urban or rural.

A critical aspect of this specification is that we allow the consumption effects to differ by the income of the household. That is, $g(t)$ denotes the income group of household i at time t constructed using cutoffs from 2014 real income data. The effects of external

[16]In the baseline measure of global price changes, we consider nominal prices of food and fuel in USD. As an alternative, we also used real prices after deflating global prices by US urban consumers' headline CPI, following Baumeister and Hamilton (2019). Our results remain unchanged and are available upon request.

[17]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 into 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 Online Appendix A in Table A3.

shocks are thus, allowed to vary by income groups. As mentioned previously, 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). $\beta_{0,\text{food}}^{g,h}$ is the coefficient of interest that captures the impact of global food price shock at time t on households of group g at horizon h; $\beta_{0,\text{oil}}^{g,h}$ is similarly the estimate for the global oil price shock. We report cumulative impulse responses below.

X denotes controls for aggregate world conditions: world industrial production as a proxy for global demand (Kilian (2009))[18]; US federal funds rate; and global financial volatility as captured by the VIX index. These aggregate global controls are interacted with household income group dummies to allow for external shocks, other than global commodity prices, to have heterogeneous consumption effects.

As we discussed previously, our main results are those where we instrument the changes in global food and oil prices that are represented above by ext. These IV results isolate variation coming from global supply shocks and also guard against omitted variable bias problems. For comparison and interpretation, we also present some OLS results that use changes in global food and oil prices directly as a shock measure. Table A5 in Online Appendix D lists all the control and instrumental variables in our household panel local projection estimation.

3.2 Heterogeneous Consumption Effects: IV Results

For the local projection household panel exercise based on the estimation of equation (3.1), where the effects on consumption are allowed to vary along the income distributions, our key IV results are in Figures 2 and 3 for food price shocks and oil price shocks respectively.[19] We present results for total consumption, non-durable consumption, and own-category consumption (fuel consumption for oil price shocks and food consumption for food price shocks). The results show that there are adverse effects on consumption, for both total and non-durable consumption, for both the shocks.

[18] As an alternative, we also used monthly world industrial production index estimated in Baumeister and Hamilton (2019) as the control for global demand. Our empirical conclusions remain unchanged and the results are available upon request.

[19] The first-stage F-statistics for these IV regressions are reported in Online Appendix D in Table A6.

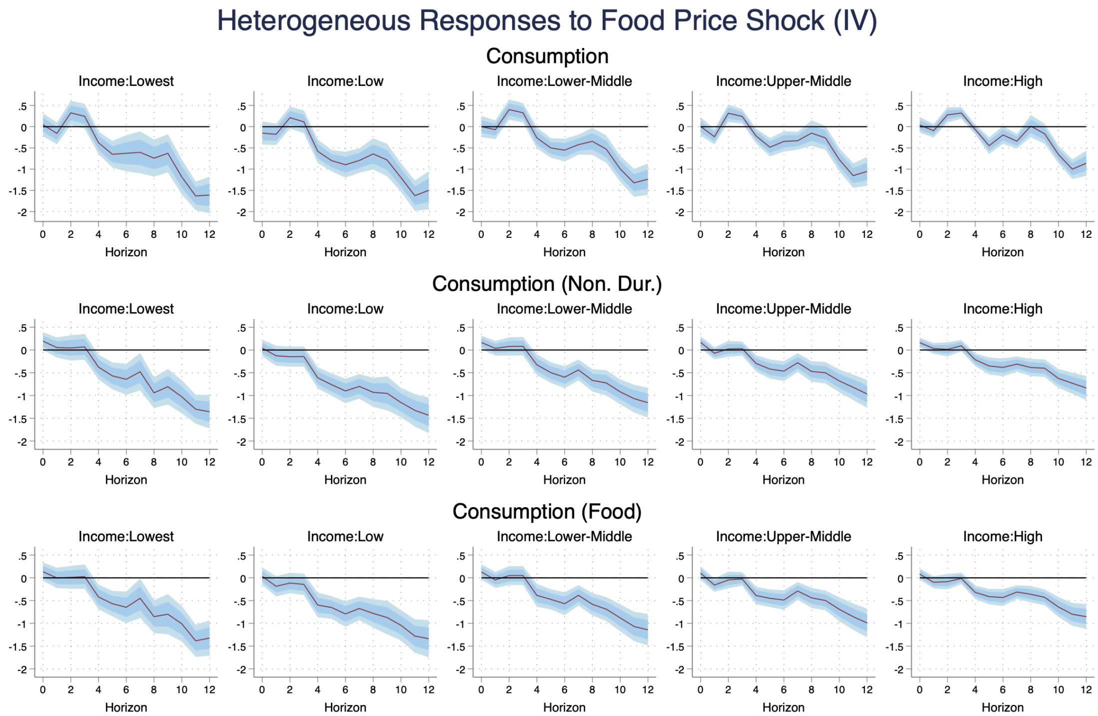

Figure 2: Response of Consumption to External Food Price Shocks by Income Quintiles (IV)

Notes: Cumulative IRFs on the basis of equation (3.1) where the external shock is log changes in the 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 is the 90% confidence interval and the dark blue region is the 68% confidence interval.

On heterogeneous effects along the income distribution, the two shocks show different patterns. For the food price shock, the lower income groups are hit harder and the negative effects become progressively less pronounced as we move to higher income groups. For the oil price shocks, the effects are more nuanced and much more symmetric along the income distribution. For instance, the negative effects on non-durable consumption are similar in magnitude for all income groups, except for the low-income group which suffers the least. The drop in consumption is slightly higher for the lowest income group, but the effects are more persistent for the two highest income groups.

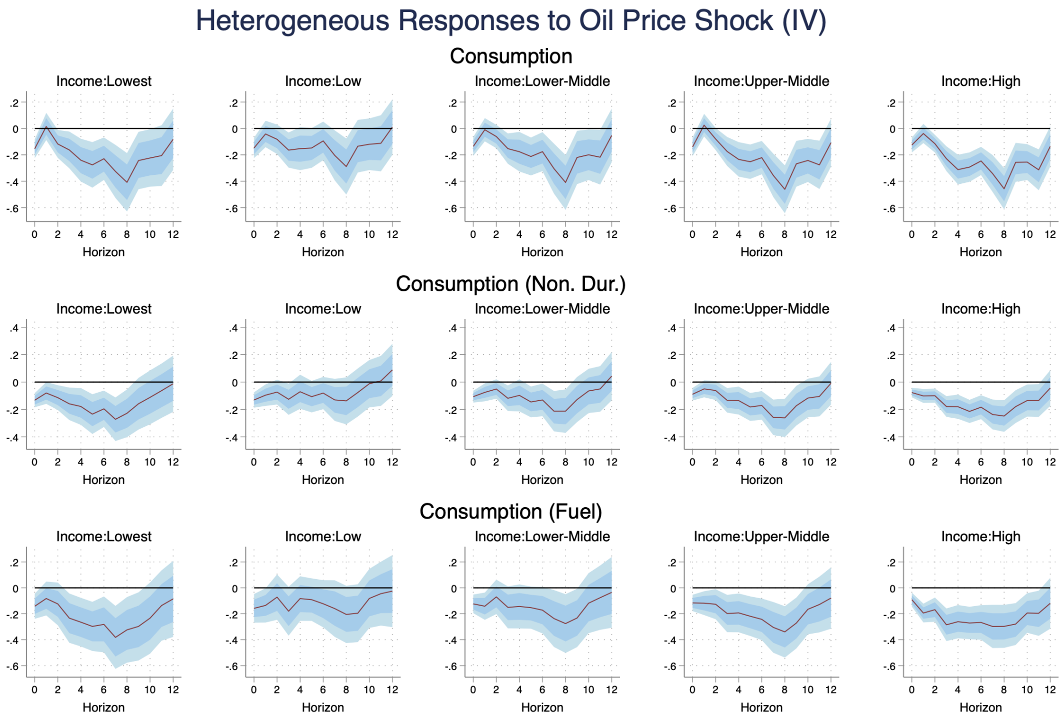

Figure 3: Response of Consumption to External Oil Price Shocks by Income Quintiles (IV)

Notes: Cumulative IRFs on the basis of equation (3.1) where the external shock is log changes in the 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 is the 90% confidence interval and the dark blue region is the 68% confidence interval.

To conclude, Figure 4 provides summary statistics of the results, using a box and whisker plot, for non-durable consumption. As we mentioned 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 the poorest, the lower-middle, the upper-middle, and the high-income groups are equally vulnerable to an exogenous rise in oil prices. Moreover, the low-income group (deciles 2 and 3) is shielded most from oil price increases but suffers most from food price increases.[20] Consistent with these patterns of heterogeneous dynamic consumption effects of global food and fuel price shocks, we show in Figures A5 and A6 in Online Appendix D.4 that state-level inequality (constructed from the underlying micro household data) clearly rises with a

[20]The low-income group (deciles 2 and 3) is even more vulnerable than the poorest income group to rising food prices, possibly due to the public distribution system shielding the consumption loss of the very poor.

rise in global food prices, but it's response to an increase in global oil prices is mixed.[21]

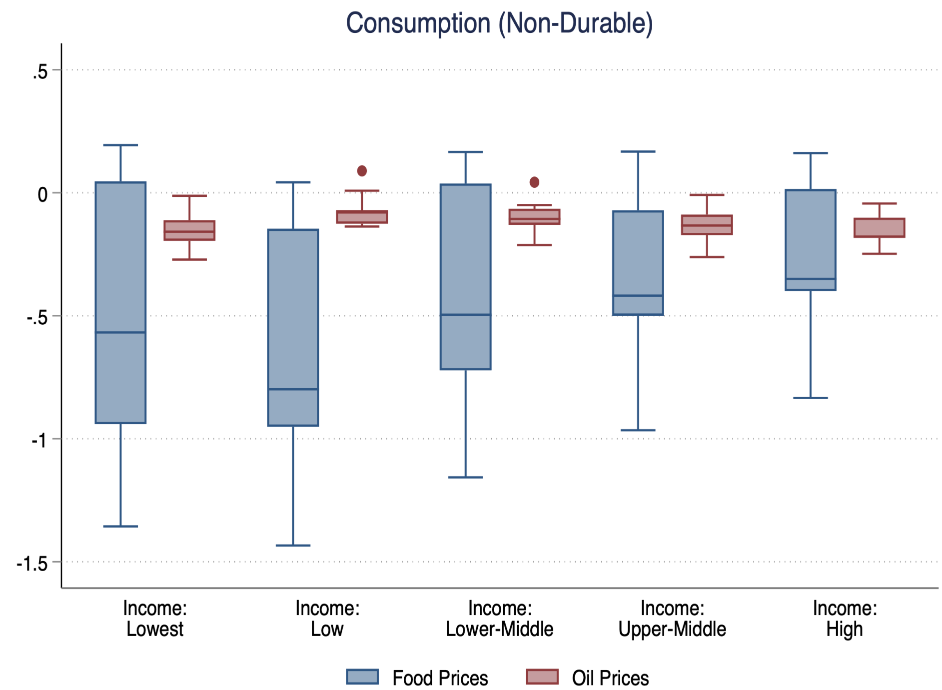

Figure 4: Summary Statistics of Response of Non-durable Consumption to Food and Fuel Price Shocks by Income Quintiles (IV)

Notes: This figure is a box and whisker plot that summarizes the responses of non-durable consumption to the two external shocks that are presented in Figures 2 and 3. The line in the center of each box represents the median impulse response estimate across thirteen horizons; the top and the bottom edges of each box represent the 75$^{\text{th}}$ and the 25$^{\text{th}}$ percentiles respectively; and the lines above and below each box represent respectively the upper and lower adjacent values calculated as in Tukey et al. (1977).

Motivated by this pattern across income groups, and to assess the statistical significance of the difference in effects across them, we show in Online Appendix D in Figure A4 the effects for all groups *relative* to the low-income group. They show that the differences are statistically significant and also go in the direction we have emphasized.

Next, to appreciate the magnitude of consumption loss due to the external shocks and the pattern of heterogeneity along the income distribution, in Table 2, we translate the elasticity estimates presented in Figure 4 to consumption loss in % terms. The first two columns of Table 2 capture the maximum negative impact of a 1 standard deviation

[21] See Online Appendix D.4 for details regarding the measures and specification for state-level inequality results.

shock in global food and oil prices (a 2.4% rise in the food price index and an 8.7% rise in Brent crude oil prices, 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, all income groups other than the low-income group suffer similarly. Moreover, the low-income group is shielded most from oil price increases but suffers most from food price increases.

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 2. In August 2022, the IMF Food Price Index was higher by 8 percent while the Brent Crude Oil Price was higher by 35 percent, compared to a year ago. For such a large rise in external food prices, the poorest two groups suffer around 12% loss in non-durable consumption and the effect declines monotonically with income. The oil price increase leads to similar negative effects of around 9% for the poorest and the two highest income groups.

Table 2: 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 (35% in Aug 2022)
Lowest	-3.33	-2.36	-10.85	-9.42
Low	-3.52	-1.19	-11.47	-4.76
Lower middle	-1.85	-1.9	-9.27	-7.38
Upper middle	-2.27	-2.34	-7.72	-9.07
High	-2.05	-2.16	-6.67	-8.60

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 4. Columns (2)-(3) refer to a 1 standard deviation shock to food prices (2.4%) and oil prices (8.7%). Columns (4)-(5) refer to the August 2022 massive rise in food prices (8%) and oil prices (35%).

4 Channels for Heterogeneous Consumption Effects

Having established these baseline results on heterogeneous effects on household consumption, we delve further into interpretation and transmission mechanisms. In particular, we aim to assess the channels that work via real income, through relative price effects (say across sectors), 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 an infinite horizon consumption-savings problem in a perfect foresight environment with unexpected shocks, where the household can trade 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

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

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.[22] 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, and w_t is real wages. 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 and savings decisions through their effects not only on labor earnings

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

$w_t L_t$, 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

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

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 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.

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

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

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 as well as heterogeneity in ex-ante positions in nominal bonds, maturity of nominal bonds, and stocks will lead to heterogeneity in consumption. Given our data, we state a key prediction that we can test below.[23]

Testable Prediction 1: From Equation (4.3), the heterogeneous response of wage income to the external price shocks leads to a heterogeneous response of 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:

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

Here, $\eta > 0$ is the elasticity of substitution and $\alpha > 0$ governs the share of the two types of consumption goods. The 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

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

[23] CPHS data contains monthly earnings information, but detailed information on ex-ante nominal portfolio positions is not available. Moreover, if nominal wages are rigid, then changes in price level can be a direct source of changes in real wages. Even in that case, the prediction below remains the same as long as we estimate effects on real wage income. We would simply write real wages as $w_t = \frac{W_t}{P_t} = \frac{W}{P_t}$ where W_t is nominal wages.

Given our data, we state a key prediction that we can test below.

Testable Prediction 2: Assuming $\eta > 1$, from Equation (4.5), if the relative price of non-durable consumption increases in response to the external price shocks, it leads to a decrease in the expenditure share of non-durable consumption.

Next, we model non-durable consumption as an iso-elastic non-homothetic CES aggregator of food and fuel.[24] Hence, expenditure shares of food and fuel ($M_i, i = F, O$ for food and fuel respectively) in non-durable consumption are given by

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

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 parameter governing income elasticity of demand (or, the slope of the Engel curve), $\sigma_\epsilon > 0$ is the price elasticity, and γ_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. More precisely, relative expenditure shares are

$$\underbrace{\log\left(\frac{M_{it}}{M_{jt}}\right)}_{\text{Relative expenditure}} = \log\left(\frac{\gamma_i}{\gamma_j}\right) - \underbrace{(\sigma_\epsilon - 1)\log\left(\frac{P_{it}}{P_{jt}}\right)}_{\text{Relative price effect}} + \underbrace{(\epsilon_i - \epsilon_j)\log\left(\frac{E_{Nt}}{P_{Nt}}\right)}_{\text{Total expenditure effect}}. \tag{4.7}$$

In Equation (4.7) above, 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 a luxury or a necessity depending on the level of real expenditure.[25]

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

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

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:

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

See Matsuyama (2022) for further details and references.

[25] An increase in the relative price of a good has a higher impact on the cost of living if the steady state expenditure share of that good is higher. More interestingly, for this class of non-homothetic demand, an increase in the relative price of the necessary good impacts the overall cost of living depending on the

As long as (overall, and various sub-components of) food is a substitute with fuel (implying an elasticity of substitution, $\sigma_\epsilon > 1$), an increase in relative prices reduces relative expenditure via the standard expenditure switching effect. If real non-durable expenditure ($\frac{E_{Nt}}{P_{Nt}}$) falls, the only way relative expenditure may increase with rising relative prices is if $\epsilon_i < \epsilon_j$. This condition, $\epsilon_i < \epsilon_j$, in a two-good framework implies that consumption of good i is a necessity. Given our data, we state a key prediction that we can test below.

Testable Prediction 3: Assuming $\sigma_\epsilon > 1$, from Equation (4.7), a *sufficient* condition for a good to be necessary is that relative expenditure in the good rises following a rise in relative prices and a fall in total real expenditure.

4.2 Empirical Evidence on Transmission Mechanisms

We now present empirical evidence on the various transmission mechanisms we developed theoretically above. In particular, our analysis here will be guided by the testable predictions.

4.2.1 Labor Earnings Channel

We start by assessing the heterogeneous real labor earnings effects of these shocks in the household panel IV local projection framework. That is, we estimate Equation (3.1), but with real 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 heterogeneous labor income responses can lead to heterogeneous consumption responses. We summarized this channel in Testable Prediction 1 in Section 4.1.1.

steady state level of real expenditure. Relatively speaking, poorer income groups' cost of living is more sensitive to an increase in the price of a necessity good, even if all income groups consider the same good to be a necessity and even if steady state expenditure shares, γ_i, are same across income groups.

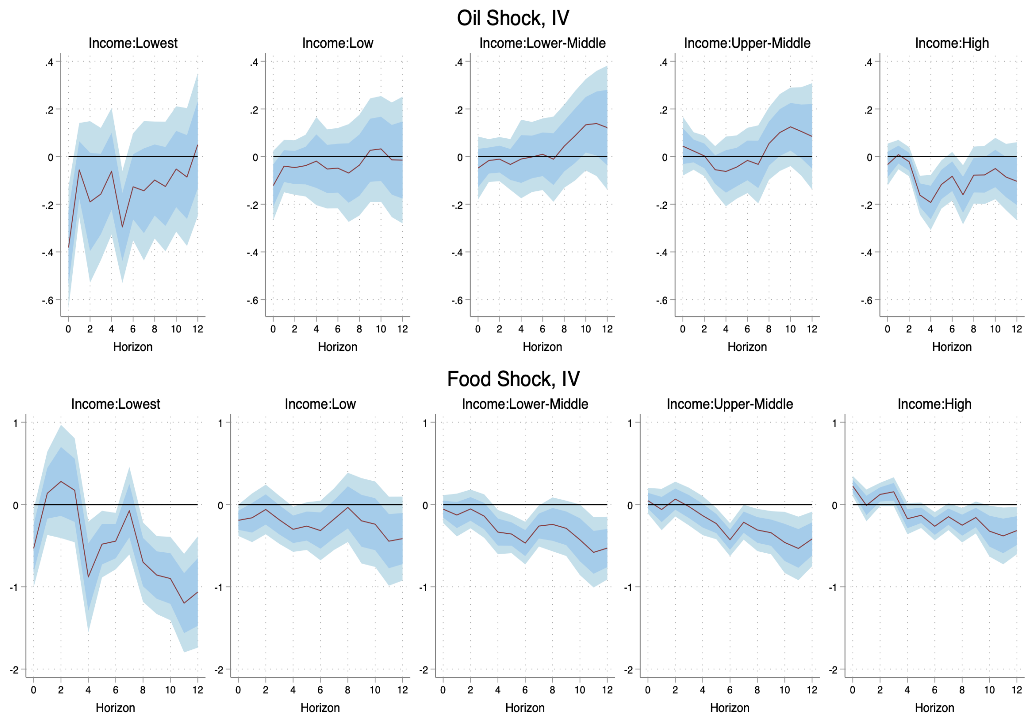

Figure 5: Response of Earnings to External Food and Fuel Price Shocks by Income Quintiles (IV)

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

Figure 5 shows the response of labor income to oil price shocks (top panel) and food price shocks (bottom panel). It is clear that food price shocks have a significant negative effect on real labor earnings throughout the income distribution. Moreover, 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 2. This suggests that heterogeneity in labor income effects is one source of heterogeneity in consumption response to food price shocks. For oil price shocks, the negative effects are more limited and are significant for the poorest group initially and for the rich over time. Nevertheless, these are still consistent with the negative consumption effects of oil price shocks for these two income groups shown in Figure 3.

4.2.2 Aggregate Price and Relative Price Channels

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. We use, for various components of CPI, state-region level monthly data from MoSPI as measures of domestic prices. We then estimate the dynamic responses of these domestic prices 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), show how aggregate inflation can affect consumption by affecting the real value of pay-offs of nominal assets and how heterogeneity in ex-ante asset positions 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 Equation (4.5) and Equation (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 domestically. Empirically, there is evidence for such effects. For instance, De Winne and Peersman (2021) have established how global food price shocks, driven by adverse weather shocks, can negatively impact real economic activity in emerging economies. This insight is also confirmed in our analysis using Indian macroeconomic data, as shown in Figure A1.

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

$$p_{s,r,t+h} - p_{s,r,t-1} = \beta_{0,u}^{h,\text{food}} ext_t^{\text{food}} \times \mathbb{1}_{r=urban} + \beta_{0,u}^{h,\text{oil}} ext_t^{\text{oil}} \times \mathbb{1}_{r=urban} + \gamma_h X_t + \sum_{d=0}^{D} \delta^h D_{t-d}$$
$$+ \sum_{j=1}^{J} \alpha_j^h (p_{s,r,t-j} - p_{s,r,t-j-1}) + \sum_{k=1}^{K} ext_{t-k}^{\text{food}} + \sum_{k=1}^{K} ext_{t-k}^{\text{oil}} + \theta_s + \zeta_r + \epsilon_{s,r,t+h} \tag{4.8}$$

where $p_{s,r,t}$ denotes (log) prices or relative prices in period t for state s and region r, 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.

D is the dummy for the Indian government's demonetization policy while X denotes controls for aggregate world conditions: world industrial production as a proxy for global demand (Kilian (2009)); US federal funds rate; and global financial volatility as captured by the VIX index. We include state and time fixed-effects and compute robust standard errors. We will present IV results where we instrument the changes in global food and oil prices by the corresponding supply shocks. 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. Table A8 in Online Appendix D.5 lists our control and instrumental variables.

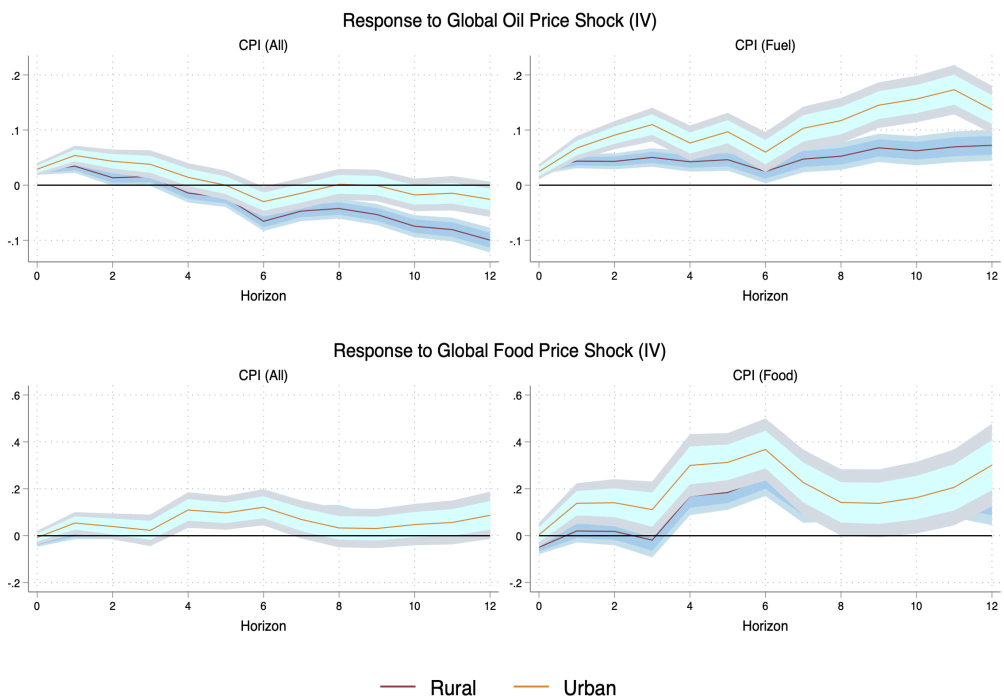

Figure 6: Response of State Level Prices to External Oil and Food Price Shocks (IV)

Notes: Cumulative IRFs on the basis of equation (4.8) where the external shock is log changes in the 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 prices. The light blue region is the 90% confidence interval and the dark blue region is the 68% confidence interval.

We present the results based on the IV specification.[26] Figure 6 shows that there is pass-through to consumer prices, both to the direct category prices (right column) as well as to overall prices (left column). Dynamic effects of global food price change on

[26]The OLS results for comparison are in Online Appendix D in Figure A7. The first-stage F-statistics for these IV regressions are in Online Appendix D in Table A9.

overall CPI very closely follow its effects on the food component of CPI.[27] Finally, global oil price shock passes through strongly to domestic energy prices (comprising of fuel, light, and transportation costs) in India as well as to headline prices, and the global oil price pass-through on local fuel prices is particularly prominent in the urban areas.

Next, to illustrate the effects of these shocks on relative prices, in Figure 7 we show the responses of three relative prices: the ratio of food price to fuel price (left column), and the ratio of food or fuel price to the non-durables consumption price (right column).[28] As is clear, 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. These results hold across both urban and rural India.

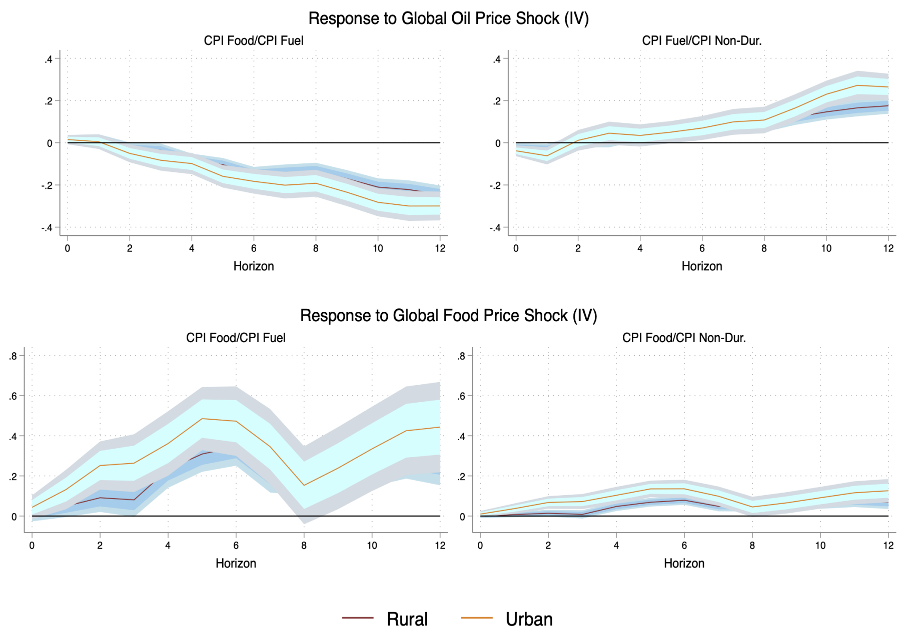

Figure 7: Response of State Level Relative Prices to External Oil and Food Price Shocks (IV)

Notes: Cumulative IRFs on the basis of equation (4.8) where the external shock is log changes in the 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 is the 90% confidence interval and the dark blue region is the 68% confidence interval.

We also look at relative price effects using more dis-aggregated food categories to investigate in more detail the pass-through to local Indian prices as well as to understand

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

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

later the results on expenditure share effects. In Figure A8 in the Appendix, we present results for relative price responses of various food components, as a ratio to fuel prices, for the case of food price shocks. It shows that in response to an exogenous increase in global food prices, relative prices of many food categories increase.

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) as well as relative prices (for example, as captured by food and fuel CPI ratios). This, certainly, has implications for consumer behaviour. Moreover, the effects on relative prices of both shocks suggest that relative consumption expenditures will be affected non-trivially by them.

4.2.3 Non-Homotheticity: Consumption Share Effects Within Non-Durables

Responses of food to fuel expenditure ratios We next investigate the effects on nominal consumption expenditure ratios within non-durables. Note that in Figure 7 we showed that relative food prices increase in response to global food price shocks while in Figure 2 we showed that real non-durable consumption expenditure falls in response to global food price shocks. Estimating effects on ratios of nominal consumption expenditures of food, with respect to non-durable 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 Equation (4.6) and Equation (4.7). In particular, Testable Prediction 3 in Section 4.1.2 had summarized that relative expenditure on food increasing in response to the food price shock, given the relative price of food and non-durable consumption expenditure responses, would be sufficient evidence for food to be categorized as a necessary consumption good.

Figure 8 presents results for food expenditure ratios with respect to non-durable consumption expenditure (top row) and fuel expenditure (bottom row). As is clear, in response to the global food price shock, the food expenditure ratio increases for the lower income groups while it decreases for the two higher income groups. Given the relative price responses in Figure 7 and the decline in real non-durable consumption in Figure 2, as pointed out in Testable Prediction 3, these consumption share responses show a role for income effects in relative demand. In particular, we infer that food is unambiguously a necessity for the lower income groups. For the richer households, the response we find could be consistent with standard expenditure switching as relative expenditure on food falls. We can however, still not rule out that food is necessary even for the richer households as relative expenditure rising is only a sufficient condition not a necessary one, as stated in Testable Prediction 3.[29]

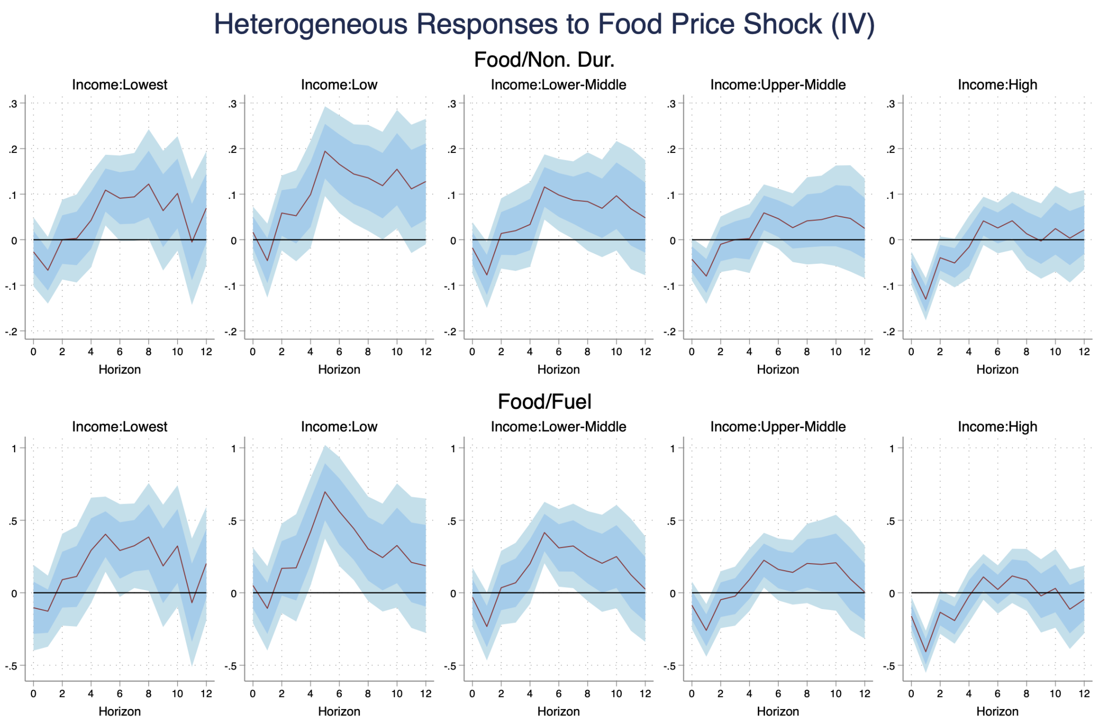

Figure 8: Response of Food Consumption Shares to External Food Price Shocks by Income Quintiles (IV)

Notes: Cumulative IRFs on the basis of equation (3.1) where the external shock is log changes in the global food price, which is instrumented by a global food supply shock. In the top panel, the dependent variable is the ratio of household nominal food to non-durable consumption expenditures and in the bottom panel, the dependent variable is the ratio of household nominal food to fuel consumption expenditures. The light blue region is the 90% confidence interval and the dark blue region is the 68% confidence interval.

Responses of detailed food categories to fuel expenditure ratios Given this evidence for food expenditure ratios, we delve into expenditure ratio results for various food components. As food expenditure is a composite of different food categories, the average response might not be indicative of non-homotheticity for all types of food expenditures. Again, Testable Prediction 3 in Section 4.1.2 had summarized that relative expenditure on food components increasing in response to the food price shock would be a *sufficient*

[29]We will address this issue below using some structural assumptions on the price elasticity parameter that governs expenditure switching.

proof for non-homotheticity, as the relative price of these food components increases (Figure A8) and total real non-durable consumption expenditure falls (Figure 2).

Figure 9 presents results for responses of various food components to fuel expenditure ratios. We also plot the relevant relative price response in the left column (from Figure A8). It shows that the evidence for non-homotheticity in preferences of the poor (including the two lowest income groups) with respect to various food categories is quite clear for sugar, oil and fats, and vegetables as the expenditure ratios for these categories increase. In addition, in these three food categories, for the rich, the expenditure ratio goes down. Moreover, Figure 9 shows that the clear pattern of lack of expenditure switching (on net) by the poor (again including both the low income groups) is prominent also for other food categories, such as pulses and spices. Interestingly, for pulses and spices, the results suggest no expenditure switching even by the rich. Thus, pulses and spices are clearly a necessary good for all income groups in India as the results for them satisfy the sufficient condition laid out in Testable Prediction 3 in Section 4.1.2.

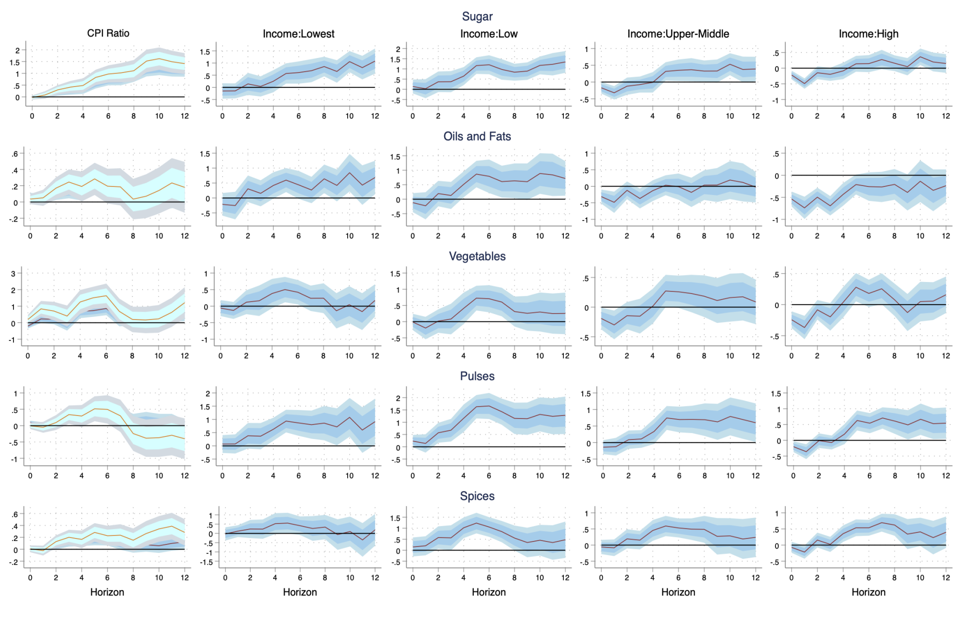

Figure 9: Response of Various Food Categories Consumption Shares to External Food Price Shocks by Income Quintiles(IV)

Notes: Cumulative IRFs on the basis of equation (3.1) where the external shock is log changes in the global food price (bottom panel), which is instrumented by a global food supply shock. The dependent variable is the ratio of household nominal food categories to fuel consumption expenditures. The left column shows the responses of the relevant relative prices. The light blue region is the 90% confidence interval and the dark blue region is the 68% confidence interval.

Estimation of income elasticity of demand parameters We now directly estimate the key income elasticity of demand parameters in Equation (4.7). In particular, we fix $\sigma_\epsilon = 2$, allowing for some expenditure switching when relative prices change, and then estimate $\epsilon_i - \epsilon_j$ by matching the dynamic impulse responses on relative expenditures and total real non-durable consumption expenditures to global price shocks across different horizons.

The results are in Table 3. In Panel A we use the results on global food price shocks, and in Panel B we use the results from both global food and oil price shocks. First, we present the estimates based on the total food to fuel expenditure ratio. That is, fixing $\sigma_\epsilon = 2$, we use the impulse responses of the food to fuel relative price from Figure 7, the food to fuel expenditure ratio from Figure 8, and real non-durable consumption expenditure from Figure 2, to estimate $\epsilon_i - \epsilon_j$ in Equation (4.7). As is clear, $\epsilon_i - \epsilon_j$ is estimated to be negative, showing that food is a necessary good for all income groups.

Next, we repeat the same exercise for various food components, using the appropriate food components to fuel relative prices and relative expenditure shares. It shows that various food components are necessary goods for all income groups as $\epsilon_i - \epsilon_j$ is negative.

Finally, note that some of the $\epsilon_i - \epsilon_j$ in Panel A are not precisely estimated. One reason is that in each exercise, we are only relying on 13 observations (the horizon of the impulse responses). In Panel B, as we mentioned above, we report estimates from repeating the same exercise as in Panel A, but using the impulse responses for both the global food and oil price shocks. As is clear, then $\epsilon_i - \epsilon_j$ are estimated more precisely to be negative.

Table 3: Estimates of Demand Function Parameters ($\epsilon_i - \epsilon_j$)

	Lowest	Low	Low-middle	Upper-middle	High
	Panel A: Estimated Using IRFs From Only Food Shocks				
Food (All)	-0.461*	-0.571*	-0.566*	-0.767**	-0.830**
	(0.163)	(0.199)	(0.188)	(0.207)	(0.220)
Sugar	-2.558***	-2.834***	-2.871***	-3.351***	-3.566***
	(0.253)	(0.222)	(0.288)	(0.490)	(0.464)
Oils and Fats	-0.529**	-0.763***	-0.510**	-0.535**	-0.573**
	(0.154)	(0.169)	(0.146)	(0.164)	(0.178)
Vegetables	-0.431	-0.890	-0.734	-1.306	-1.347
	(0.526)	(0.555)	(0.578)	(0.682)	(0.788)
Pulses	-0.018	-0.395	-0.129	-0.142	-0.248
	(0.334)	(0.467)	(0.432)	(0.519)	(0.572)
Spices	-0.099	-0.353	-0.392	-0.560*	-0.875**
	(0.166)	(0.248)	(0.200)	(0.237)	(0.259)
	Panel B: Estimated Using IRFs From Food and Oil Shocks				
Food (All)	-0.515***	-0.654***	-0.627***	-0.731***	-0.673**
	(0.115)	(0.100)	(0.135)	(0.170)	(0.183)
Sugar	-2.006***	-2.182***	-2.171***	-2.389***	-2.380***
	(0.171)	(0.103)	(0.187)	(0.288)	(0.310)
Oils and Fats	-0.647***	-0.837***	-0.515***	-0.350**	-0.245
	(0.097)	(0.074)	(0.076)	(0.116)	(0.206)
Vegetables	-0.733*	-1.200***	-1.081**	-1.412**	-1.349*
	(0.297)	(0.232)	(0.340)	(0.454)	(0.536)
Pulses	-0.777**	-1.393***	-0.950**	-1.004*	-0.999*
	(0.253)	(0.241)	(0.284)	(0.364)	(0.427)
Spices	-0.185	-0.670***	-0.472**	-0.755**	-0.992**
	(0.112)	(0.144)	(0.127)	(0.217)	(0.269)

Notes: This Table reports the estimates of $\epsilon_i - \epsilon_j$ obtained by estimating Equation (4.7) in a regression framework after fixing $\sigma_\epsilon = 2$ and using as data the impulse responses of relative prices, relative expenditures, and real non-durable consumption expenditure. Each row represents estimates from a separate regression, with 13 observations used in Panel A and 26 observations used in Panel B. The columns represent the various income groups. $\epsilon_i - \epsilon_j < 0$ indicates that good i (food and various food categories here) is a necessary consumption good.

5 Discussion, Sensitivity Analyses, and Extensions

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

5.1 OLS Results on Consumption and Income

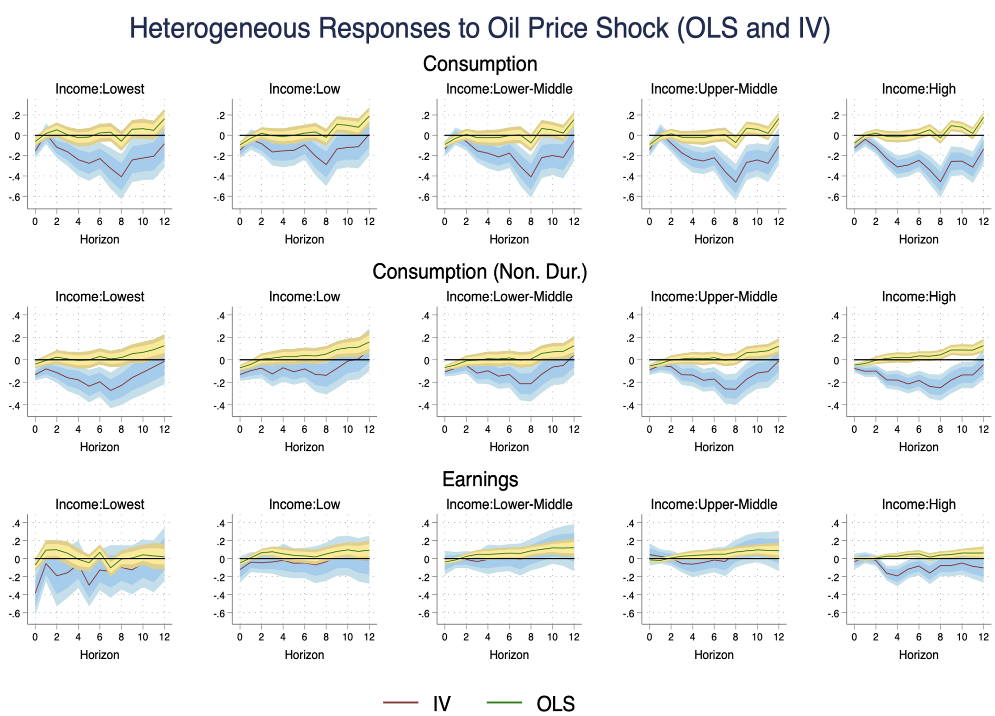

Figure 10: Response of Consumption and Earnings to External Oil Price Shocks

Notes: Cumulative IRFs on the basis of equation (3.1) where the external shock is log changes in the global oil price. In the IV version, the log changes in global oil price is instrumented by a global supply shock. The dependent variable is log changes in household consumption, non-durable consumption, and labor earnings. The light blue region is the 90% confidence interval and the dark blue region is the 68% confidence interval.

As we discussed before, our IV estimates isolate global supply side variation in global commodity prices, which is important to avoid mixing in the effects of supply and global demand shocks as well as guarding against omitted variable bias problems. We now further show the importance of the IV estimates by presenting in detail the OLS results for oil price shocks. Based on household data and estimation of equation (3.1), Figure 10 present the OLS results to a key question of the paper: How does the dynamic response of consumption and income to global oil price shocks vary by ex-ante income quintiles? We show results for total and non-durable consumption as well as wage income. For comparison, we also plot the IV results we presented earlier in Figures 3 and 5.

As is clear, in the OLS results, as predicted, the consumption effects are not consistently and persistently negative for any income group. Moreover, the earnings effects are even positive for the higher income groups. Thus, as expected, richer Indian households 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. Thus, it is imperative to isolate demand and supply side variation while studying the distributional consequences of global price shocks.[30]

5.2 Expenditure Switching: Non-Durable Consumption Share Effects

We investigate the effects on the nominal consumption expenditure ratio of non-durable to total consumption to show that expenditure switching is a reasonable assumption. In Figure A10 we show that global food price shocks increase the relative price of non-durables while global oil price shocks, after a delay, decrease the relative price of non-durables. Then, 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 A10 presents results for the response of the 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, this ratio increases for the global oil shock, while it decreases for the global food shock.[31] In addition, the response of the non-durable consumption shares are very similar across various income groups, suggesting that relative price movements are the main determinant, as captured by a homothetic CES aggregator in equation (4.5).

[30] As Kilian (2009) originally noted for aggregate effects, here, for distributional effects too, not all oil shocks are alike! Similar, albeit not statistically significant, differences between OLS and IV results are observed in the case of food price changes in Figure A9.

[31] The results for the food price shock are comparatively noisier towards the end of the horizon.

5.3 Sensitivity Analyses and Extensions

We now describe several sensitivity checks for our key results and some extensions to our baseline framework. As our first robustness check, we estimate heterogeneous consumption and earnings effects for the two commodity price shocks separately, as opposed to our baseline joint estimation of the effects of the two shocks in a single estimation equation. This allows us to assess if the joint estimation strategy affects the results by controlling for the general equilibrium effects of the oil price shock on food prices. The results are in Figures A11 and A12 and comparing those to their baseline counterparts in Figures 2, 3, and 5, we conclude that the results are the same.

Second, we continue to use our baseline approach of joint estimation of effects of both shocks, but now do not use any controls and fixed effects for household characteristics.[32] The results are in Figures A13 and A14 for food shocks and oil shocks respectively. The results do not change compared to those that included these household-level fixed effects and which we presented earlier in Figures 2, 3, and 5. This provides evidence that our IV estimation successfully isolates exogenous variation such that adding household-level controls and fixed effects does not affect the results.

Next, we address the issue that our answer to the key research question may be sensitive to how we assign individuals to different income groups. In our baseline results summarized in Figure 4, 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. We next 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 (Deaton (2019)). Indeed, characteristics of households by per capita income deciles, as reflected in Table A10, 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 ac-

[32] In this specification, we thus only include aggregate controls that are interacted with the income groups as well as residence state by calendar month and residence state by calendar year fixed effects.

cording to equation (3.1). Summary statistics of non-durable consumption response, estimated using panel IV regressions, are in Figure A15. The results in Figure A15 reflect the same pattern of heterogeneous consumption response as in Figure 4.

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 A11. While more than 80% of households remain in the same income group over time (as captured by the diagonal entries of Table A11), 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 IV local projection framework of equation 3.1 while restricting the transition matrix such that no household is allowed to move more than two (absolute) steps in the transition matrix. The resulting summary statistics of non-durable consumer response is in Figure A16. These results again are similar in nature to the baseline results of Figure 4.

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, the lowest and highest income groups suffer equally from an increase in global oil prices.

Finally, motivated by the vast regional heterogeneity of India, we do an extension of our baseline empirical framework. In this 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:

$$\begin{aligned} c_{i,t+h} - c_{i,t-1} &= \beta_{0,\text{food}}^{g,h,r} ext_t^{\text{food}} \times \mathbb{1}_{i\in g(t)} \times \mathbb{1}_{i\in\text{urban}} + \beta_{0,\text{oil}}^{g,h,r} ext_t^{\text{oil}} \times \mathbb{1}_{i\in g(t)} \times \mathbb{1}_{i\in\text{urban}} \\ &+ \sum_{j=1}^{J} \alpha^h (c_{i,t-j} - c_{i,t-j-1}) + \sum_{k=1}^{K} \beta_{k,\text{food}}^h ext_{t-k}^{\text{food}} + \sum_{k=1}^{K} \beta_{k,\text{oil}}^h ext_{t-k}^{\text{oil}} + \sum_{d=0}^{D} \delta^h D_{t-d} \\ &+ \gamma^{g,h} X_t \times \mathbb{1}_{i\in g(t)} + \delta_{\text{c},t} + \delta_{\text{l},t} + \delta_{\text{e},t} + \delta_{\text{city},t} + \delta_{\text{age},t} + \mathbb{1}_{i\in\text{s}} \times \mathbb{1}_{\text{year}} + \mathbb{1}_{i\in\text{s}} \times \mathbb{1}_{\text{month}} + \epsilon_{i,t+h} \end{aligned} \tag{5.1}$$

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

Results for consumption responses are presented in Figure A17, and the corresponding earnings results in Figure A18, where we show for each income group, the difference in estimates for urban households compared to rural households. Figure A17 shows that the differential consumption effects are not statistically significant, except for oil shocks for the highest income group. For that income group, urban households' consumption is relatively less affected by oil shocks (recall that this shock affected consumption effects negatively for this income group as shown in Figure 3). Figure A18 shows that on earnings, the differential effects are statistically significant for the higher income households for the food shocks and also often for the oil shocks. Thus, urban households' earnings are relatively less affected by both shocks for the higher income groups.

5.4 Discussion and Related Literature

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 A19 we compute summary statistics to compare earnings and non-durable consumption responses from Figures 2, 3, and 5. For all income groups other than the poorest, effects on consumption are larger in magnitude than those 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 A20. 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.) 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 A12.[33]

We also note that our results showing a strong response of consumption to these shocks (even non-durable consumption), compared to wage income, is reminiscent of the positive effect of unanticipated inflation on household saving, observed in the seminal work of Deaton (1977). As an explanation, Deaton (1977) offers the fundamental in-

[33] Data source is Basic Statistical Return of Reserve Bank of India, 1998-2016.

sight that individual consumers have no possible means of distinguishing relative price changes from absolute price changes and this mechanism is likely to be at work for us as well. Finally, our result also connects to the unconditional stylized facts from the emerging market business cycle literature.[34]

Another important insight emerges from Figure A19 while comparing the effects on earnings with the effects on non-durable consumption for food price shocks. Earnings effects of the exogenous rise in food price are clearly much larger for the poorest than for the poor (Figure 5), but non-durable consumption effects are comparable (Figure 4). This suggests a role for the public distribution system as an insurance mechanism for those below the poverty line.[35]

Second, as seen in Figure 5, what might be an economic mechanism at work that gives a clear role for the earnings channel for food price shocks? We earlier discussed how such shocks can and do cause an economic contraction. In addition, this can also be rationalized based on the fact that most of the poorest work in the informal sector in India, as documented in Table A13, where there is no inflation adjustment in nominal wage income.[36] 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.[37] However, with a rise in global food prices and its direct effect on domestic food prices, the cost of living of the poor rises disproportionately due to the higher share of food in the consumption basket of the poor.[38] This however, does not set off the same nominal wage adjustment process in the informal sector, and as a result, we observe a

[34]For instance, 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).

[35]Our lowest income group is below any reasonable poverty line. See, Shrinivas, Baylis, and Crost (2024) for a recent reference for the impact of the public distribution system.

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

[37]We do observe an initial decline in the real earnings of the poor immediately after the oil supply shock.

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

decline in the real earnings of the poor.[39]

Third, in a summary statistics format, in Figure A21 we compare the non-durable and total consumption responses to global food and oil price shocks from the IV panel results presented in Figures 2 and 3. Remarkably, the elasticity of total consumption is uniformly larger than that of non-durable consumption, pointing towards a larger response of durable consumption to external price shocks. This excess volatility of durable consumption is a well-known fact in other contexts.[40]

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 results show robust evidence that lower income deciles are affected more by an exogenous increase in food prices, while both tails of the income distribution are affected similarly by an exogenous increase in fuel prices. We also find that these heterogeneous consumption responses largely mirror the pattern of heterogeneity in earnings response to these global price shocks. Examining relative expenditure responses, in light of relative price effects, allows us to uncover patterns of non-homotheticity in non-durable consumption. We find that food, compared to fuel, is a necessary consumption good for all income groups in India. Our analysis provides a novel way of identifying necessary consumption components by relying on a non-homothetic isoelastic CES demand structure and impulse response matching using external instruments.

Our findings have 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 optimal monetary policy in a heterogeneous agent open economy model, allowing for the necessary nature of food in the consumption basket and an energy sector.

[39] Fall in real purchasing power is one of the key reasons why people dislike inflation (Stantcheva (2024)).

[40] See, for example, Alvarez-Parra, Brandao-Marques, and Toledo (2013). This finding can be rationalized in canonical models of consumption smoothing. Note that total consumption includes non-durable, durable, and service consumption.

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Appendix A 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 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. We use data from Jan 2014 to Dec 2019.

We construct income, earnings, and consumption categories closely following the definitions given by Coibion et al. (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, pensions, dividends, interest and deposits, provident fund, and insurance. These categories are an exhaustive list of all income sources collected in the CPHS survey. 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 the sale of assets and rent. Our (labor) earnings measure is constructed using only the category of income from wages and overtime bonuses.

We construct consumption closely matching the categories constructed by Coibion et al. (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.

External shock measure

We use IMF's Global Price of Food Index (Nominal USD) and Brent crude oil prices (USD) at monthly frequency as our data for global food and oil prices. We construct global price changes 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 a monthly frequency. The base year is 2012 and data is available from January 2011. The data is dis-aggregated by geography as well as by-products. Geographically, the data are available for 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 and non-durables. 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.

The non-durable price index includes food and the composite fuel prices. It is calculated as

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

Online Appendix A Summary Statistics by Income

Table A1: Summary Statistics by Income Decile

Decile	No. of Hhs	Income	Earnings	Consumption	Non-dur. Share	Food Share
1	33,830.51	827.37	504.42	2,520.58	0.78	0.62
2	5,644.08	3,943.66	3,191.57	3,908.62	0.79	0.65
3	8,093.39	4,899.28	4,238.48	4,295.64	0.79	0.64
4	10,576.03	5,899.26	5,218.08	4,716.47	0.78	0.63
5	12,287.31	6,923.61	6,101.26	5,145.57	0.77	0.61
6	12,892.10	8,177.10	6,997.05	5,543.09	0.77	0.60
7	14,493.92	9,834.17	8,274.90	5,944.41	0.76	0.59
8	16,485.14	12,095.56	9,660.60	6,532.69	0.75	0.58
9	19,543.08	16,126.54	12,189.33	7,344.10	0.75	0.56
10	29,928.75	32,483.79	21,010.59	9,434.76	0.73	0.52

Notes: This table presents some summary statistics by income deciles. Income and consumption are in real terms where they are deflated by the state-region level consumer price index (base 2012). The statistics are calculated by adjusting for sampling weights and non-response factors provided by the Center for Monitoring Indian Economy. Non-durable and food share refer to the shares of non-durable and food in total consumption.

Table A2: Income Composition by Income Groups

Income Group	Earnings	Transfers	Capital Income (Broad)	Pensions
Lowest	0.44	0.18	0.02	0.03
Low	0.84	0.08	0.04	0.01
Lower Middle	0.87	0.03	0.06	0.02
Upper Middle	0.80	0.02	0.12	0.04
High	0.68	0.01	0.22	0.05

Notes: This table presents some summary statistics by income groups, where it shows shares of various sources of income. The statistics are calculated by adjusting for sampling weights and non-response factors provided by the Center for Monitoring Indian Economy.

Table A3: Distribution of Socio-Economic Groups by Income Categories

	Q_1	Q_2	Q_3	Q_4	Q_5
Panel A: Region					
Urban	58	53	64	73	81
Rural	42	47	36	27	19
Panel B: Education Category					
Upto 7th Std	48	67	57	46	25
Upto 12th Std	35	29	36	39	38
≥ College Graduate	16	4	7	15	38
Panel C: Religion					
Buddhist	0	0	0	1	1
Christian	2	1	1	2	2
Hindu	85	87	85	84	85
Jain	0	0	0	0	1
Khasi	0	0	0	0	0
Muslim	10	11	12	10	7
Other Religion	0	0	0	0	0
Sikh	3	1	2	3	5
Panel D: Caste Category					
Intermediate Caste	13	8	8	10	14
OBC	37	39	41	40	32
SC	17	28	25	20	12
ST	7	9	6	4	3
Upper Caste	26	17	19	25	39

Notes: This table presents summary statistics on some socio-economic variables by income deciles. The statistics are calculated by adjusting for sampling weights and non-response factors provided by the Center for Monitoring Indian Economy. The columns within an income group add up to 100%.

Online Appendix B Estimation of the Food Price Shock IV

Table A4: 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 A4) which comprise 13 industrial metals and 24 food prices. 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 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.[41]

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 Kose et al. (2008) explain, a principal component method is, however, not well suited for estimating models under exclusion restrictions. Model estimation using the 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 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

[41] 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.

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 the global food price index to construct our food commodity shock that we used as an instrument. In Figure A1 we demonstrate how an adverse food supply shock, measured using our method, leads to a negative impact on the Indian macroeconomy with falling real economic activity (proxied by industrial production and which happens after some lag), rising consumer prices, depreciating nominal exchange rate, and a tanking local stock market.

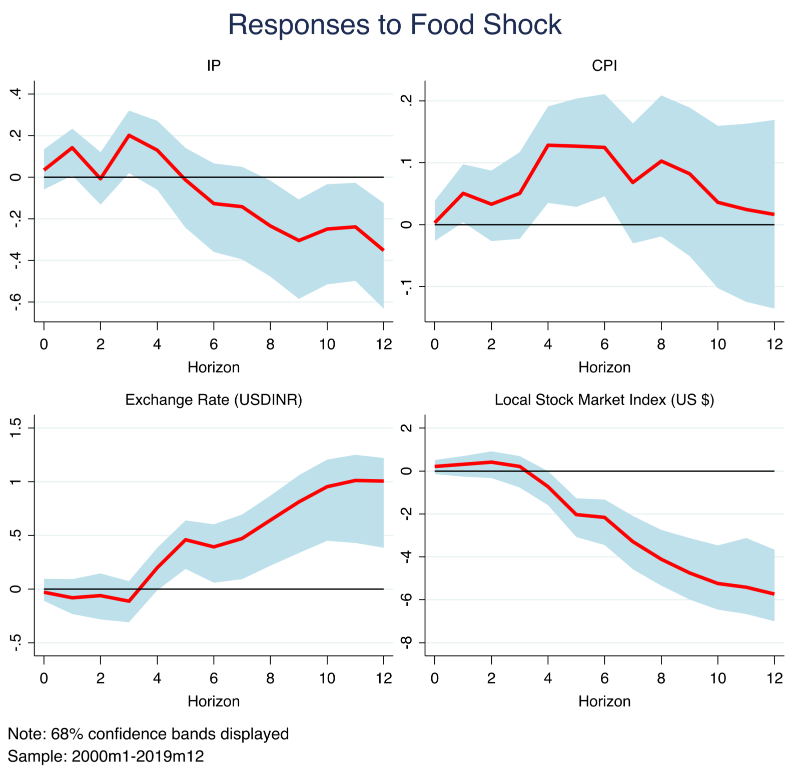

Figure A1: Macroeconomic Effects of Food Price Shocks

Notes: This figure plots the impulse response of Indian industrial production, CPI, exchange rate, and local stock market index to an adverse (positive) food supply shock that raises global food prices. The impulse responses are estimated from a Structural VAR with 12 lags and Choleski ordering of the variables. The food supply instrument is constructed using a dynamic factor model as described in Online Appendix B. Stock market and exchange rate data are collected from the Global Economic Monitor of the World Bank, while the IP and CPI data are collected from the FRED database.

Online Appendix C Global Price Changes and IVs

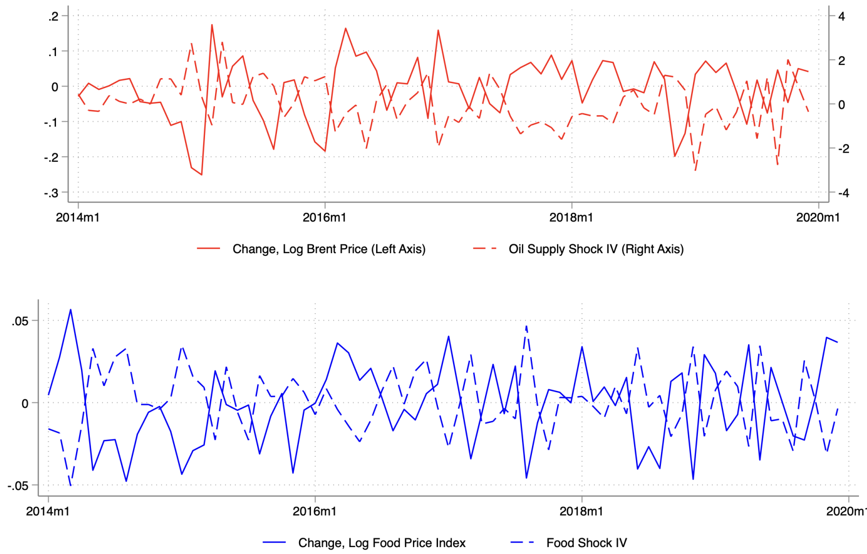

Figure A2: Oil and Food Price Shocks and the Respective Instrumental Variables

Notes: This figure plots the time series of oil (top panel) and food (bottom panel) price shocks and the respective IVs. The oil price shock series is the month-on-month change in log Brent crude oil prices; food price shock is the month-on-month change in the log global food price index published by the IMF. The supply instrument for oil price shocks is taken from Baumeister and Hamilton (2019). The food supply instrument is constructed using a dynamic factor model as described in Online Appendix B.

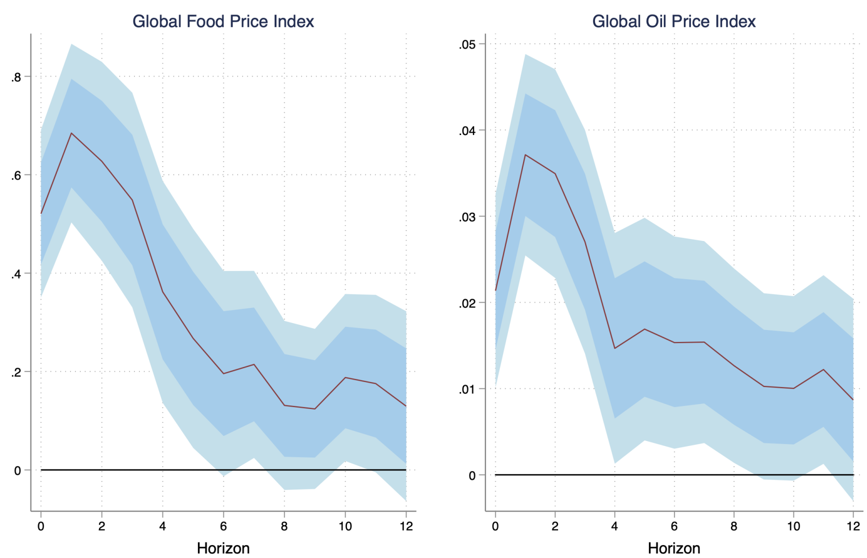

Figure A3: Pass-through of the Supply Shocks to Global Oil and Food Prices

Notes: This figure plots the impulse responses of global food and fuel prices to the corresponding negative supply shocks estimated using a local projection framework. The oil price shock series is the month-on-month change in log Brent crude oil prices; food price shock is the month-on-month change in the log global food price index published by the IMF. The supply instrument for oil price shocks is taken from Baumeister and Hamilton (2019). The food supply instrument is constructed using a dynamic factor model as described in Online Appendix B.

Online Appendix D Details on Empirical Specifications and Results

D.1 List of Controls and IVs in Household Regressions

Table A5: 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. Data on all aggregate world condition controls are obtained from the FRED.

D.2 First-Stage F-stats for Household IV Specifications

Table A6: F-statistics for Panel Local Projection IV Regressions of Household Consumption

	(1)	(2)
	Consumption (Total)	Consumption (Non-durable)
	Panel A : Global Food Price Shock & Food Supply IV	
First stage F-stats	4,705.4	4,696.3
	Panel B : Global Oil Price Shock & Oil Supply IV	
First stage F-stats	1,410.4	1,372.6

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)).

D.3 Responses Relative to Group 2

In Figure A4, we present results relative to the low-income group for both food and oil price shocks.

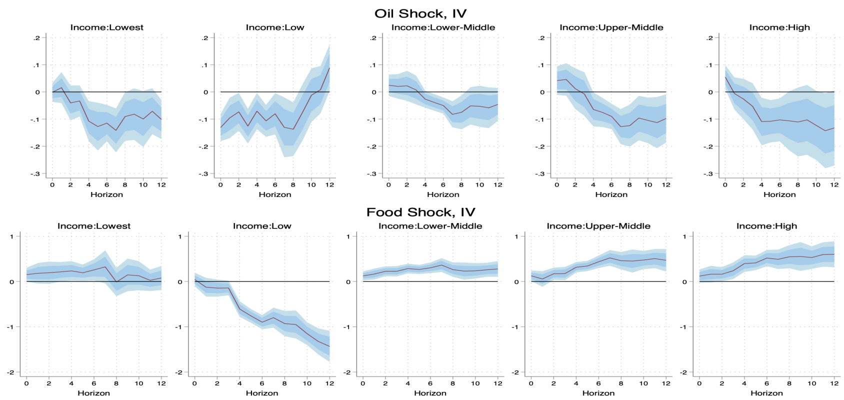

Figure A4: Response of Non-Durable Consumption to External Oil and Food Price Shocks by Income Quintiles

Notes: Cumulative IRFs on the basis of equation (3.1) where the external shock is log changes in the global Brent oil and food prices. The IRFs are presented relative to the second (Income: Low) group. The external shocks are instrumented by global supply shocks. The dependent variable is log changes in households' non-durable consumption. The light blue region refers to the 90% confidence interval and the dark blue region is the 68% confidence interval.

D.4 Effects on Regional Inequality

Here, 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:

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

where $Cineq_{s,t}$ denotes various measures of state-level inequality (in logs) 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 in equation (4.8).

We present IV results regarding the effects of global price shocks on regional inequality 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 specification is given in equation (D.1). We report cumulative impulse responses below. Table A7 lists our control and instrumental variables.

Figures A5 and A6 present answers to the key question of this section based on equation (D.1): How does regional consumption inequality evolve dynamically in response to external food and oil price changes? Figure A5 presents the IV results for the food price shock. Broadly speaking, 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.

Figure A6 presents the IV results for the oil price shock. It shows 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 traditional inequality measures might not capture the subtle ways in which households are differentially affected along the income distribution by oil price shocks. The effects of oil shocks on regional inequality hence appear to be more nuanced, consistent with what we uncover from detailed household-level data.

Table A7: 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.

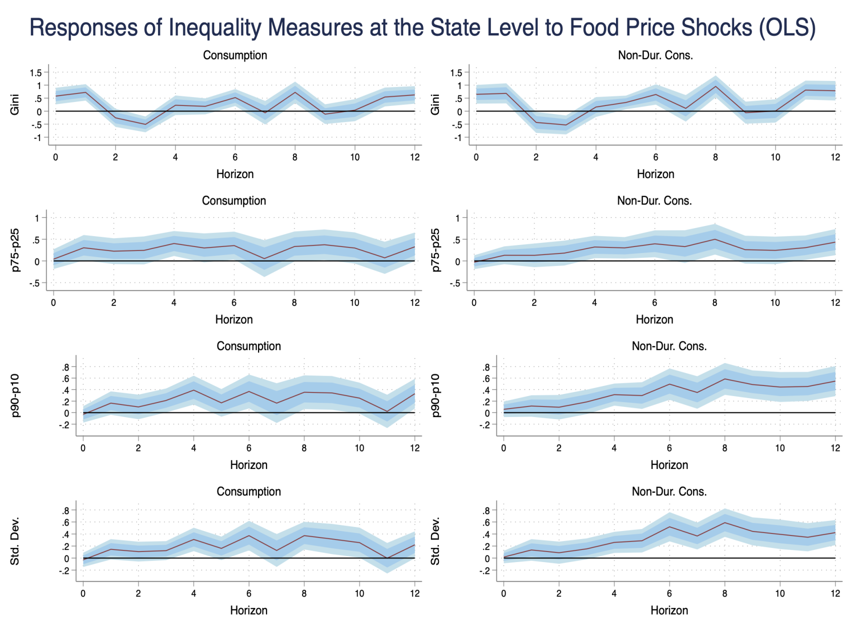

Figure A5: Response of Regional Inequality to External Food Price Shocks (IV)

Notes: Cumulative IRFs on the basis of equation (D.1) where the external shock is log changes in the 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.

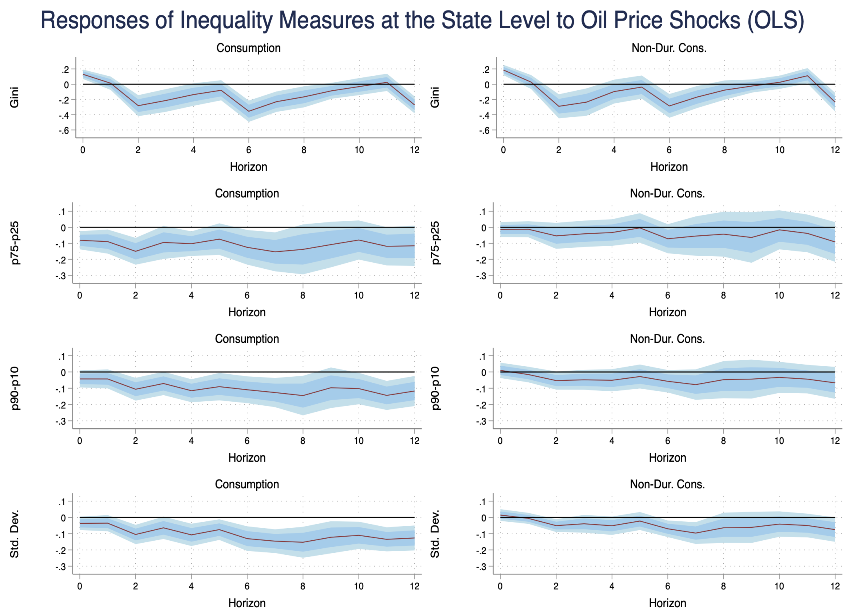

Figure A6: Response of Regional Inequality to External Oil Price Shocks (IV)

Notes: Cumulative IRFs on the basis of equation (D.1) where the external shock is log changes in the 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.

D.5 Effects on Regional Prices

D.5.1 List of Controls and IVs in Regional Regressions

Table A8: 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.

D.5.2 First-Stage F-stats for Regional IV Specifications

Table A9: F-statistics for Panel Local Projection IV Regressions of State-Geography Level Prices

	(1)	(2)	(3)
	CPI (All)	CPI (Food)	CPI (Fuel)
	Panel A : Global Food Price Shock & Food Supply IV		
First stage F-stats	3,635.9	3,614.5	2,384.9
	Panel B : Global Oil Price Shock & Oil Supply IV		
First stage F-stats	1,809.0	1,839.8	1,229.3

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 (3) show the F-statistics for estimation of effect on CPI (headline), CPI (Food), and CPI (Fuel) respectively.

D.5.3 OLS Results on Regional Price Effects of External Shocks

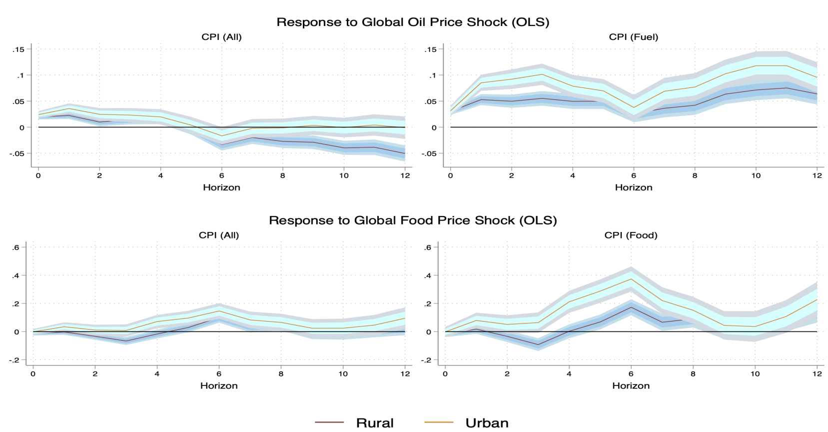

Figure A7: Response of State Level Prices to External Oil and Food Price Shocks (OLS)

Notes: Cumulative IRFs on the basis of equation (4.8) where the external shock is log changes in the global Brent price in the top panel and log changes in global food price in the bottom panel. These are OLS estimates. The dependent variable is log changes in state level prices. The light blue region is the 90% confidence interval and the dark blue region is the 68% confidence interval.

D.5.4 Detailed Food Category Relative Price Results

We look at relative price effects using more dis-aggregated food categories to investigate in more detail how the external price shocks pass-through to local Indian prices as well as to understand later the results on expenditure share effects. In Figure A8 we present results for relative price responses of various food components, as a ratio to fuel prices, for the case of food price shocks. That is, Figure A8 presents in a more dis-aggregated form the results that we presented above in the second row of Figure 7. 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 the 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, the increase in relative prices of food categories occurs in both rural and urban India.

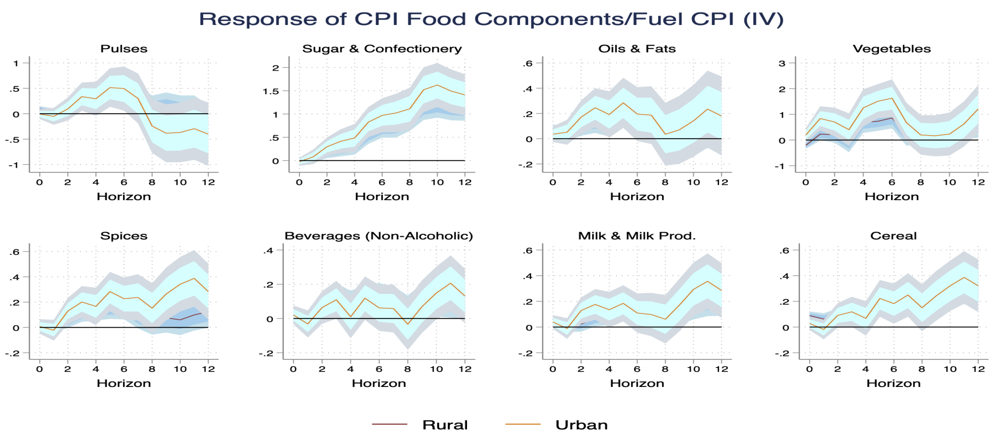

Figure A8: Response of State Level Relative Prices to External Food Price Shocks (IV)

Notes: Cumulative IRFs on the basis of equation (4.8) where the external shock is log changes in the 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 is the 90% confidence interval and the dark blue region is the 68% confidence interval.

Online Appendix E Additional Results

E.1 OLS and IV Comparison for Food Price Shocks

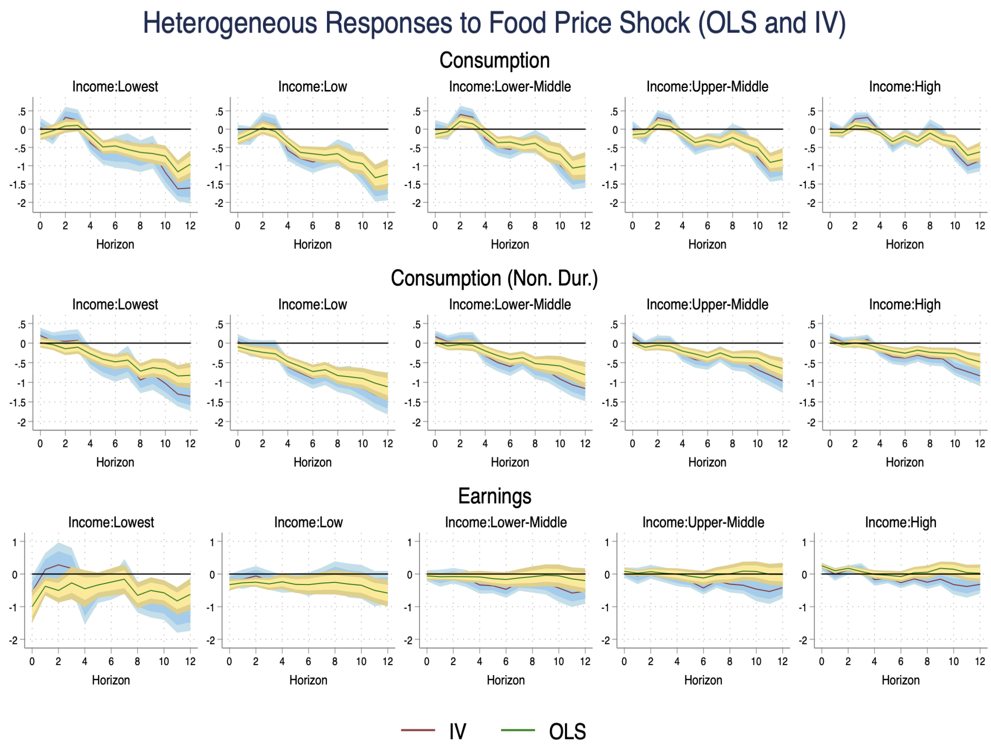

Figure A9: Response of Consumption and Earnings to External Food Price Shocks by Income Quintiles

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

E.2 Expenditure Switching of Non-durables

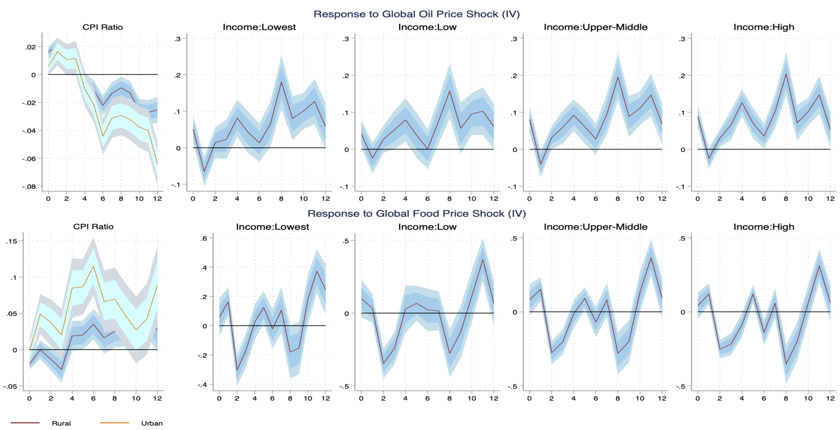

Figure A10: Response of Non-durable to Total Price Ratio and Non-durable Consumption Share to External Oil and Food Price Shocks (IV)

Notes: Cumulative IRFs on the basis of equation (3.1) where the external shock is log changes in the global Brent 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. The dependent variable is the non-durable consumption share in total expenditures. The left column plots the response of the non-durable price to the overall price.

E.3 Sensitivity Analysis: Non-Joint Estimation

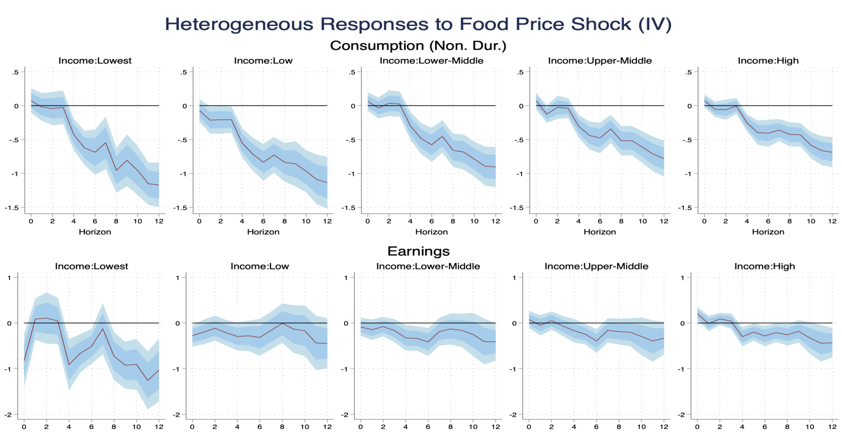

Figure A11: Response of Consumption to External Food Price Shocks by Income Quintiles (IV)

Notes: Cumulative IRFs on the basis of equation (5.1) where the external shock is log changes in the 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 is the 90% confidence interval and the dark blue region is the 68% confidence interval. Compared to the baseline specification, in this sensitivity analysis, we allow for the effects of one global price shock at a time.

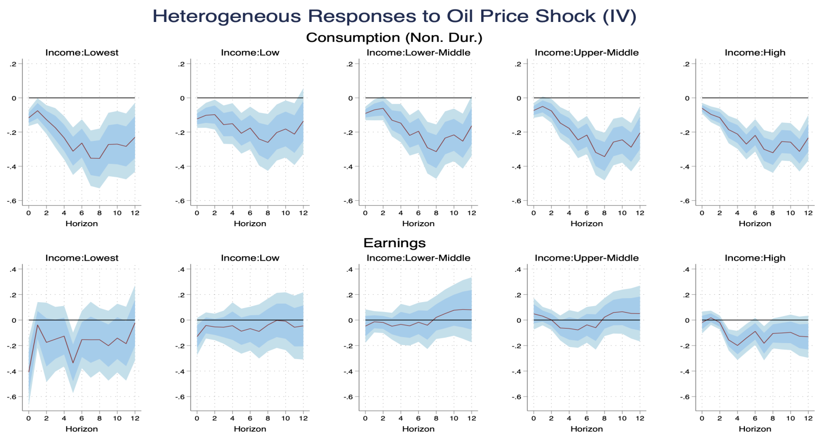

Figure A12: Response of Consumption to External Food Price Shocks by Income Quintiles (IV)

Notes: Cumulative IRFs on the basis of equation (5.1) where the external shock is log changes in the 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 is the 90% confidence interval and the dark blue region is the 68% confidence interval. Compared to the baseline specification, in this sensitivity analysis, we allow for the effects of one global price shock at a time.

E.4 Sensitivity Analysis: Without Household Fixed Effects

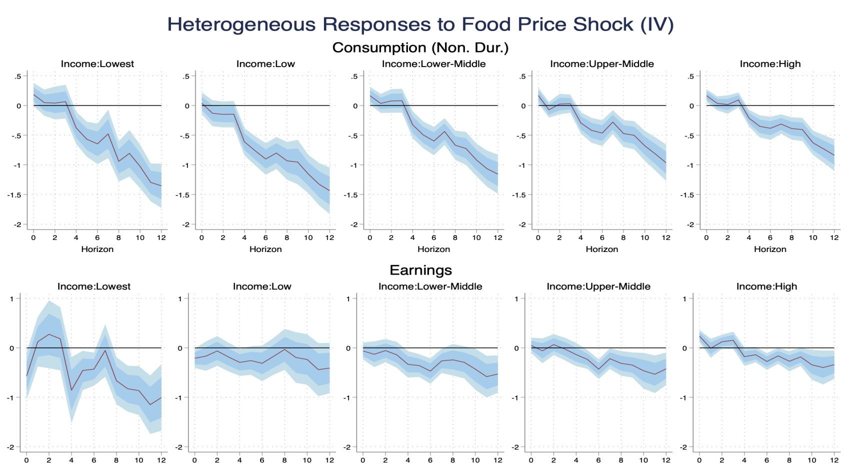

Figure A13: Response of Consumption to External Food Price Shocks by Income Quintiles (IV)

Notes: Cumulative IRFs on the basis of equation (5.1) where the external shock is log changes in the 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 is the 90% confidence interval and the dark blue region is the 68% confidence interval. Compared to the baseline specification, in this sensitivity analysis, we remove all household-specific fixed effects.

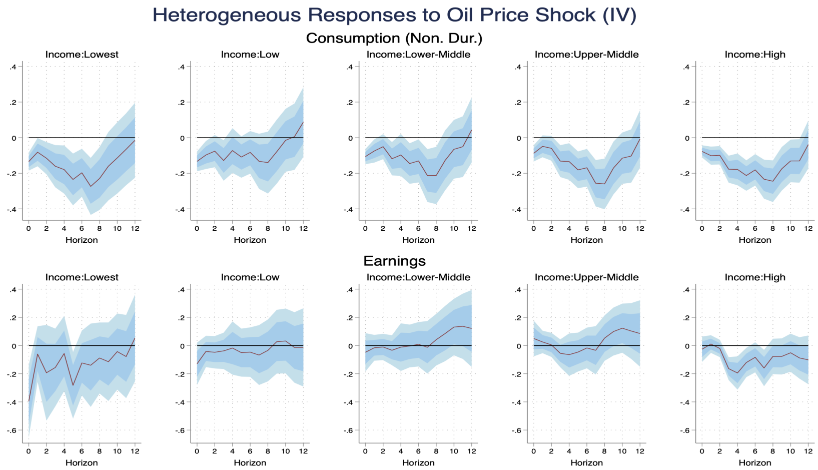

Figure A14: Response of Consumption to External Food Price Shocks by Income Quintiles (IV)

Notes: Cumulative IRFs on the basis of equation (5.1) where the external shock is log changes in the 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 is the 90% confidence interval and the dark blue region is the 68% confidence interval. Compared to the baseline specification, in this sensitivity analysis, we remove all household-specific fixed effects.

E.5 Sensitivity Analysis: Groups Based on Per Capita Income

Table A10: Summary Statistics by Income Decile (Based on Per Capita Household Income)

Decile	No. of Hhs	Income		Earnings		Consumption		Non-durable Share	Food Share
		Household	Per Capita	Household	Per Capita	Household	Per Capita	Household	Household
1	42,337.14	827.37	268.50	504.42	164.66	2,520.58	654.01	0.78	0.62
2	5,233.60	3,943.66	1,157.92	3,191.57	898.11	3,908.62	1,091.64	0.79	0.65
3	7,558.11	4,899.28	1,313.74	4,238.48	1,105.80	4,295.64	1,110.46	0.79	0.64
4	10,032.06	5,899.26	1,509.89	5,218.08	1,311.62	4,716.47	1,174.17	0.78	0.63
5	11,114.61	6,923.61	1,717.32	6,101.26	1,489.47	5,145.57	1,248.62	0.77	0.61
6	12,660.66	8,177.10	1,985.20	6,997.05	1,660.61	5,543.09	1,321.05	0.77	0.60
7	14,333.30	9,834.17	2,304.20	8,274.90	1,898.74	5,944.41	1,371.32	0.76	0.59
8	15,783.64	12,095.56	2,790.53	9,660.60	2,162.31	6,532.69	1,488.61	0.75	0.58
9	18,688.34	16,126.54	3,667.80	12,189.33	2,677.45	7,344.10	1,652.61	0.75	0.56
10	28,236.15	32,483.79	7,331.44	21,010.59	4,690.10	9,434.76	2,114.24	0.73	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 state-geography CPI (all, 2012=100). Non-durable and food share refer to consumption shares of non-durable and food consumption.

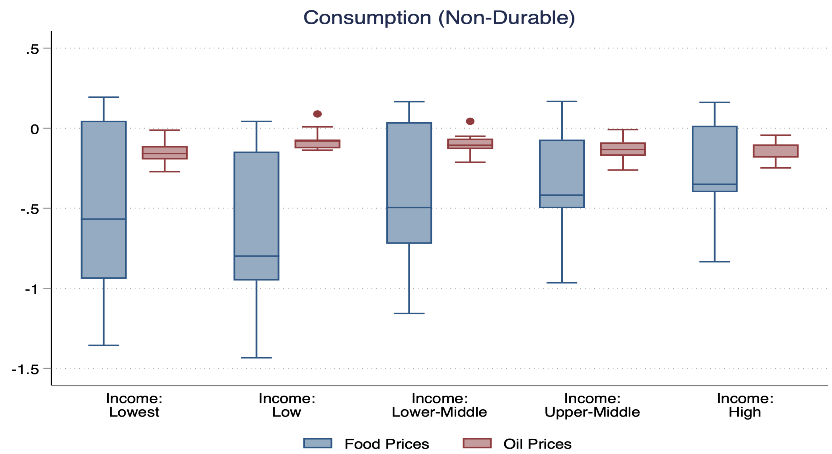

Figure A15: Summary Statistics of Response of Non-durable Consumption to Food and Fuel Price Shocks by Per Capita Income Quintiles (IV)

Notes: This figure 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. The line in the center of each box represents the median impulse response estimate across thirteen horizons; the top and the bottom edges of each box represent the 75^{th} and the 25^{th} percentiles respectively; and the lines above and below each box represent respectively the upper and lower adjacent values calculated as in Tukey et al. (1977).

E.6 Sensitivity Analysis: Restricting the Income Transition Matrix

Table A11: Transition Matrix of Real Income

	Q_1	Q_2	Q_3	Q_4	Q_5	Total
Q1	81.02	3.02	3.94	6.20	5.82	100
Q2	7.58	73.65	14.86	2.76	1.15	100
Q3	4.13	5.22	79.50	10.11	1.04	100
Q4	4.55	0.69	6.61	83.60	4.56	100
Q5	6.98	0.54	1.30	7.40	83.78	100

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

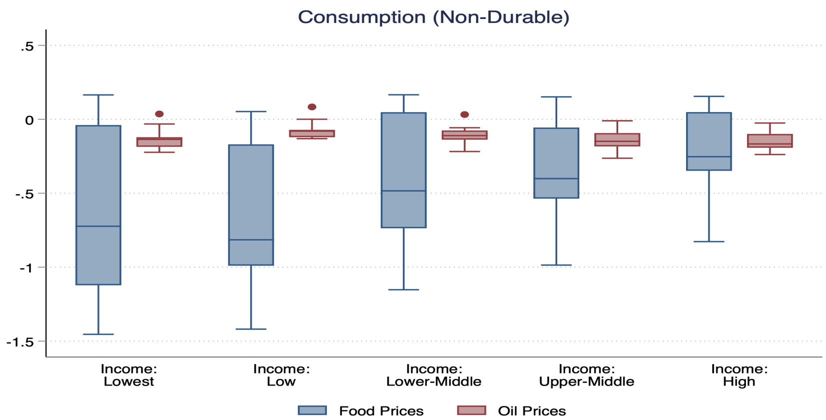

Figure A16: Summary Statistics of Response of Non-durable Consumption to Food and Fuel Price Shocks by Income Quintiles with restricted transition matrix (IV)

Notes: This figure 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. The line in the center of each box represents the median impulse response estimate across thirteen horizons; the top and the bottom edges of each box represent the 75$^{\text{th}}$ and the 25$^{\text{th}}$ percentiles respectively; and the lines above and below each box represent respectively the upper and lower adjacent values calculated as in Tukey et al. (1977).

E.7 Extension: Rural Urban Comparison

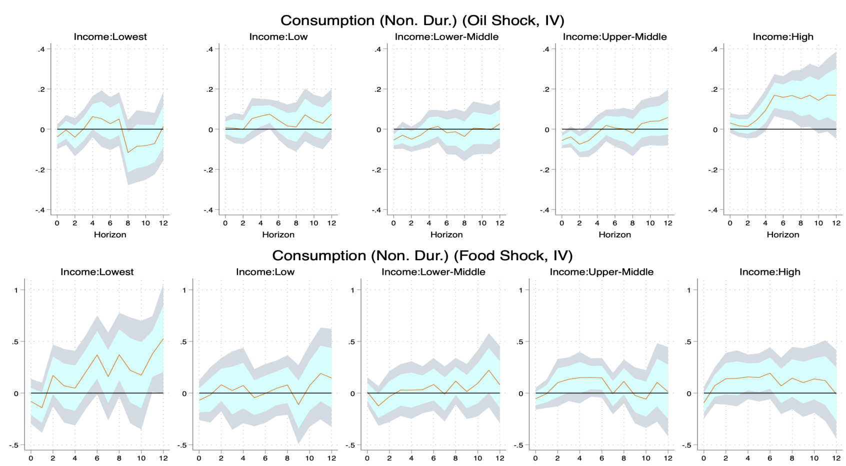

Figure A17: Response of Consumption to External Food Price Shocks by Income Quintiles (IV)

Notes: Cumulative IRFs on the basis of equation (5.1) where the external shock is log changes in the global food and oil prices, which are instrumented by the corresponding supply shocks and the dependent variable is log changes in household consumption. The gray region is the 90% confidence interval and the blue region is the 68% confidence interval. For each income group, the estimates show the differential impact on the urban sample.

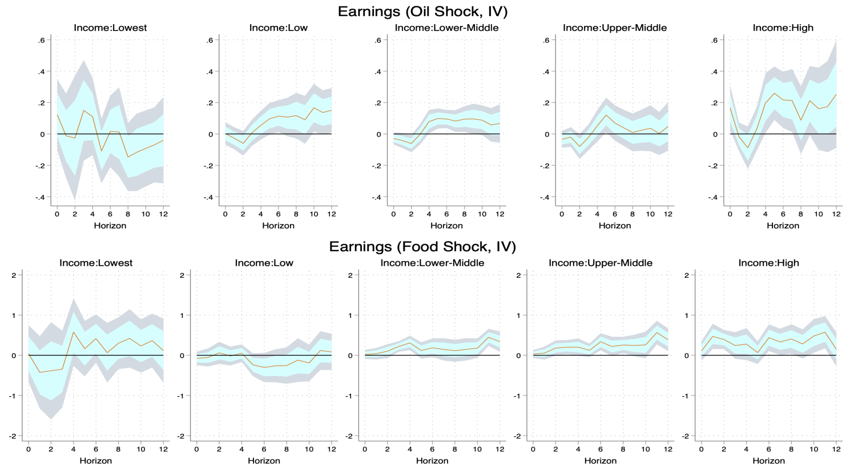

Figure A18: Response of Consumption to External Food Price Shocks by Income Quintiles (IV)

Notes: Cumulative IRFs on the basis of equation (5.1) where the external shock is log changes in the global food and oil prices, which are instrumented by the corresponding supply shocks and the dependent variable is log changes in household earnings. The gray region is the 90% confidence interval and the blue region is the 68% confidence interval. For each income group, the estimates show the differential impact on the urban sample.

E.8 Discussion Results

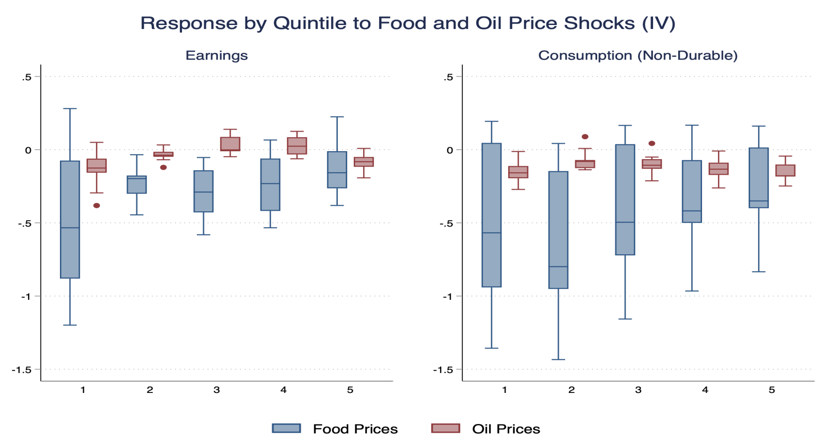

Figure A19: Summary Statistics of Response of Earnings and Non-durable Consumption to Food and Fuel Price Shocks by Income Quintiles (IV)

Notes: This figure is a box and whisker plot that summarizes the responses of labor earnings and non-durable consumption to the two external shocks that is presented in Figures 2, 3, and 5. The line in the center of each box represents the median impulse response estimate across thirteen horizons; the top and the bottom edges of each box represent the 75^{th} and the 25^{th} percentiles respectively; and the lines above and below each box represent respectively the upper and lower adjacent values calculated as in Tukey et al. (1977).

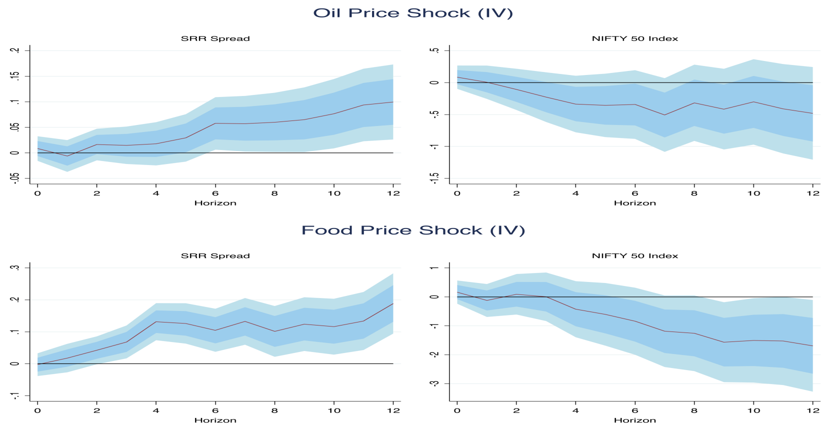

Figure A20: Response of Short Term Interest Rate Spread and Stock Prices to Food and Fuel Price Shocks (IV)

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

In Figure A20, in the left columns, we use monthly time series data on short-run (3 months) interest rate spread (relative to the U.S.) as the dependent variable, Y, and Indian industrial production and CPI as well as dummies for the global financial crisis, taper tantrum, and demonetization as controls, X, in a local projection framework:

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

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 from January 2000 to March 2018.

Table A12: 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

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

For the estimates reported in Table A12, we use the administrative lending rate data at the 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.

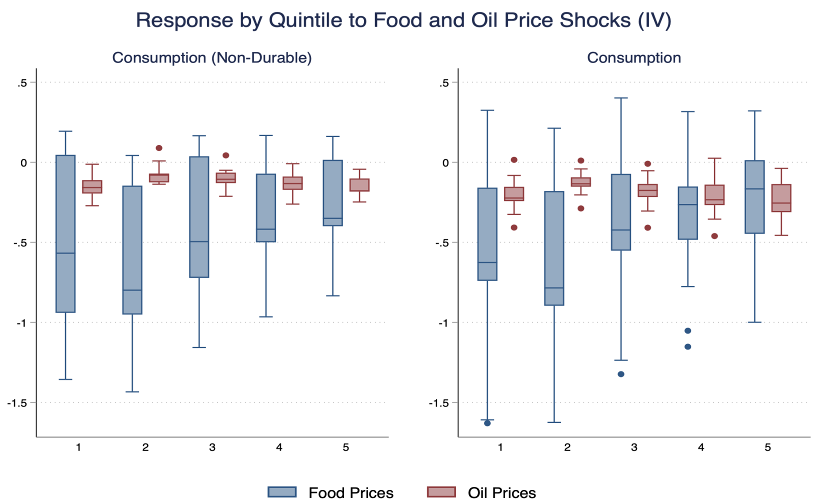

Figure A21: Summary Statistics of Response of Total and Non-durable Consumption to Food and Fuel Price Shocks by Income Quintiles (IV)

Notes: This figure is a box and whisker plot that summarizes the responses of total and non-durable consumption to the two external shocks that are presented in Figures 2 and 3. The line in the center of each box represents the median impulse response estimate across thirteen horizons; the top and the bottom edges of each box represent the 75^{th} and the 25^{th} percentiles respectively; and the lines above and below each box represent respectively the upper and lower adjacent values calculated as in Tukey et al. (1977).

Table A13: 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.