Board of Governors of the Federal Reserve System

International Finance Discussion Papers

ISSN 1073-2500 (Print)
ISSN 2767-4509 (Online)

Number 1414

July 2025

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Please cite this paper as:
Bhattarai, Saroj, Arpita Chatterjee, and Gautham Udupa (2025). "Food, Fuel, and Facts: Distributional Effects of Global Price Shocks," International Finance Discussion Papers 1414. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/IFDP.2025.1414.

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

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Abstract

We estimate distributional implications of global food and oil price shocks by utilizing monthly panel data on consumption and income from India, and an IV strategy that removes variation coming from global demand shocks. While both shocks lead to stagflationary aggregate dynamics, they differ in terms of distributional consequences. Consumption of lower income deciles is affected more by exogenous increases in food prices, while consumption of both tails of the income distribution is affected similarly by exogenous increases in oil prices. These heterogeneous negative consumption responses largely mirror the pattern of heterogeneity in wage income responses. Increases in relative expenditure of food, despite a rise in the relative local price of food, provides clear evidence for non-homothetic demand in non-durable consumption. Estimating the slopes of the Engel curve by impulse response matching, we find that food, compared to fuel, is a necessary consumption good for all income groups. Comparing the model predictions with the empirical consumption responses, we decompose the role played by wage income, relative price changes, and non-homotheticity in explaining our results.

JEL classification: E31, E32, F62, O11

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

[*]We thank Oli Coibion, Ippei Fujiwara, Joaquin Garcia-Cabo, Xing Guo, Nir Jaimovich, Diego Kanzig, Matthew Klepacz, Logan Lewis, Giacomo Mangiante, Petr Sedlacek, Sanjay Singh, Daniel Xu, and seminar and conference participants at Federal Reserve Board, NC State University, JHU-SAIS, Carleton University, AEA Annual Meeting, CAFRAL Conference, West Coast Workshop in International Finance, Joint Bank of Lithuania and Poland Conference, CEBRA Workshop for Commodities and Macroeconomics, IJCB Conference, Econometric Society Australasian Meeting, RBA Annual Conference, UWA, HKU, SERI Conference, UNSW, IIM-Bangalore, Midwest Macro Conference, ISI-Delhi, Ashoka University, American University, Johns Hopkins University, UC Santa Cruz and ANU Crawford School for helpful comments. We thank Sowmya Ganesh and Suraj Kumar for research assistance. This research presents views of the authors and not that of the Federal Reserve Board or the Federal Reserve System. First version: July 2022. This version: July 2025.

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1 Introduction

We have seen large movements in *relative prices* globally recently, due to both sector-specific shocks (such as commodity-specific supply shocks) as well as policy changes that affect specific sectors directly (such as tariffs). A particularly notable example of such a relative price change, and the focus of this paper, is the increase in *global* oil and food prices. These external shocks have raised major concerns worldwide, particularly in emerging markets, whose economies are often more exposed and vulnerable to global shocks.

Economists sometimes predict relative price increases to have little, if any, effects on aggregate consumption as they presume consumers will shift their spending toward sectors that have become relatively cheaper. However, this reasoning overlooks potential negative effects on *earnings* that can result from such price shifts, which will, in turn, reduce overall consumption. Moreover, in emerging market economies (EMEs), these shocks—particularly those in food and fuel—can have an out-sized impact, as they affect the livelihoods of a large portion of the population. These shocks are further expected to exacerbate existing inequality in these countries by having strong effects on *inflation*, and leading to disproportionate increases in cost-of-living for the poorer people due to the necessary nature of food and/or fuel in consumption.

In EMEs, as global price shocks are likely to have stagflationary effects–simultaneously slowing growth and fueling inflation–while also raising such distributional concerns, they have unsurprisingly been at the forefront of policymakers' agendas. 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. Elevated inflation will complicate the trade-offs central banks face between containing price pressures and safeguarding growth ... 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.*

Previous work provides rigorous evidence on the impact of such global price shocks on the overall macroeconomy.[1] Olivi, Sterk, and Xhani (2023) and Afrouzi, Bhattarai, and Wu (2024) offer important theoretical insights on how sector-specific shocks can lead to aggregate stagflationary dynamics. However, rigorous evidence on the distributional consequences of such shocks, as well as on the channel of transmission of such shocks operating from income to

[1] See among others, Hamilton (2003), Kilian (2009), Baumeister and Hamilton (2019), Kanzig (2021), De Winne and Peersman (2016), and De Winne and Peersman (2021).

overall consumption, is limited. The emerging 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 (2024)) focuses on advanced economies and (explicitly or implicitly) assumes 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 increases 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.[2]

We find clear distributional consequences in India due to 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 total (real) consumption effects on poorer income groups. While an exogenous rise in global fuel prices also clearly has adverse effects on consumption, the pattern of heterogeneity, and consequently the impact on inequality, is more subtle as the poorest and the two richest household groups are similarly affected. We show that a key transmission mechanism through which overall consumption falls is through lower wage income. This explains why total consumption and various category-specific consumption display a common pattern of heterogeneity in response to global price shocks. Finally, matching dynamic impulse responses of consumption expenditure shares and price responses through the lens of a non-homothetic demand structure, we estimate differences in slopes of Engel curves to establish that food is indeed a necessary consumption good for all households in India.

For our empirical analysis, we utilize a comprehensive monthly household 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 (real) 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.[3]

To ensure a causal interpretation of our findings, we devise an instrumental variable (IV)

[2] We use the terms non-homothetic demand and a necessary consumption good 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. 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.

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

strategy. The key concern with OLS estimation is that of omitted variable bias arising due to global demand shocks. As the literature on the macroeconomic impact of oil shocks emphasizes, separating the effects of global demand shocks from those of 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 at a minimum conflate the effects of both types of shocks. In our setting, however, they would also lead to biased estimates. Specifically, global demand shocks are well-known drivers of global commodity prices and they directly also affect Indian household consumption through many channels of exposure. This bias is expected to be positive, which means we anticipate the OLS estimates to be less negative than the IV estimates.

To tackle this challenge, we employ an IV approach that is tailored to removing the variation coming from global demand shocks, using supply-side instruments for the change in global oil and food prices. 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 an aggregate common factor as a proxy of global demand, estimated by imposing sign restrictions in a dynamic factor model to capture comovement of all commodity prices with global demand. With the dynamic factor model, we also further extract a food-specific factor that captures comovement of only food commodity prices.[4]

Our main findings in more detail are as follows. First, global food and oil price increases are stagflationary for India. We reach this conclusion from estimates based on aggregate data as well as estimates of average effects based on the household consumption and regional consumer price data. Second, the negative consumption effects of these shocks show robust heterogeneity along the income distribution. An exogenous increase in food prices affects households in the lower income deciles more, and the negative consumption effects become progressively less severe as we move up the income distribution. In contrast, an exogenous increase in fuel prices decreases 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 decreases the least for oil price shocks. These differential effects are not only statistically significant, but also economically meaningful.[5]

[4]Using an IV also helps address any reverse causality concerns. If one assumes India to be a small open economy with no effects operating from local conditions to global commodity prices, then reverse causality is not much of a concern. But since India is growing fast, it might be more credible not to assume it ex-ante and rather use an IV that isolates variation coming from the supply-side outside India.

[5]The maximum impact of a one-standard deviation food price shock accounts for 10% of the unconditional volatility in non-durable consumption for the low-income group, while it explains only 5% of the volatility for the highest income group. In contrast, the maximum impact of a one-standard deviation oil price shock explains 5.5% of the unconditional volatility in non-durable consumption for the poorest income group, 5% for the highest income group, and just 3.2% for the low-income group.

We then utilize the IV framework to further investigate the mechanisms that cause such heterogeneous effects in consumption. We develop a parsimonious and tractable model to motivate the transmission mechanisms, but even without going into details of the model, the economics behind the transmission mechanisms can be explained well intuitively. As we find that not just own-category category consumption, but also cross-category and overall measures of consumption fall in response to increases in food and fuel prices, it already strongly suggests wage income declines. Therefore, we first estimate the heterogeneous wage earnings effects of the global price shocks. Our analysis reveals that food price shocks lead to a consistent negative effect on real wage incomes, 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 wage income effects on the lowest and highest income groups, which is also aligned with the negative consumption effects for these groups.

Our IV estimates reveal substantive differences from the corresponding OLS estimates. For instance, while OLS results indicate an increase in real earnings for the high-income group following an oil price increase, the IV results exhibit a decrease instead. This finding of a positive bias in OLS estimates 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. Moreover, for oil shocks, OLS estimates of consumption effects are not consistently and persistently negative for any income group. Finally, for consumption effects, the OLS estimates are robustly biased upwards for food shocks as well.

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 predict expenditure-switching effects following such a 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 (e.g., the ratio of nominal food expenditure to nominal fuel expenditure) increases for the lower income groups, which is not consistent with expenditure switching as the only force 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 relative demand and expenditure shares. With this finding as motivation, we proceed further econometrically. Using the dynamic impulse responses of relative food prices, relative food expenditures, and real non-durable consumption expenditure together, we estimate the difference in Engel curve slopes for food and fuel and 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.[6]

Our final set of results come from a comparison of empirical impulses to those predicted by the model. As a first exercise, we take as given the estimated total consumption responses and relative price of food responses to a food price shock and predict the non-durable consumption response according to the model's demand structure. We show that this model prediction is well aligned to the empirical response of non-durable consumption. This decomposition shows that just the relative price of food going up explains very little of the non-durable consumption drop. This then motivates us to explore what drives the total consumption decline. As we discussed above, our theoretical framework shows wage income as a common driver of all categories of consumption. We construct a measure of present discounted value of wage income using the empirical wage income response and show that using it instead of total consumption in the exercise above continues to predict a drop in non-durable consumption that is close to the empirical response. This exercise thus clearly depicts the roles of wage income and relative price channels in explaining non-durable consumption responses to the global food price shock.

Our paper is related to several strands of the literature. The two-way relationship between global oil prices and the U.S. macroeconomy has been studied extensively by Hamilton (2003), Barsky and Kilian (2004), and Kilian (2009). We first demonstrate stagflationary 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. As our main contribution, we then estimate distributional effects of global oil prices on household consumption, 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. (2024)). Our results are consistent in some important substantive fronts with those in Kanzig (2023). First, 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. Second, like in Kanzig (2023), we also find evidence consistent with "leaning-in" monetary policy as short-term interest rates in the economy rise in response to such shocks.

These channels are even stronger for food price shocks in our paper. We illustrate the stagflationary effects of the global food price shocks on the Indian macroeconomy that go together with a rise in short-term interest rates. In two-sector sticky-price models, if external

[6] 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. These give rise to log-linear Engel curves for food and fuel, similar to Banks, Blundell, and Lewbel (1997). Our theoretical framework and econometric analysis use 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.

commodity price shocks lead to aggregate inflation, then by acting like "cost-push" shocks that introduce a policy trade-off for central banks, they can cause a recession and lead to a fall in wage earnings domestically. The possibility of oil price shocks as negative aggregate supply shocks has traditionally received more attention in advanced economies (see Afrouzi et al. (2024) for a recent example), where the key mechanism arises theoretically due to oil's role as an intermediate input. However, food price shocks can also have similar effects due to food being a necessary consumption good. For instance, Olivi et al. (2023) show theoretically that a supply shock in a sector that produces a necessary consumption good, which we show empirically is food in the Indian context, can act as an aggregate cost-push shock.[7]

Empirically, De Winne and Peersman (2021) have previously established how global food price shocks, driven by adverse weather shocks, can negatively impact real economic activity in middle-income countries. The literature on the macroeconomic effects of global food price shocks, such as De Winne and Peersman (2016) and Peersman (2022), has examined the aggregate or sectoral effects of food price shocks. We contribute by estimating regressive distributional effects, at the household level, of a rise in global food prices.

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 external supply shocks. In our IV specification for the global food price change, the instrument we develop is novel as we estimate a dynamic factor model with sign restrictions using data from a broad cross-section of commodity prices to isolate aggregate demand and food-specific factors from global food price dynamics. In this context, for both global price changes, one of our contributions is to show a positive omitted variable bias in OLS estimates. This holds both in terms of average effects, connecting with the literature on oil price shocks, as well as the distributional effects.

In one important difference from the recent literature on distributional effects of 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. Our inference relies on estimated differences in the slopes of the Engel curves for food and fuel. Combining household panel data and time series shocks, as we mentioned above, we develop a novel method that relies on *dynamic variation* to estimate slopes of the Engel curve using external instruments. On this methodological front, we complement work that estimates Engel curves using internal instruments in a GMM setting.[8]

On the substantive front, our estimation reveals that food, relative to fuel, is a necessary con-

[7] Bergman, Jaimovich, and Saporta-Eksten (2024) provides a general framework for understanding distributional implications of sectoral demand and supply shocks in the presence of nonhomotheticity in demand in a flexible price setting. In the presence of nominal rigidities, in practice, central banks might also respond to sector-specific commodity price shocks due to their out-sized effects on inflation expectations (see, for example, Malmendier, Ospina, and Weber (2021) and Coibion and Gorodnichenko (2015)).

[8] See Deaton (2019) and Lewbel (2008) for comprehensive reviews.

sumption good for all income groups. We then show how non-homothetic preferences affect the *dynamic response* of food consumption or the food consumption share when shocks affect income. Thus, for instance, when food is a necessary consumption good, we show in a model-based exercise that real food consumption falls by less (than under homothetic preferences) when income declines, and we provide evidence that the food expenditure ratio increases when food becomes relatively more expensive.[9]

Our empirical framework assessing the impact of macro shocks using micro panel data also relates to the literature that has 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), Amberg, Jansson, Klein, and Picco (2022) and Andersen, Johannesen, Jørgensen, and Peydró (2023) estimate the heterogeneous household effects of monetary policy shocks along the liquid asset or income distribution in Norway, Sweden and Denmark. In building on this body of work, our paper focuses on the distributional implications of an external sector-specific shock that leads to a contractionary monetary policy response in the context of an emerging market. We tailor our theoretical model to understanding responses of various categories of consumption under a wage income change and a relative-price change, and focus on how these responses differ along the income distribution by using detailed household panel consumption, income, and expenditure shares data at a monthly frequency.

2 Data and Stylized Facts

We now discuss our data and present some stylized facts.

2.1 Data Description

Our paper studies implications of macro shocks, captured by global commodity price movements, on micro level household consumption. Our household data is from the Consumer Pyramid Household Survey (CPHS) dataset, a survey conducted by the Centre for Monitoring Indian Economy (CMIE).[10] CPHS has surveyed over 232,000 unique households since 2014 and it uniquely provides detailed consumption and income/ earnings at household level in a single

[9] As we discuss in detail later, our focus in the paper is not on average/steady-state differences in food expenditure share or energy expenditure share across income groups, which is also a type of non-homotheticity.

[10] CMIE data was obtained by Gautham Udupa under the purview of CAFRAL licenses. Arpita Chatterjee or Saroj Bhattarai did not have any unauthorized access to this data while working on this paper.

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.[11]

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; 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; and the scanner data studied in the inflation inequality literature does not contain household level panel information on earnings/ income. It is indeed rare to have a monthly panel of detailed household consumption and earnings for such a large sample of households.

We construct consumption, income, and earnings measures following 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, transport, communication, and intoxicants), durable consumption (appliances, furniture, jewelry, clothing, electronics, toys, cosmetics), and service consumption (entertainment, beauty services, fitness services, restaurants, etc). We present results on total consumption and non-durable consumption separately in all our analysis. We denote total consumption of cooking fuel, electricity, transport, and communication as fuel consumption.[12]

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 and electricity expenditure for which the deflator is given directly by MoSPI, but also expenditure on transportation and communication, 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 electricity, and transport and communication price indices with the weights provided by MoSPI.[13] This detailed state-region level monthly panel of price data also allows us

[11] The data is available till 2024. In order to avoid Covid-related disruptions in conducting the household survey, we performed our analysis using data until the end of 2019.

[12] The average share of non-durable consumption in total consumption is 89% and the average share of earnings in total income is 75 % in our dataset.

[13] We use the most detailed state-region (urban or rural) level monthly deflator available for India at a monthly frequency, 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,

to examine the degree to which global price shocks pass-through to local consumer prices in a key test of our transmission mechanism.

Income is the sum of various comprehensive sources of household income such as wage and rental income. 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.[14] The Global Price of Food Index is an index of 28 different food commodity prices, where the weights are global import shares.

2.2 Summary Statistics Along the Income Distribution

Our key research question is regarding distributional implications of global price shocks. To answer this question, for context, it is important to understand how household consumption and earnings on average differ along the income distribution in our data. To this end, we present several summary statistics from our household panel data, along the deciles of the initial period (2014) real household income, in Appendix B. Most importantly, we present in Table A1 summary statistics on average (across households and months) monthly income, monthly consumption, share of non-durable consumption, share of earnings in income and share of food and fuel consumption by various income deciles.

The poorest income group is 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. No significant variation in fuel share is observed across income groups. [15]

These statistics motivate us to divide households in five 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

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.

[14]We downloaded the global food price index and the brent crude oil price index from the St. Louis Fed FRED data base. The links, respectively, are https://fred.stlouisfed.org/series/PFOODINDEXM and https://fred.stlouisfed.org/series/POILBREUSDM.

[15]We do not include expenditures on rent, EMIs, health, and education in our measure of total consumption. Also, note that while overall fuel share does not vary across income distribution, type of fuel use vary.

on real income in 2014 and assign each household to a group based on those cutoffs.[16] Various characteristics of the baseline income groups are summarized in Table A2.

2.3 Global Commodity Prices and Aggregate Consumption Inequality

In this Section, we present evidence from the raw data on comovement between global commodity prices and consumption inequality in India, where we construct the measures of aggregate inequality from the underlying household data. This serves as motivation for our econometric exercise.

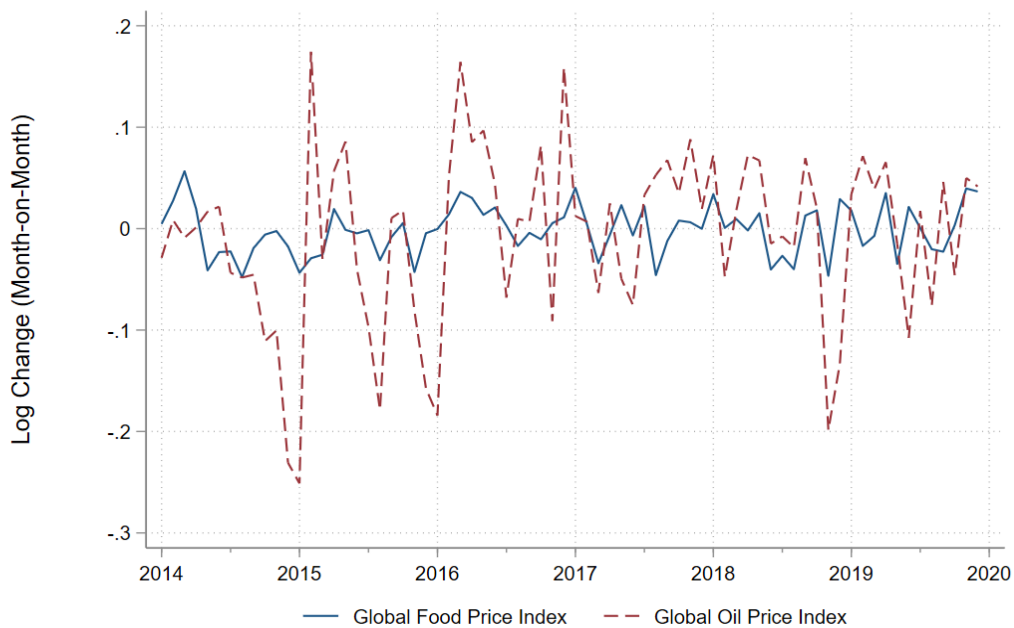

Figure 1: Changes in Global Food and Fuel Prices

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

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.[17]

[16]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 Appendix E.3. We have conducted a broad set of robustness analysis regarding how households are assigned to income groups.

[17]Correlation between the two series is 0.34 in our sample. Some co-movement such as this is to be expected

We construct various aggregate measures of consumption inequality from the underlying micro household data: Gini coefficient, SD (standard deviation) of log changes in consumption, and the 90th-10th and 75th-25th measures of dispersion. In Table 1, we present correlations of various measures of consumption inequality with one period lagged values of global food and oil price changes. The correlations are positive, and are higher for global food price changes than for 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.

3 Distributional Effects of Global Commodity Price Shocks

In this Section, we establish econometrically a set of facts regarding the distributional effects of global food and oil shocks on household consumption. We use a household panel local projection framework to estimate heterogeneous dynamic effects of global oil and food price shocks, after we purge out the impact of global demand shocks on global commodity prices using instrumental variables. We first document the average effects of global price shocks on household consumption, and then turn to the distributional implications.

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.

3.1 Panel Local Projection Framework

Our household-level panel local projection model with interaction effects is:

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

Here, c_i is the log of *real* consumption for household i for various measures of consumption (namely, total, non-durable, food and fuel consumption). Real consumption is obtained by deflating nominal consumption expenditures of various categories by the corresponding deflators (specific to total, non-durable, food and fuel CPI) for the state and region in which household i resides. ext^{food} and ext^{oil} stand for measures of the global food and oil price shocks respectively; $\mathbb{1}_{i\in \text{s}} \times \mathbb{1}_{\text{year}}$ 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-region specific trends and regional variation in seasonality respectively (which control for, among others, local weather conditions); and D is the dummy for the Indian government's demonetization policy, which is allowed to have lagged effects for up-to three periods. 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.[18]

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 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). Here $\beta^{g,h}_{0,\text{food}}$ 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; $\beta^{g,h}_{0,\text{oil}}$ 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

[18] Our specification leads to robust inference in the micro panel local projection framework with heterogeneous effect of macroeconomic shocks (Almuzara and Sancibrián (2024)).

for global demand (Baumeister and Hamilton (2019)); 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 such external events, other than global commodity prices, to have heterogeneous consumption effects. Table A4 in Appendix D lists full details of our household panel local projection estimation.

3.2 Endogeneity Concerns in Assessing the Distributional Implications

Our empirical exercise is an example of using micro data to estimate responses to macro shocks. Arguably, Indian household consumption and Indian economic conditions have no discernible effect on global food and oil prices, thereby mitigating reverse causality concerns for the OLS estimation of the household panel local projection Equation (3.1). However, even under this assumption, OLS versions of our estimation framework still conflate the effects of various underlying shocks that lead to changes in world oil and food prices, leading to biased estimates due to omitted variable bias problems.

Isolating global supply-side variation therefore is crucial in our exercise to guard against omitted variable bias problems. Omitted variable bias is most salient for the case of global demand shocks as Indian households are likely to have *direct* exposure to the global demand shocks, and the global demand shocks in turn are well-known drivers of global commodity prices. To address this issue, we take an Instrumental Variable (IV) approach in which we focus on removing the variation coming from global demand shocks. In particular, 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), who estimate a Bayesian VAR using oil price, oil production, oil inventory, and world industrial production data. An oil supply shock is then identified as a movement along the downward sloping demand curve by imposing sign restrictions.

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 rely on an approach that uses a broad cross-section of prices.

We use commodity prices data (a panel of 37 non-energy commodity prices including 13 industrial inputs and metals and 24 food prices) in the time period 1990-2022 and estimate a dynamic factor model using Bayesian methods. Our main focus is on estimating a common factor that captures the comovement of a broad range of global commodity prices, due to global demand conditions, by imposing sign restrictions. We residualize changes in the global food price index with such a common factor, as well as a food-specific factor that captures co-movement only among the food commodity prices, also estimated using the dynamic factor model. Our estimation method is outlined in Appendix C. With this approach, we address an important concern for omitted variable bias, as we remove the variation from global demand shocks.[19] We provide several details about the IVs in Appendix C.[20] We plot the changes in global commodity prices and their IVs, the respective supply shocks, in Figure A2 in the Appendix.

The macroeconomic effects of an increase in global food prices driven by supply shocks on the Indian economy are illustrated in Figure A3 in Appendix C. Our estimation framework is a four-variable Bayesian VAR where we treat our measure of food supply shock as an external shock. The rise in global food shocks is clearly stagflationary for the Indian economy with a contraction in economic activity and a rise in prices, leading to a contractionary monetary policy response. The same exercise for Baumeister and Hamilton (2019)'s adverse oil supply shock shows similar macroeconomic effects, as illustrated in Figure A4.[21]

3.3 Average Consumption Effects: Comparison of OLS and IV results

Before we present the distributional implications, it is useful for context to understand the average effects of global food and fuel price shocks on household consumption. These results are presented for total, non-durable, and own-category (fuel consumption for oil price shocks and food consumption for food price shocks) consumption in Figure 2.[22] The top row of Figure 2 shows the effects of a rise in global oil prices on household consumption, while the bottom row

[19] Omitted variable bias can also arise if local conditions can drive global food prices for certain commodities, especially rice. We address this issue in a robustness exercise following our main results, but we note that rice price constitutes only 2% of the food price index we use, which should mitigate such concerns. We also use location-calendar month and location-calendar year fixed effects to control for such local, say weather, shocks.

[20] Economic activity shock from the Bayesian VAR capturing the energy market dynamics in Baumeister and Hamilton (2019) and the common factor estimated from the Bayesian estimation of comovement in non-energy commodity prices in our exercise are illustrated together in Figure A1. They roughly capture similar movements in global business cycles, with an average correlation of 0.23.

[21] Lakdawala and Singh (2019) make similar observations for the oil supply shock using a different method .

[22] In the notation of the household panel local projection described in Equation (3.1), households' dynamic responses β^h_{food} and β^h_{oil} are not allowed to differ by income group g while evaluating the average effects.

shows the effects of a rise in global food prices. We first focus on the IV estimates of the impulse responses (in blue) where the global price movements are instrumented by the respective supply shocks. The conclusion is unambiguous: rise in global commodity prices reduces real consumption of households over time, and this conclusion holds for total, non-durable, and own-category consumption.

We also utilize Figure 2 to demonstrate the omitted variable bias problem in the OLS estimates of the impulse responses (in yellow). The OLS estimates capture both global demand and commodity-specific supply shocks. Since global demand shocks inevitably and directly impact Indian household consumption, this leads to an omitted variable bias in the OLS estimation, as we explained earlier. Moreover, since positive global demand shocks are likely to have a positive impact on both Indian household consumption and global commodity prices, the direction of the bias is positive. In the IV estimation, once we eliminate the impact of global demand shocks on commodity prices, we expect the IV estimates to be more negative than the corresponding OLS estimates.[23] This direction of bias is evident for both oil and food shocks in Figure 2, though the difference between OLS and IV is more stark in the case of oil. Global oil prices are known to be extremely sensitive to global demand shocks, while global food prices are arguably more influenced by idiosyncratic supply shocks. Thus, in the OLS estimates, when global oil prices rise due to a demand shock driven boom in global output, Indian households also experience consumption growth directly through this business cycle effect and this, in turn, leads to an erroneous conclusion of positive effects on household consumption of a rise in global oil prices.

[23] Also, IV estimates will capture variation that is independent of local economic conditions.

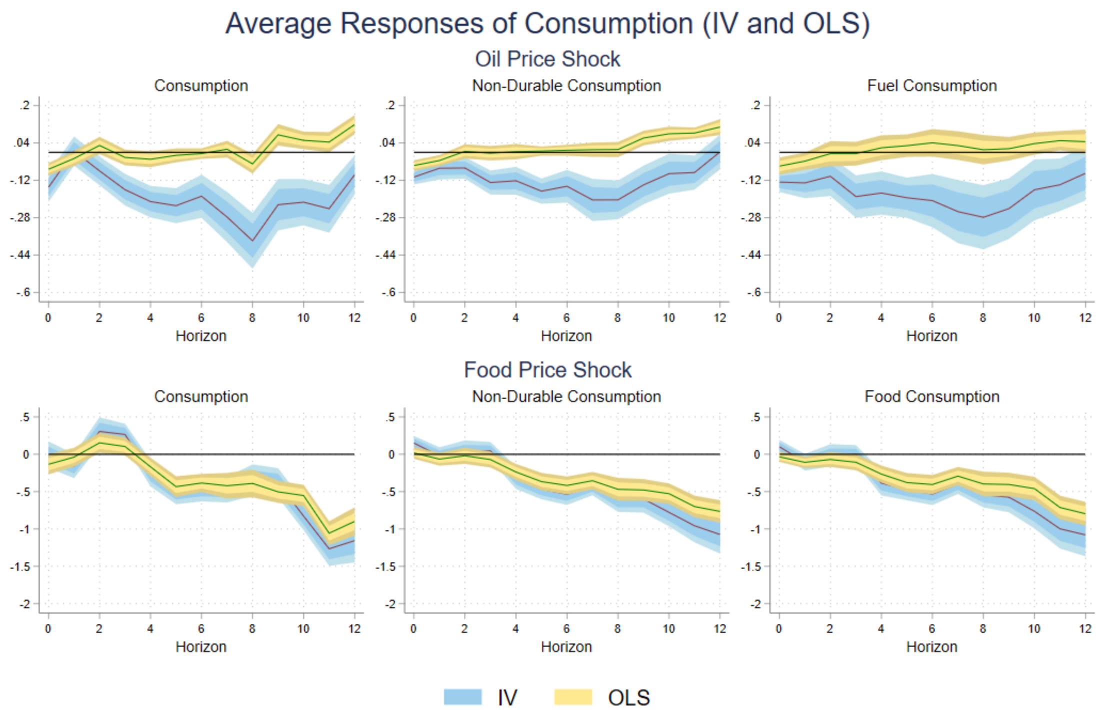

Figure 2: Response of Consumption to External Food and Oil Price Shocks (IV and OLS)

Notes: Cumulative IRFs on the basis of Equation (3.1), without the interaction effects by income groups, where the external shock are log changes in the global food and oil price, which are instrumented by a global food supply and oil supply shock respectively, 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.

3.4 Heterogeneous Consumption Effects: IV Results

After establishing the average negative effects of global commodity price movements on household consumption and the importance of accounting for the omitted variable bias in OLS estimates using an IV strategy, we return to the local projection household panel exercise based on the IV estimation of Equation (3.1), where the effects on consumption are allowed to vary along the income distribution. This is our baseline empirical exercise for establishing facts on heterogeneous effects of global food and fuel price changes.

3.4.1 Main results on heterogeneous effects

Our key IV results are in Figures 3 and 4 for food price shocks and oil price shocks, respectively.[24] We present results for total consumption, non-durable consumption, and own-category consumption. The results show that there are adverse effects on all measures of consumption for

[24] The first-stage F-statistics for these IV regressions are reported in Appendix D in Table A5.

both the shocks and that these adverse effects are heterogeneous along the income distribution.

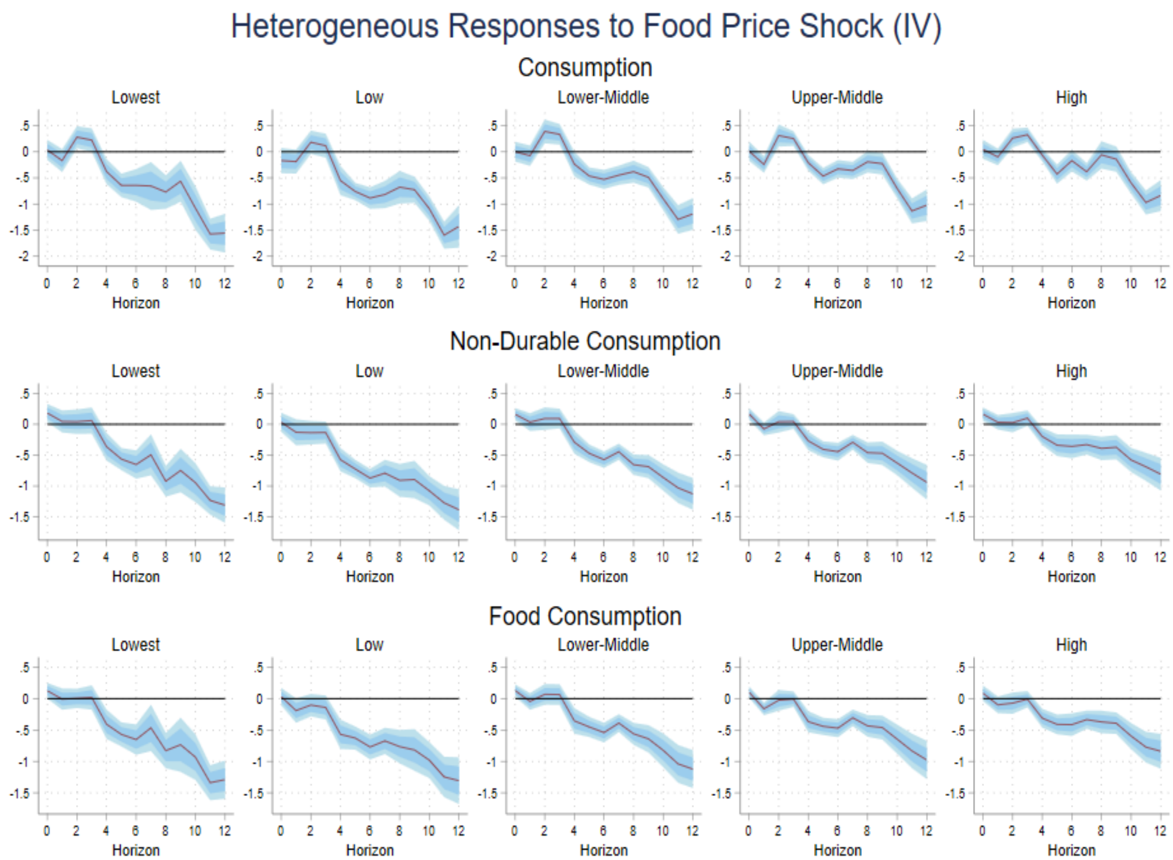

Figure 3: Response of Consumption to External Food Price Shocks by Income Quintiles (IV)

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.

Intriguingly, in terms of 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 peak 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 negative effects are more persistent for the two highest income groups. So overall, the two tails of the distribution suffer more for the oil price shocks.

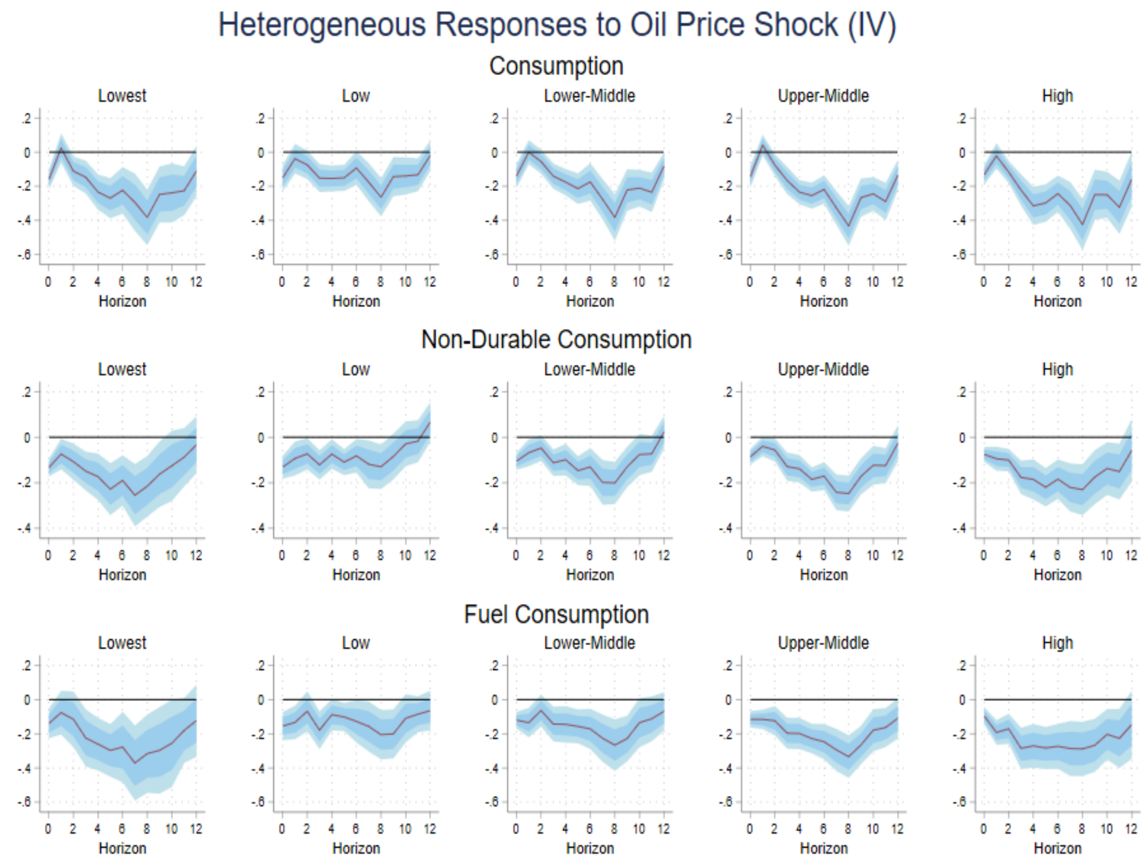

Figure 4: Response of Consumption to External Oil Price Shocks by Income Quintiles (IV)

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.

Very importantly, the dynamic pattern of heterogeneity in consumption responses for both oil and food shocks is quite similar across various consumption aggregates and categories. Thus, a rise in global food prices has regressive effects on total, non-durable, and own-category consumption. Moreover, a rise in global oil prices has larger effects on total, non-durable, and own-category consumption at the two extremes of the income distribution. Moreover, note that as non-durable consumption is a sum of food and fuel consumption, these results imply that a food price shock leads to a drop in fuel consumption while an oil price shock leads to a drop in food consumption, and the pattern of heterogeneity in the cross-category responses is also remarkably similar.[25] If these shocks were simply relative price shocks, these across-category consumption drops would not occur as expenditure-switching would lead to across-category consumption increases. We note this inference now and will revisit it in more detail when we

[25] In Figure A5 in the Appendix we show these across-category consumption responses explicitly.

assess transmission mechanisms.

We now summarize the key facts regarding how exogenous global food and oil price shocks impact Indian household consumption:

- Fact 1: Increases in global food and oil prices lead to reduction in real household consumption for total, non-durable, and own-category consumption (see, Figure 2).

- Fact 2: An exogenous rise in global food prices leads to larger negative consumption effects on poorer households, whereas an exogenous rise in global oil prices has larger negative effects on the two tails of the income distribution (see, Figures 3 and 4, respectively.) Poorer income groups suffer a substantially larger consumption loss across all horizons following an exogenous rise in global food prices, whereas the poorest, the upper-middle, and the high-income groups are equally vulnerable to an exogenous rise in oil prices. Moreover, the low-income group is shielded most from oil price increases but suffers most from food price increases.

- Fact 3: The pattern of heterogeneity across income groups in terms of how consumption responds to global price shocks is similar across total, non-durable, and own-category consumption, and this common dynamics of various consumption aggregates across income groups is a qualitatively important pattern we analyze further in Section 4.2.1.

Next, we present statistical significance of the pattern of heterogeneity, discuss their quantitative magnitude and economic significance, and highlight the importance of addressing endogeneity concerns for establishing these distributional effects.

3.4.2 Statistical significance of the heterogeneous effects

Is the pattern of heterogeneous consumption responses in Figures 3 and 4 statistically significant? We have documented in Fact 2 above that the low-income group suffers the largest real consumption loss in response to increases in global food prices and the smallest real consumption loss in response to increase in global oil prices. In order to assess the statistical significance of the heterogeneity in consumption effects, we now treat the low income group as the baseline while estimating the panel local projection framework of Equation (3.1). Dynamic responses of real non-durable consumption to global food (bottom row) and oil (top row) price shocks are plotted in Figure 5. The dynamic responses for the low income group are still the *total effect*, as in Figures 3 and 4, while impulse response for the rest of the groups show the *differential effects* on the corresponding group relative to the low income group.

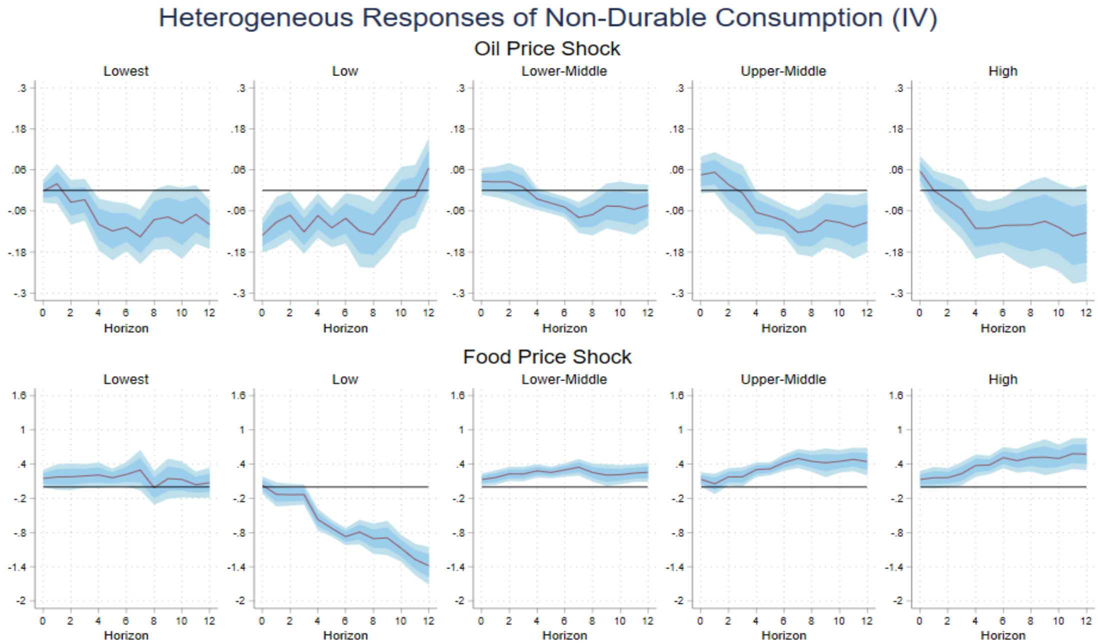

Figure 5: Relative (to Low Income Group) Response of Non-durable Consumption to External Food and Oil Price Shocks by Income Quintiles (IV)

Notes: Cumulative IRFs on the basis of Equation (3.1) where the external shock is log changes in the global food or oil price, which is instrumented by the corresponding supply shock and the dependent variable is log changes in household non-durable consumption. Column 2, for the low income group, shows the total effects for this baseline group, while the rest of the columns show the relative effect compared to the low income group. The light blue region is the 90% confidence interval and the dark blue region is the 68% confidence interval.

The statistical significance (at 90 %) of the negative differential effects for all income groups relative to the low income group, in the top row of Figure 5, confirm that in response to an increase in global oil prices, all income groups suffer (statistically) significantly larger consumption losses relative to the low income group. The bottom row depicts an opposite picture: the differential effect is not significantly different from zero for the lowest income group, but all the higher income groups show a significant (again, at 90%) positive differential effect, implying that with increases in global food prices, higher income groups suffer (statistically) significantly lower real consumption losses.[26]

[26]We show in Figure A6 in the Appendix that the conclusions regarding statistically significant differences in consumption responses across income groups hold even if we estimate the panel local projection model of Equation (3.1) separately for global oil and food price shocks. The only noticeable difference is the larger total negative effect of global oil price increase on the low income group in Figure A6 (when the estimation is done separately for the two shocks) vis-a-vis Figure 5 (when the estimation is done jointly). This larger baseline effect of global oil prices when the estimation is done separately likely reflects a positive effect of a rise in global oil prices on global food prices, which is controlled for in the joint estimation.

3.4.3 Economic significance of the heterogeneous effects

Are these distributional implications of global price shocks economically meaningful? To answer this, we compute the magnitude of consumption loss due to the external shocks that differs along the income distribution, in Table 2. Here we translate the elasticity estimates presented in Figures 3 and 4 to consumption loss for total (panel A) and non-durable consumption (panel B). The first two rows of each panel in Table 2 capture the maximum negative impact of a 1 standard deviation 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 again 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 and there is a clear pattern of monotonicity along the income distribution, while for an exogenous oil price increase, the lowest, upper-middle, and high income groups suffer similarly. In addition, the low-income group is protected most from oil price increases but suffers most from food price increases.

To appreciate the magnitude of this consumption loss and the heterogeneity in effects, we present in Table 2 the unconditional volatility (standard deviation) of log changes in real non-durable consumption and total consumption for the various income groups. As a percentage of the unconditional volatility in non-durable consumption, the maximum effect of a 1 standard deviation food price shock explains 8 % for the poorest income group, 10 % for the low-income group, and 5 % for the highest income group. In contrast, as a percentage of the unconditional volatility in non-durable consumption, the maximum effect of a 1 standard deviation oil price shock explains 5.5 % for the poorest income group, 3.2 % for the low-income group, and 5 % for the highest income group.[27]

[27] Unconditionally, consumption change is more volatile at the two ends of the distribution and least volatile for the low-income group. Assuming a log utility function in total consumption, the magnitude of real total consumption loss reported in panel A of Table 2 can be given a welfare interpretation under the assumption that these estimated effects are accurate non-linearly.

Table 2: Magnitude of Real Consumption Loss from Global Price Shocks

	Lowest	Low	Low-middle	Upper-middle	High
	Panel A: Total Consumption				
1 SD Food Shock	-0.039	-0.039	-0.032	-0.028	-0.024
	(-.034 , -.043)	(-.035 , -.043)	(-.028 , -.036)	(-.024 , -.031)	(-.02 , -.027)
1 SD Oil Shock	-0.033	-0.023	-0.033	-0.038	-0.037
	(-.025 , -.042)	(-.017 , -.029)	(-.026 , -.04)	(-.031 , -.044)	(-.029 , -.045)
SD of log changes	0.427	0.373	0.387	0.402	0.423
	Panel B: Non-durable Consumption				
1 SD Food Shock	-0.032	-0.034	-0.028	-0.023	-0.02
	(-.028 , -.036)	(-.029 , -.039)	(-.024 , -.031)	(-.019 , -.027)	(-.016 , -.024)
1 SD Oil Shock	-0.022	-0.011	-0.017	-0.021	-0.02
	(-.015 , -.029)	(-.009 , -.014)	(-.013 , -.022)	(-.017 , -.026)	(-.014 , -.026)
SD of log changes	0.394	0.345	0.347	0.353	0.364

Notes: This table shows the maximum loss in real total and non-durable consumption in response to 1 standard deviation shock to food prices (2.4%) and oil prices (8.7%) for the five income groups based on the estimates of elasticities presented in Figures 3 and 4. Standard errors are reported in the parenthesis. It also reports the unconditional volatility (standard deviation of log changes in real total and non-durable consumption) in each panel.

3.4.4 Importance of IV estimation of heterogeneous negative effects

As we discussed in detail earlier, our IV estimates avoid omitted variable bias problems that arise in OLS estimates due to the presence of global demand shocks. We now show the importance of the IV estimation strategy for assessing heterogeneous effects by presenting in detail the OLS results for oil price shocks in Figure 6. For comparison, we also plot the IV results we presented earlier in Figure 4.

In the OLS results of Figure 6, as predicted, the consumption effects are not consistently and persistently negative for any income group. Thus, as expected, if higher oil prices are caused by a positive global demand shock, Indian households are likely to benefit because of their various exposures to global demand. Moreover, the extent of this positive bias can be differential along the income distribution and needs to be assessed rigorously statistically. It is therefore imperative to remove the variation coming from global demand shocks while studying the distributional consequences of global price shocks. Similar differences are observed in the case of food price changes in Figure A7 in the Appendix, which shows that IV estimates are consistently more negative than the OLS estimates.[28]

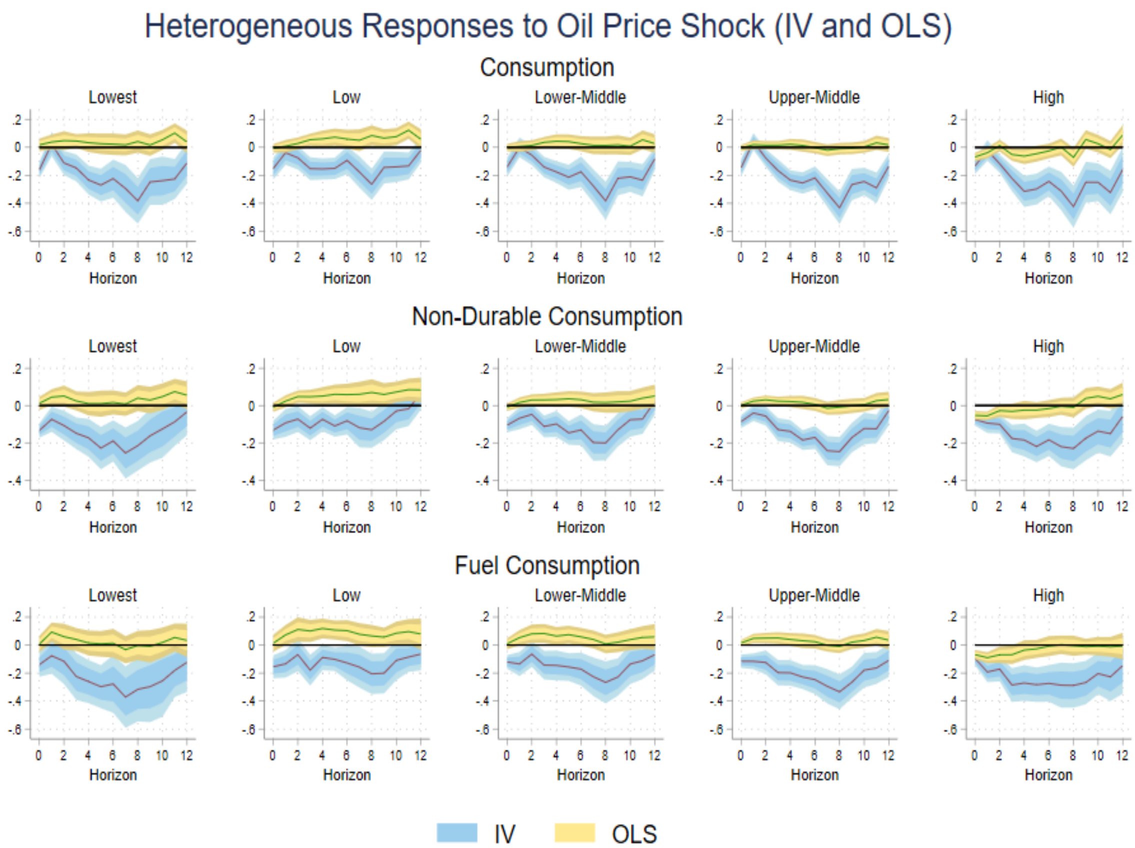

Figure 6: Response of Consumption to External Oil Price Shocks by Income Quintiles (IV and OLS)

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 fuel consumption. The light blue region is the 90% confidence interval and the dark blue region is the 68% confidence interval.

4 Channels for Heterogeneous Consumption Effects

Having established the baseline facts about how global food and fuel price shocks lead to heterogeneous effects on household consumption, we delve into interpretation and transmission mechanisms. To this end, we build a dynamic consumption-saving model for households belonging to different income groups. Conceptually, our framework allows for a variety of mech-

[28] Figure A7 shows, on average, narrower gaps between OLS and IV estimates compared to Figure 6. This is consistent with the more prominent role global demand dynamics play in determining oil prices, while food prices are often driven by crop-specific supply shocks.

anisms through which global food and fuel price changes can lead to heterogeneous consumption effects. In view of the empirical facts we establish in Section 3, we focus on the channels of transmission that work via real income, through relative price effects, and those that reflect non-homotheticity in preferences. We then turn to examining empirical veracity of these channels by comparing model predictions with the empirical facts.

4.1 Transmission Mechanisms: Dynamic Consumption-Saving Model

As in Auclert (2019), we consider an infinite-horizon consumption-savings problem in a perfect foresight environment with unexpected shocks, where household i belonging to income group g can trade nominal and real assets of different maturities.[29]

The household chooses $\left\{C_{i,t}, \frac{B_{i,t}}{P_t^g}, \frac{B_{i,2,t}}{P_t^g}, L_{i,t}\right\}$ to maximize lifetime utility

$$\sum_{t=0}^{\infty} (\beta^g)^t \left[\frac{C_{i,t}^{1-\sigma^g}}{1-\sigma^g} - \frac{L_{i,t}^{1+\phi^g}}{1+\phi^g}\right]$$

subject to a sequence of flow budget constraints

$$C_{i,t} + Q_t b_{i,t} + Q_{2,t} b_{2,i,t} + S_t E_{i,t} = b_{i,t-1}\frac{1}{\Pi_{i,t}^g} + Q_t b_{2,i,t-1}\frac{1}{\Pi_{i,t}^g} + (S_t + D_t) E_{i,t-1} + w_{i,t}^g L_{i,t}, \quad (4.1)$$

where $C_{i,t}$ is total household consumption index, $L_{i,t}$ is labor, $B_{i,t}$ is holdings of one-period risk-free nominal bonds, $B_{2,i,t}$ is holdings of two-period risk-free nominal bonds, and $E_{i,t}$ is holdings of stocks.[30] 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.

Here $P_{i,t}^g$ is the nominal price level, $\Pi_{i,t}^g = \frac{P_{i,t}^g}{P_{i,t-1}^g}$ is gross inflation, and $w_{i,t}^g$ is real wages. $P_{i,t}^g$ differ across income groups because different households i reside in different regions and may experience different underlying prices, and also because different income groups have different consumption shares for various commodities.[31] Here, $b_{i,t} = \frac{B_{i,t}}{P_{i,t}^g}$ is the real holdings of the one-period nominal bonds of household $i \in g$ and $b_{2,i,t} = \frac{B_{2,i,t}}{P_{i,t}^g}$ is the real holdings of the two-period nominal bonds. Finally, $\beta^g \in (0,1)$ is the discount factor, $\frac{1}{\sigma^g}$ is the intertemporal elasticity of substitution, and $\frac{1}{\phi^g}$ is the Frisch elasticity of labor supply. All parameters of the utility function

[29] In our empirical results, we assigned households to various income groups according to the initial income distribution, while allowing switching over time.

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

[31] In general, prices may differ across households for a variety of reasons such as the variety or quality they consume. In our empirical application, prices of disaggregated commodities such as food or fuel differ by households only to the extent that these households reside in different locations.

potentially differ by income group.

The total consumption index $C_{i,t}$ is modeled as a standard homothetic constant elasticity of substitution (CES) aggregate of non-durable consumption ($C_{N,i,t}$) and the rest of goods ($C_{S,i,t}$), with the elasticity of substitution parameter η^g and the share of non-durable consumption ($1-\alpha^g$) allowed to differ across income groups, as given by

$$C_{i,t} = \left[\left(1-\alpha^g\right)^{\frac{1}{\eta^g}} C_{N,i,t}^{\frac{\eta^g-1}{\eta^g}} + \left(\alpha^g\right)^{\frac{1}{\eta^g}} C_{S,i,t}^{\frac{\eta^g-1}{\eta^g}} \right]^{\frac{\eta^g}{\eta^g-1}} \tag{4.2}$$

which leads to differences in the ideal price index $P^g_{i,t}$, as given by

$$P^g_{i,t} = \left[\left(1-\alpha^g\right) P^g_{N,i,t}{}^{1-\eta^g} + \alpha^g P^g_{S,i,t}{}^{1-\eta^g} \right]^{\frac{1}{1-\eta^g}}. \tag{4.3}$$

Note that the overall price index and inflation is going to differ by income group g, *even if* all households face the same individual category-specific prices, due to the model allowing for the possibility of different income groups consuming different baskets of consumption. We allow the real wage to also potentially differ across income groups to allow for the possibility that different income groups may work in different occupations and both earn different nominal wages and also face a different deflator.

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 $w^g_{i,t} L_{i,t}$, but also through revaluations of financial positions by affecting inflation and asset prices $\Pi^g_{i,t}$, 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

$$\sum_{s=0}^{\infty} \rho^g_{i,t,t+s} C_{i,t+s} = \left[\frac{1}{\Pi^g_{i,t}} \left(b_{i,t-1} + Q_t b_{2,i,t-1}\right) + \left(S_t + D_t\right) E_{i,t-1} \right] + \sum_{s=0}^{\infty} \rho^g_{i,t,t+s} \left(w^g_{i,t+s} L_{i,t+s} \right) \tag{4.4}$$

where

$$\rho^g_{i,t,t} = 1; \rho^g_{i,t,t+s+1} = \prod_{j=0}^{s} R^g_{i,t+j+1}{}^{-1}; R^g_{i,t+j+1} = \frac{1}{Q_{t+j} \Pi^g_{i,t+j+1}}.$$

The intertemporal budget constraint, Equation (4.4), states that the present discounted value of consumption, using time-varying interest rates for discounting and different deflators allowing for consumption basket heterogeneity, 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 portfolio and stocks in turn can then generate heterogeneity in consumption effects.

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

$$\rho^g_{i,t,t+s+1} = \prod_{j=0}^{s} \frac{\beta^g C_{i,t+j}}{C_{i,t+j+1}},$$

by manipulating Equation (4.4), we get the solution for consumption as

$$C_{i,t} = \left(1-\beta^g\right)\left[\frac{1}{\Pi^g_{i,t}}\left(b_{i,t-1}+Q_t b_{2,i,t-1}\right)+\left(S_t+D_t\right)E_{i,t-1}+\sum_{s=0}^{\infty}\rho^g_{i,t,t+s}\left(w^g_{i,t+s}L_{i,t+s}\right)\right]. \tag{4.5}$$

Equation (4.5) 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 clearly 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. Inflation inequality, such that different income groups experience different inflation rates based on their consumption basket, can also lead to heterogeneous consumption affects both by devaluing initial nominal portfolio at a different rate and by having heterogeneous impact on the real discount factor and real wage income. Let us define presented discounted value of labor income and market value of initial financial positions as

$$Y^g_{i,t} \equiv \left[\frac{1}{\Pi^g_{i,t}}\left(b_{i,t-1}+Q_t b_{2,i,t-1}\right)+\left(S_t+D_t\right)E_{i,t-1}+\sum_{s=0}^{\infty}\rho^g_{i,t,t+s}\left(w^g_{i,t+s}L_{i,t+s}\right)\right],$$

which means we can write the solution for consumption[32] as

$$C_{i,t} = \left(1-\beta^g\right)Y^g_{i,t}. \tag{4.6}$$

Our data is extremely rich in terms of detailed consumption and earnings information, as well as additional labor market indicators such as occupation. Heterogeneous response of wage income to external price shocks is the key transmission channel we analyze later.

Note that in the empirical evidence presented in Section 3, we have clearly documented that the pattern of heterogeneous response to global food and fuel price shocks is similar across

[32]In the log utility framework, $1-\beta^g$ is the constant marginal propensity of consume (MPC) which cannot explain dynamics of consumption. In a more general utility function, MPC can be time-varying.

aggregate consumption and various subcategories of consumption (see Figures 3 and 4). How does heterogeneity in wage income responses help us understand heterogeneity in not just the aggregate consumption response, but also in non-durable and category-specific consumption? To answer this question, we need to model the household's expenditure allocation problem across various consumption categories.

Given that total consumption $C_{i,t}$ is a standard constant elasticity of substitution (CES) aggregator of non-durable consumption goods and the rest, the standard expenditure minimization problem implies that the optimal relative expenditure share between non-durable and total consumption are completely governed by relative prices. However, the level of real non-durable consumption is a function of aggregate consumption $C_{i,t}$ and hence, is affected by heterogeneous wage income responses, given the intertemporal budget constraint, Equation (4.5):

$$C_{N,i,t} = \left(1-\alpha^g\right)\left(\frac{P^g_{N,i,t}}{P^g_{i,t}}\right)^{-\eta^g} C_{i,t} = \left(1-\alpha^g\right)\left(\frac{P^g_{N,i,t}}{P^g_{i,t}}\right)^{-\eta^g} \left(1-\beta^g\right) Y^g_{i,t} \tag{4.7}$$

where $P^g_{N,i,t}$ and $P^g_{i,t}$ are prices of the non-durable and total consumption goods respectively. Log-differencing Equation (4.7) we obtain an expression for the dynamics of non-durable consumption for all $h \geq 0$:

$$\Delta log(C_{N,i,t+h}) = -\eta^g \Delta log(\frac{P^g_{N,i,t+h}}{P^g_{i,t+h}}) + \Delta log(C_{i,t+h}) = -\eta^g \Delta log(\frac{P^g_{N,i,t+h}}{P^g_{i,t+h}}) + \Delta log(Y^g_{i,t+h}). \tag{4.8}$$

Dynamics of real non-durable consumption response is governed by changes in relative price, $\frac{P^g_{N,i,t}}{P^g_{i,t}}$ and changes in total consumption, which in turn reflects changes in wage income, $w^g_{i,t+s}L_{i,t+s}$.

We model non-durable consumption as a non-homothetic isoelastic CES aggregator of food and fuel, where category specific demand ($f \in$ (food, fuel)) is given by:

$$log(C^g_{f,i,t}) = log(\gamma^g_f) - \sigma^g_\epsilon log\left(\frac{P_{f,i,t}}{P^g_{N,i,t}}\right) + \varepsilon^g_f log\left(\frac{E_{N,i,t}}{P^g_{N,i,t}}\right) \tag{4.9}$$

where $E_N \equiv P_N C_N$ is the total expenditure on non-durable consumption, ε^g_f is the slope of Engel curve, γ^g_f is the share of f in nondurable, σ^g_ϵ is the (price) elasticity of substitution, and P^g_N is the ideal price index for nonhomothetic CES.[33] Combining the category-specific demand

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

$$[\sum_{f=1}^{n} \gamma_f^{\frac{1}{\sigma}} U(\mathbf{x})^{\frac{\varepsilon_f - \sigma_\epsilon}{\sigma_\epsilon}} x_f^{1-\frac{1}{\sigma_\epsilon}}]^{\frac{\sigma_\epsilon}{\sigma_\epsilon - 1}} \equiv 1,$$

where $\sigma_\epsilon > 0$ ensures global quasi-concavity and $\frac{\varepsilon_f - \sigma_\epsilon}{1-\sigma_\epsilon} > 0$ ensures global monotonicity. Given total expenditure

Equation (4.9), demand function for non-durable Equation (4.7), and the intertemporal budget constraint Equation (4.5), we obtain demand functions for different categories of nondurable, expressed in log-difference term for all $h \geq 0$ as:

$$\Delta log(C^{g}_{f,i,t+h}) = -\sigma^{g}_{\epsilon}\Delta log\left(\frac{P_{f,i,t+h}}{P^{g}_{N,i,t+h}}\right) - \varepsilon^{g}_{f}(\eta^{g}-1)\Delta log\left(\frac{P^{g}_{N,i,t+h}}{P^{g}_{i,t+h}}\right) + \varepsilon^{g}_{f}\Delta log Y^{g}_{i,t+h} \tag{4.10}$$

The common driver of the dynamic response of total consumption Equation (4.5), non-durable consumption Equation (4.8), and category-specific consumption Equation (4.10) is the dynamic response in wage income. This is the key channel of transmission on which we focus. Relative prices, that is the non-durable price relative to the overall price index, and the food or fuel price relative to the non-durable price, also matter for the dynamics of consumption response. Pass-through of global price shocks on local prices is an important channel of transmission which we also examine empirically.

Slope of the Engel curve, denoted by ε^{g}_{f}, influences the response of category-specific consumption as shown in Equation (4.10). In the case of homothetic demand, ε^{g}_{f} equals one, which implies relative expenditure is only influenced by relative prices. In the presence of non-homotheticity, relative expenditures also respond to changes in total expenditure

$$\underbrace{\log\left(\frac{E_{food,i,t}}{E_{fuel,i,t}}\right)}_{\text{Relative nominal expenditure}} = \log\left(\frac{\gamma^{g}_{food}}{\gamma^{g}_{fuel}}\right) - \underbrace{(\sigma^{g}_{\epsilon}-1)\log\left(\frac{P_{food,i,t}}{P_{fuel,i,t}}\right)}_{\text{Relative price effect}} + \underbrace{(\varepsilon^{g}_{food}-\varepsilon^{g}_{fuel})\log\left(\frac{E_{N,i,t}}{P^{g}_{N,i,t}}\right)}_{\text{Total expenditure effect}} \tag{4.11}$$

where $E_f \equiv P_f C_f$. In Equation (4.11) above, a good f is a necessity if and only if $\varepsilon_f < \bar{\varepsilon}$ and a luxury if and only $\varepsilon_f > \bar{\varepsilon}$, where $\bar{\varepsilon}$ is the budget-share weighted average of ε_k. [34]

As long as food is a substitute with fuel (implying an elasticity of substitution, $\sigma_\epsilon \geq 1$, with the equality holding for a Cobb-Douglas case where the goods are neither substitutes nor complements), an increase in relative prices weakly 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 then may increase with rising relative prices under $\sigma_\epsilon \geq 1$ is if $\epsilon_{food} < \epsilon_{fuel}$. This condition, $\epsilon_f < \epsilon_k$, in a two-good framework implies that good f is a necessary good. We use the

on this bundle of consumption, $E_N \equiv P_N C_N$, the cost of living index (P^{g}_{N}) is implicitly given by:

$$[\sum_f \gamma^{g}_{f}(\frac{E_N}{P^{g}_{N}})^{\epsilon^{g}_{f}-1}(\frac{P_f}{P^{g}_{N}})^{1-\sigma^{g}_{\epsilon}}]^{\frac{1}{1-\sigma^{g}_{\epsilon}}} \equiv 1.$$

See Matsuyama (2022) for further details and references.

[34] 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.

response of relative nominal expenditure to relative prices to rigorously test the assumption of a necessary consumption good and to estimate the differences in the slopes of the Engel curves.

We are now ready to state the two key testable predictions of the model, where we focus on how they help us understand the heterogeneous consumption effects from Section 3:

- Testable Prediction 1: From consumption Equation (4.6), non-durable consumption Equation (4.8), and category-specific consumption Equation (4.10), the heterogeneous response of wage income to the external price shocks leads to a *common* heterogeneous response of consumption, non-durable consumption, and own-category consumption.

- Testable Prediction 2: When $\sigma_{\epsilon} \geq 1$, from Equation (4.11), 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. Moreover, Equation (4.11) presents a framework for estimation of $\epsilon_{food} - \epsilon_{fuel}$, given the impulse responses of a) relative nominal expenditure of food to fuel; b) relative price to food to fuel; and c) real non-durable consumption expenditure.

4.2 Empirical Evidence on Transmission Mechanisms

The theoretical model presented in Section 4.1 and the consumption, labor earnings, and regional price data presented in Section 2.1 allow us to empirically examine three questions, as listed in the testable predictions above. Do household earnings respond to global food and fuel price shocks heterogeneously and does the pattern of heterogeneity parallel the common pattern of heterogeneous consumption responses we document in Section 3? Do global food and fuel prices pass-through to local consumer prices in India and impact relative prices? Finally, can we decipher the presence of non-homothetic demand and estimate the slope of Engel curve by studying how relative expenditures across consumption categories respond to global price shocks? These are the questions we examine in Sections 4.2.1, 4.2.2, and 4.2.3, respectively.

4.2.1 Heterogeneous response of wage income

We now assess 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 (4.4), and the solution for consumption, Equation (4.6), have shown how heterogeneous labor income responses can lead to heterogeneous total consumption responses. Critically, the same mechanism of heterogeneous earnings responses are reflected in non-durable consumption, Equation (4.8), and own category consumption, Equation (4.10).

Figure 7 shows the response of earnings 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, analogously to their negative consumption effects in Figure 3. This suggests that heterogeneity in labor income effects is parallel to the heterogeneity in total, non-durable, and own-category consumption effects in Figure 3. For oil price shocks, the negative effects are more limited and are significant for the poorest group initially and for the rich over time. Qualitatively, this pattern is still consistent with the negative consumption effects of oil price shocks for these two tails of the income distribution in Figure 4. In Figure 7 we also present the mean OLS estimates for comparison. We observe the pattern of upward bias in OLS estimates for wage income effects due to omitted variable bias arising from global demand shocks. These results are consistent with our earlier results comparing OLS and IV estimates for consumption in Figure 6 for oil shocks.

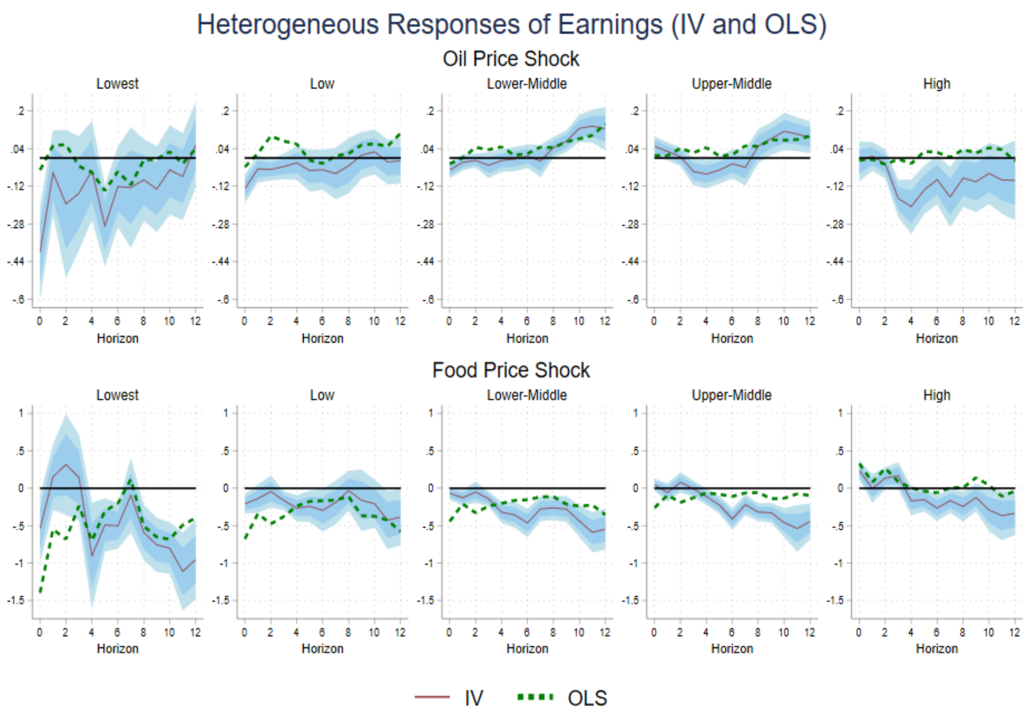

Figure 7: Response of Earnings to External Food and Oil Price Shocks by Income Quintiles (IV and OLS)

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.

4.2.2 Pass-through of global commodity price shocks to local consumer prices

An important channel via which external commodity price shocks can affect household consumption is through its impact on local consumer prices. In the theoretical framework described in Section 4.1, local prices affect aggregate and category-specific consumption via aggregate CPI, price of non-durable relative to overall CPI, and price of food or fuel relative to non-durable CPI.[35] We empirically estimate pass-through of external price shocks on these 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. This rich regional price data was described in more detail in Section 2.1.

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:

$$p_{s,r,t+h} - p_{s,r,t-1} = \beta_{0,r}^{h,\text{food}} ext_t^{\text{food}} \times \mathbb{1}_{r=urban} + \beta_{0,r}^{h,\text{oil}} ext_t^{\text{oil}} \times \mathbb{1}_{r=urban} + \gamma_h X_t + \sum_{d=0}^{D} \delta^h D_{t-d}$$
$$+ \sum_{j=1}^{J} \alpha_j^h (p_{s,r,t-j} - p_{s,r,t-j-1}) + \sum_{k=1}^{K} ext_{t-k}^{\text{food}} + \sum_{k=1}^{K} ext_{t-k}^{\text{oil}} + \theta_s + \zeta_r + \epsilon_{s,r,t+h} \quad (4.12)$$

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. Here, 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 (Baumeister and Hamilton (2019)); US federal funds rate; and global financial volatility as captured by the VIX index. We include state and calendar-month and calendar-year fixed effects and compute robust standard errors. In our IV results, we instrument the changes in global food and oil prices by the corresponding supply shocks. We report cumulative impulse responses. Table A6 in Online Appendix D.4 lists our control and instrumental variables.

We present the results based on the IV specification.[36] Figure 8 shows that there is pass-through to consumer prices, both to the direct category prices (second column) as well as to overall prices (first column). Dynamic effects of global food price change on overall CPI very closely follow its effects on the food component of CPI. Global oil price shock passes through

[35] The intertemporal budget constraint, Equation (4.4), and the solution for consumption, Equation (4.5), 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 (4.7) and Equation (4.10).

[36] The OLS results for comparison are in Appendix D in Figure A8. The first-stage F-statistics for these IV regressions are in Appendix D in Table A7.

strongly to domestic energy prices (comprising of fuel, electricity, and transportation and communication costs) as well as to headline prices, and the global oil price pass-through on local fuel prices is particularly prominent in the urban areas. Finally, as the third and fourth columns of Figure 8 show, global food and fuel prices increase relative price of food and fuel respectively (where we plot two relative prices, with the first one relative to non-durable CPI).[37]

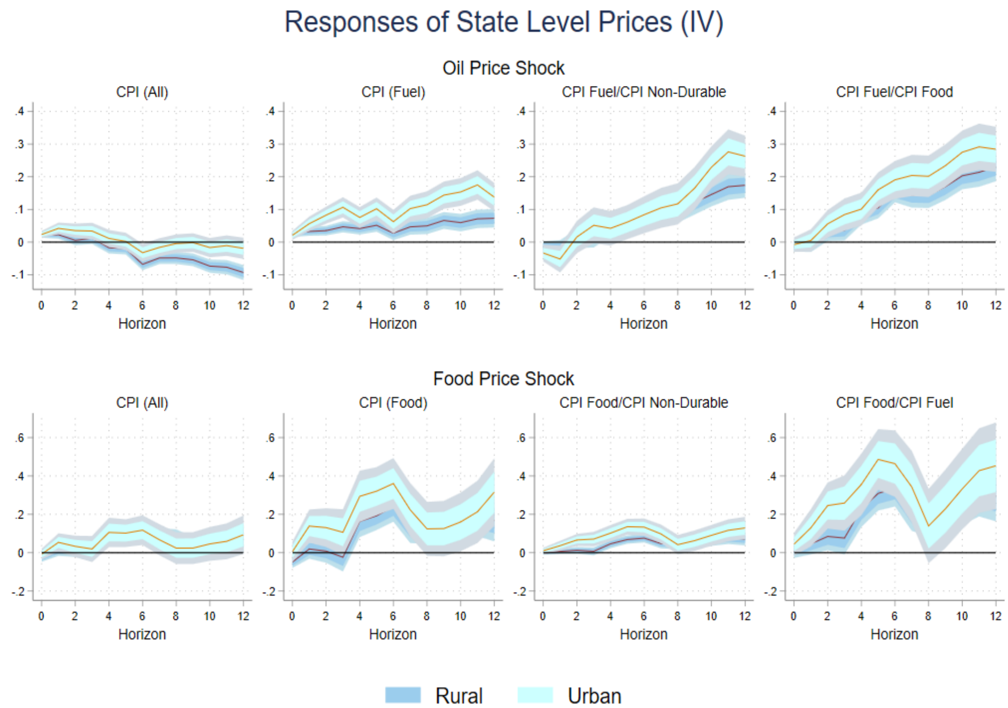

Figure 8: Response of State Level Prices to External Oil and Food Price Shocks (IV)

Notes: Cumulative IRFs on the basis of Equation (4.12) 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.

The maximum impact of global price changes on the corresponding component of CPI and on the overall CPI is summarized in Table 3. Both global food and oil prices have a larger impact on CPI (food) and CPI(fuel) in urban areas. The impact of global food prices on the overall CPI is in line with the share of food in the CPI basket, while the impact of global oil prices on the overall CPI is larger than its share, implying broader price effects of a rise in global oil prices. This is intuitive given the role of oil as an intermediate input in production of many goods.[38]

[37]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 later the results on expenditure share effects. In Figure A9 in the Appendix, we present results for relative price responses of various food components.

[38]The elasticity of CPI (fuel) to global oil price changes we report here is comparable to the estimates in the

Table 3: Response to Global Price Shocks (IV) (in %)

	Panel A: Response to Global Oil Price Shocks		
	All	Fuel	Share of Fuel in CPI
Rural	0.023	0.073	15.5
	(0.010, 0.035)	(0.045, 0.101)	
Urban	0.042	0.175	15.3
	(0.024, 0.06)	(0.013,0.22)	

	Panel B: Response to Global Food Price Shocks		
	All	Food	Share of Food in CPI
Rural	0.134	0.241	54.2
	(0.085, 0.182)	(0.162, 0.32)	
Urban	0.118	0.361	36.3
	(0.04, 0.195)	(0.228, 0.493)	

Notes: This Table reports the maximum effect on levels of CPI of global price shocks, obtained by estimating Equation (4.12) and which were reported in Figure 8. Standard errors are in parenthesis. CPI weights (Base year 2012) are from MOSPI.

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 (as captured by overall CPI) as well as relative prices (as captured by food to fuel price ratios and relative prices with respect to non-durable CPI).

4.2.3 Non-Homotheticity of non-durables and necessary consumption good

While movement in relative prices and earnings affect the level of real consumption for various categories, earnings/ total expenditure affects *relative* expenditure only in the presence of non-homotheticity, as is clear from Equation (4.11). If different components of non-durable consumption are substitutable, an increase in relative price leads to a reduction in the corresponding relative expenditure via standard expenditure switching channel.

Effects on nominal food expenditure share With this theoretical framework, we investigate the effects of global price changes on nominal consumption expenditure ratios within non-

literature. See, for example, Alp, Klepacz, and Saxena (2023) for cross-country evidence.

durables.[39] In this exercise, we estimate the effects of global food and fuel price shocks on nominal expenditure ratios of food and fuel. Thus here, the dependent variables in Equation (3.1) are the nominal expenditure ratios: $\frac{E_{food,i,t}}{E_{N,i,t}}$ and $\frac{E_{food,i,t}}{E_{fuel,i,t}}$.

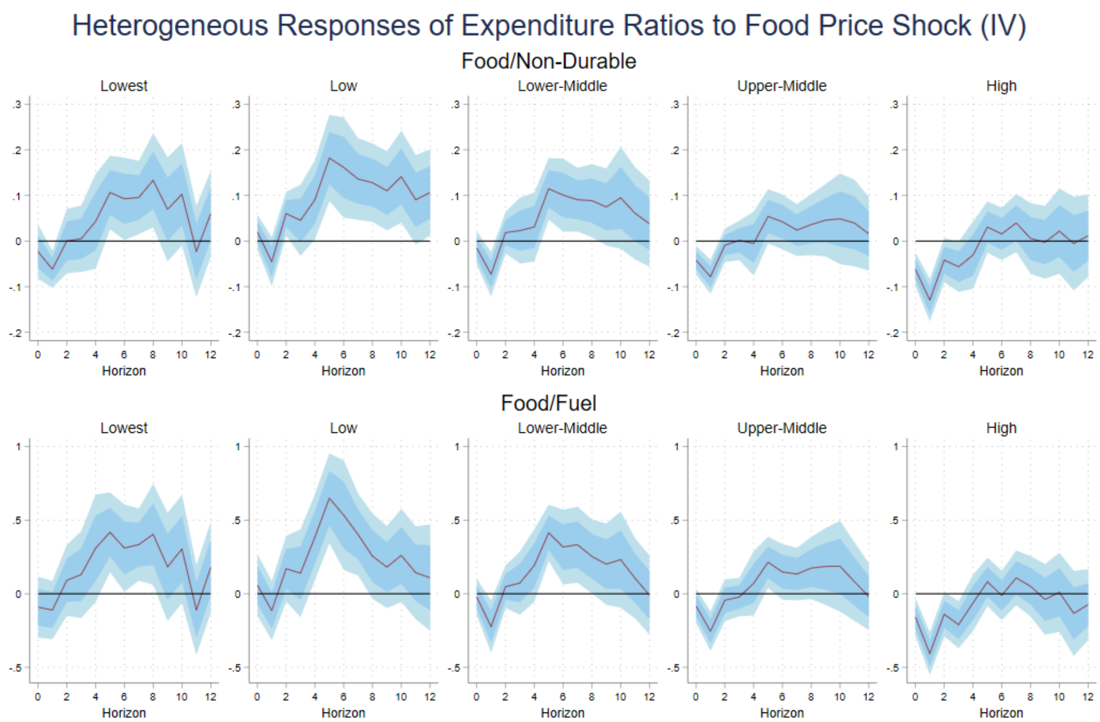

Figure 9: Response of Food Expenditure Shares to External Food Price Shocks by Income Quintiles (IV)

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.

Figure 9 presents results for food-to-non-durable and food-to-fuel expenditure ratios with respect to the global food price shock. In response to the global food price shock, relative local price of food increases (with respect to non-durables and fuel), as we showed previously in Figure 8. Figure 9 shows that this shock leads the low income groups to *increase* their relative expenditure on food, while the relative expenditure on food falls clearly only for the high income group. Since the expenditure switching channel always decreases relative expenditure on the good that is relatively more expensive, these relative expenditure responses of the low income groups indicate an impact of total expenditure on the expenditure shares due to non-homotheticity. Given the decline in real non-durable consumption in Figure 3 in response to

[39]Expenditure switching results for non-durable relative to total consumption is presented in the Appendix D.5. We find that relative expenditure on non-durable is mainly governed by relative prices.

rise in global food prices, these expenditure share responses in fact imply that food is unambiguously a necessity for the lower income groups, as we explained in Testable prediction 2. We show similar results for sub-categories of food expenditure ratios in Appendix D.6.[40]

Estimation of income elasticity of demand parameters While the response of relative expenditure to global price shocks can inform us qualitatively about the presence of non-homothetic demand and in some cases even provide unambiguous evidence, our empirical exercise next allows us to directly estimate the key income elasticity of demand parameters in Equation (4.11). The estimation of differences in the slope of the Engel curve between food and fuel will rely on the structure of non-homothetic demand described in Section 4.2.3. In particular, we fix σ_ϵ, allowing for some expenditure switching when relative prices change, and then estimate $\varepsilon^g_{food} - \varepsilon^g_{fuel}$ by matching the dynamic impulse responses on relative expenditures and total real non-durable consumption expenditures to global price shocks across different horizons.

Given Equation (4.11), dynamics of relative expenditure share of food and fuel is[41]:

$$\Delta \log\left(\frac{E_{food,i,t+h}}{E_{fuel,i,t+h}}\right) = -(\sigma_\epsilon - 1)\Delta \log\left(\frac{P_{food,t+h}}{P_{fuel,t+h}}\right) + (\varepsilon_{food} - \varepsilon_{fuel})\Delta \log\left(\frac{E_{i,N,t+h}}{P_{i,N,t+h}}\right)$$

Dynamic responses of relative (nominal) expenditure on food, $\frac{E_{food,t+h}}{E_{fuel,t+h}}$, are presented in Figure 9 and that of real non-durable expenditure, $\frac{E_{N,t+h}}{P_{N,t+h}}$, are in Figure 3. Dynamic responses of relative prices, $\frac{P_{food,t+h}}{P_{fuel,t+h}}$, are demonstrated in Figure 8. Exploiting *dynamic variation* in the responses and calibrating the parameter σ_ϵ, we minimize the distance between

$$\frac{\Delta \log\left(\frac{E_{food,t+h}}{E_{fuel,t+h}}\right)}{\Delta ext_t} + (\sigma_\epsilon - 1)\frac{\Delta \log\left(\frac{P_{food,t+h}}{P_{fuel,t+h}}\right)}{\Delta ext_t} \quad and \quad \frac{\Delta \log\left(\frac{E_{Nt+h}}{P_{Nt+h}}\right)}{\Delta ext_t}$$

It is important for estimation that the responses of variables described above is different across horizons h. Given that we estimate heterogeneous consumption responses across income groups, the second step of estimation is carried separately for each income group. This allows us to estimate the difference in the slope of the Engel curve for each income group g: $\varepsilon^g_{food} - \varepsilon^g_{fuel}$.

The results are in Table 4, where we fix $\sigma_\epsilon = 2$.[42] In the first row, we present the estimates

[40] 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 2. We will address this issue below with a structural estimation of Engel curve slopes.

[41] Note that in our empirical application food or fuel prices differ across households i only to the extent they reside in different regions

[42] Note that for the purpose of estimation, we utilize the IRFs in response to both global food and oil shocks, though using only global food shocks leads to qualitatively similar results. We also get qualitatively similar, but statistically different, results fixing $\sigma_\epsilon = .8$, which implies that food and fuel are gross complements.

based on the total food to fuel expenditure ratio. Estimates of $\varepsilon^{g}_{food} - \varepsilon^{g}_{fuel}$ is negative for all income groups, showing that food is a necessary good for everyone, irrespective of income. In the other rows, we show robustness of our main result if we consider 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.

Table 4: Estimates of Demand Function Parameters ($\epsilon_i - \epsilon_j$)

	Lowest	Low	Low-middle	Upper-middle	High
Food (All)	-0.359***	-0.407***	-0.394**	-0.414**	-0.657**
	(0.095)	(0.091)	(0.106)	(0.117)	(0.179)
Sugar	-1.412***	-1.523***	-1.432***	-1.425***	-2.338***
	(0.128)	(0.106)	(0.139)	(0.171)	(0.317)
Oils and Fats	-0.343**	-0.404***	-0.239	-0.134	-0.217
	(0.103)	(0.098)	(0.125)	(0.190)	(0.227)
Vegetables	-0.507*	-0.755***	-0.675**	-0.811**	-1.335*
	(0.215)	(0.188)	(0.230)	(0.266)	(0.540)
Pulses	-0.968***	-1.337***	-1.057***	-1.103**	-1.165*
	(0.241)	(0.233)	(0.258)	(0.296)	(0.433)
Spices	-0.402*	-0.708***	-0.593**	-0.737**	-1.009**
	(0.145)	(0.162)	(0.162)	(0.223)	(0.279)

Notes: This Table reports the estimates of $\epsilon_i - \epsilon_j$ obtained by estimating Equation (4.11) 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 26 observations (corresponding to IRFs for the two shocks for 13 horizons) used in estimation. The columns represent the various income groups. $\epsilon_i - \epsilon_j < 0$ indicates that good i (food here) is a necessary consumption good.

4.3 Mapping Model Mechanisms to Empirical Facts

In this Subsection, we formally assess the degree to which the transmission mechanisms highlighted in the model in Section 4.1 and empirically established in Sections 4.2.1, 4.2.2, and 4.2.3 help us understand the key facts regarding the distributional effects of global price shocks on household consumption established in Section 3.4.

How well does the theoretical model capture the estimated dynamics of non-durable and category-specific consumption, given the estimated impulse responses of total consumption and relative prices? We address this first in Figure 10 focusing on the food price shock. In particular, in the first row of Figure 10, the estimated line plots the impulse responses of real non-durable consumption from Figure 3 while the predicted line plots the model-consistent responses of real non-durable consumption on the basis of Equation (4.8) when the relative price estimates are obtained from Figure 8, the real consumption responses are obtained from Figure 3, and the price elasticity of demand, η^g, is fixed at 2 $\forall$ g. The good fit between the estimated and predicted impulse responses in the first row of Figure 10 is remarkable. For example, the predicted impulse responses explain between 82% to 92% of variation in real non-durable consumption dynamics for food shock. Relative prices play a relatively minor role as demonstrated by the dashed line in the first row of Figure 10, where the dashed plot is constructed using only the relative price term of Equation (4.8) and the relative price estimates are obtained from Figure 8. Thus, the increase in relative price leads to some decline in non-durable consumption, but the majority comes from a fall in wage income, as we show next.

That is, having established the general good fit of our theoretical model to the empirical estimates and the importance of total consumption responses in explaining non-durable consumption, we next turn to ask: How far can wage income dynamics explain the dynamics of total consumption responses? In particular, we rely on the intertemporal budget constraint, Equation (4.5). We construct proxies of present discounted future earnings (three month average) using the estimated future wage earnings responses from Figure 7 and compute the predictions for non-durable consumption (again, on the basis of Equation (4.8)) using our proxy of present discounted earnings in place of total consumption. The results are in the dashed lines in the second row of Figure 10 and depict a good fit. Goodness of fit for non-durable consumption using this measure of present discounted earnings vary between 69 % to 80 % (as opposed to 82% to 92% if we use total consumption dynamics as in the first row).

We use the third row of Figure 10 to demonstrate the role of non-homotheticity in explaining the (level) response of real food consumption in response to an increase in global food prices. In the third row of Figure 10, the estimated line plots the impulse responses of real food consumption from Figure 3 while the predicted lines plots the model-consistent responses of real food consumption on the basis of Equation (4.10) when the relative price estimates are obtained from Figure 8 and the real consumption responses are obtained from Figures 3. In this case, both the price elasticities of demand, σ_ϵ^g and η^g are fixed at 2 $\forall$ g and the slope of Engel curve for food (ε^g_{food}) is obtained from Table 4 (after the slope of Engel curve for fuel (ε^g_{fuel}) is normalized to unity). In the predicted (homothetic) version, i.e., the dashed line, the slope of Engel curve for food is normalized to unity instead of using the estimated Engel curve slopes from Table 4. The dashed line shows larger negative responses in food consumption for all income groups, demonstrating how households protect necessary food consumption in the face of adverse income shocks when demand is non-homothetic.

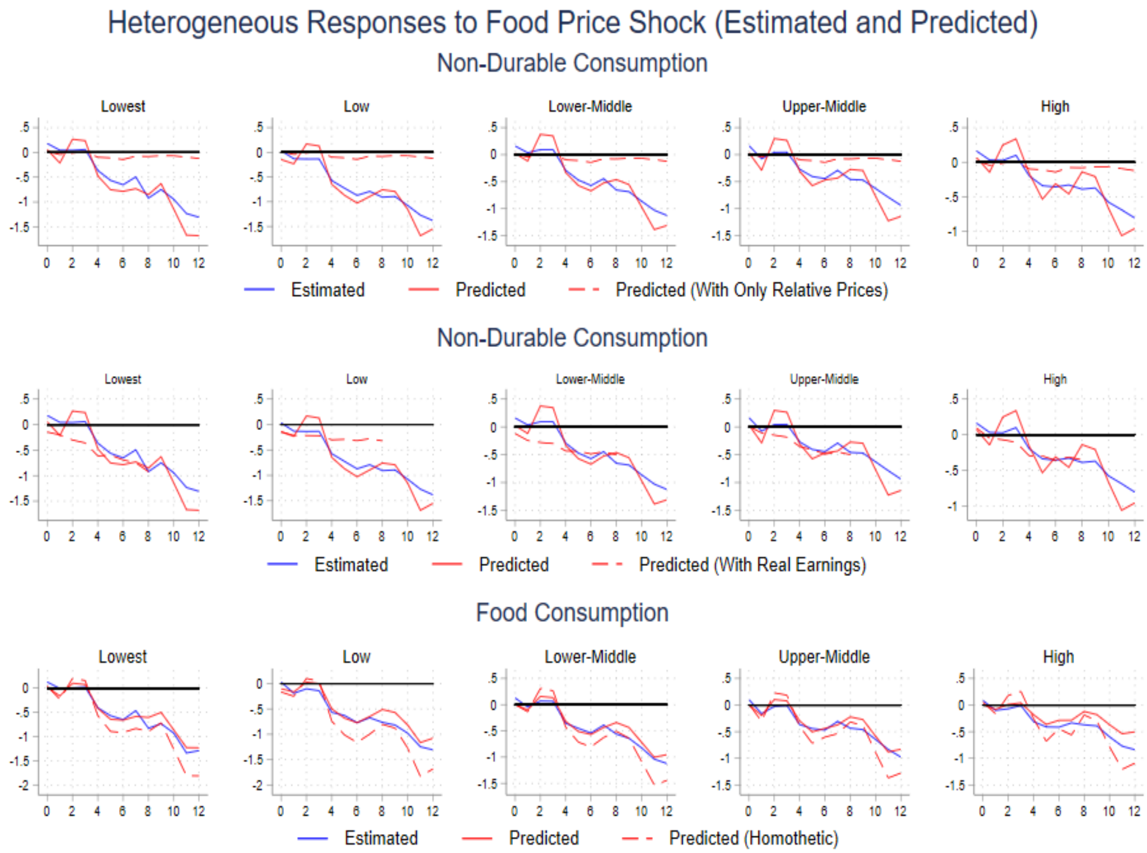

Figure 10: Response of Real Non-durable and Food Consumption to External Food Price Shocks by Income Quintiles (Data vs Theory)

Notes: The first row: Estimated refers to mean estimates of the Cumulative IRFs of real non-durable consumption to global food price shocks from Figures 3. Predicted refers the model-consistent responses of real non-durable consumption on the basis of Equation (4.8) when the relative price estimates are obtained from Figure 8 and the real consumption responses are obtained from Figure 3 (fixing η^g at 2 $\forall$ g.). The second row: Estimated refers to mean estimates of the Cumulative IRFs of real non-durable consumption to global food price shocks from Figures 3. The Predicted (with real earnings) line, in dash, refers to the model prediction where the dynamics of the total consumption term of Equation (4.8) is replaced by a smoothed (3 month average) proxy of present discounted labor earnings from Figure 7 while the relative price estimates are still obtained from Figure 8. Predicted line, in solid, is same as the first row. The third row: Estimated refers to mean estimates of the Cumulative IRFs of real food consumption to global food price shocks from Figure 3. Predicted refers the model-consistent responses of real non-durable consumption on the basis of Equation (4.10) when the relative price estimates are obtained from Figure 8 and the real consumption responses are obtained from Figures 3. Both the price elasticities of demand, σ_{ϵ}^{g} and η^g are fixed at 2 $\forall$ g, slope of Engel curve for food (ε_{food}^{g}) is obtained from Table 4, after the slope of Engel curve for fuel (ε_{fuel}^{g}) is normalized to unity. For comparison, in the Predicted (Homothetic) version, the dashed line, Engel curve slope for food is fixed at unity.

5 Further Evidence, Discussion, and Sensitivity Analysis

In this Section, we present some complementary evidence, discuss further our results, and establish robustness of distributional effects of global price shocks on consumption.

5.1 Further Evidence

First we present three sets of complementary evidence that corroborate our main findings.

Response of consumption inequality at state level We have documented from micro data (Fact 2 in Section 3.4) that an increase in global food prices has a larger adverse effect on poorer income groups, while an increase in global oil prices hits both tails of the income distribution similarly. Consistent with this, we show in Figures A12 and A13 in Appendix E.1 that various measures of state level inequality (constructed from the same underlying micro data used in our baseline empirical exercise) clearly rise with a rise in global food prices. The response of state level inequality to an increase in global oil prices is however mixed.[43]

Occupation-specific earnings responses Figure 7 showed that an increase in global food prices has a larger adverse effect on wage income of poorer income groups, while an increase in global oil prices hits wage income of both tails of the income distribution similarly. It is useful to explore further what causes this differential pattern of heterogeneous effects on household earnings in response to global commodity price shocks.[44]

One explanation could be that there are composition effects due to differential shares of various occupations across income groups and that different occupations are exposed differentially to the commodity price shocks.[45] To investigate further, we use individual level (as opposed to household level used in Section 4.2.1) earnings and occupation data from the Consumer Pyramid Household Survey. As shown in Table A2, poorer income groups are more likely to be employed in informal occupations, while higher income households are more likely to be in formal or self-employed/business occupations. To further corroborate our heterogeneous earnings response, we then examine how earnings of different occupation groups respond to global commodity price shocks using a panel local projection estimation strategy. Figure 11 presents our results. As the bottom panel confirms, informal occupation groups suffer larger real earnings losses with a rise in global food prices, confirming the regressive nature of global food price shock. The rise in global oil prices continues to have an inverse U-shaped impact, with both informal and self-employed/business groups suffering larger real earnings losses.

[43]See Appendix E.1 for details. Our measures of inequality are similar to Coibion et al. (2017) who find significant impact of contractionary monetary policy shocks on consumption and income inequality in the US.

[44]The empirical literature on monetary policy finds different patterns of heterogeneity in labor income responses to the same type of shock. Thus, for contractionary monetary policy shocks, Andersen et al. (2023) find a clearly monotonic pattern while Amberg et al. (2022) find an inverse U-shaped pattern. In our case, the underlying external shocks are different, but they both lead to a contractionary policy response to the external shocks, and our impulse responses capture both the direct relative price effects and the indirect GE effects.

[45]The differential exposures by occupation might be due to institutional features of wage contracts that govern rigidity or indexation to inflation or due to differences across occupations in terms of complementarity of labor with commodity use in production.

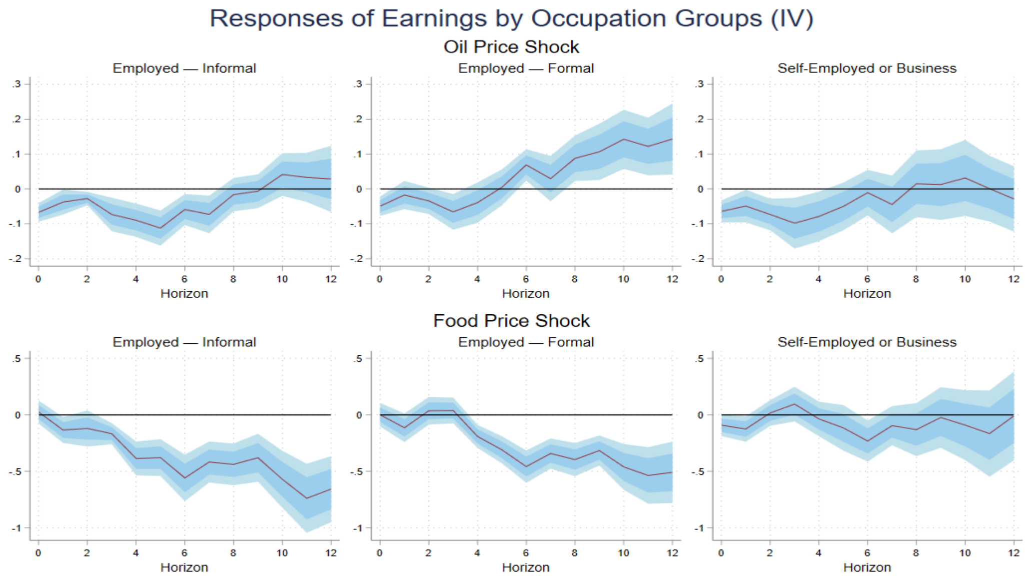

Figure 11: Response of Earnings to External Food and Fuel Price Shocks by Occupation Groups(IV)

Notes: Cumulative IRFs on the basis of equation (3.1) , but with interaction effects by occupation groups instead of income groups, 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.

Impact of global food price shocks on the agriculture sector India is a net exporter of agricultural goods, although agriculture constitutes a relatively modest, less than 10%, share in the total export basket of India for our time period.[46] In this context, conditional on our IV strategy having isolated variation in food prices that is exogenous to Indian local supply shocks, one might ask: Does a positive food price shock lead to an increase in India's agricultural exports? This might be expected as higher global food prices, that happen due to exogenous reasons, provide incentives for exporters in India to sell abroad. To answer this question, we use monthly Indian export price index from the IMF and monthly product level export volume data (seasonally adjusted) from COMTRADE. Our empirical framework is a Bayesian VAR where our food IV is used as an exogenous shock. Estimated impulse responses are presented in Figure A14 in the Appendix, and they show a clear increase both in Indian agricultural exports and the export price index following a positive food price shock.

While agriculture exports increase, the main focus of our paper is on the distributional effects of global price shocks. To assess how agricultural producers might be affecting our results, we undertake the following exercise. We first note that agricultural households in our data are distributed across income groups. Thus, it is not the case that agricultural households are exclu-

[46] See, Chatterjee and Subramanian (2020) for recent data on sectoral composition of India's exports.

sively in the lowest income group. Next, we re-estimate our baseline specification for wage income effects excluding agricultural households from the sample.[47] Figure A15 in the Appendix shows that the distributional effects of a global food price shock on real earnings are robust.

5.2 Further Discussion of Main Results

In this Section, we discuss three aspects of our empirical results: first, a relatively larger effect of global oil shock on total consumption relative to non-durable; second, comparing the magnitude of distributional effects on total consumption versus earnings, and third, a rather nuanced role of share-heterogeneity in understanding our key results regarding distributional effects of global price shocks on household consumption.

Comparison of total consumption and non-durable consumption responses From the results in Table 2, we note that while global food price shocks explain a similar share of variation for non-durable or total consumption, global oil price shocks explain a higher share of variation of total consumption.[48] For example, for the highest income group, a 1 standard deviation oil shock explains 5 % of the variation in non-durable consumption, but nearly 9 % of variation in total consumption. This suggests that there might an additional transmission mechanism that affects durable spending by the high income households in response to global oil shocks.

Comparison of effects on total consumption versus earnings Comparing Figures 3 and 4 with Figure 7, we note that for all income groups other than the poorest, effects on total consumption are larger in magnitude than those on labor earnings. Theoretically, the solution for consumption in Equation (4.5) shows that a relatively larger response of total 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. Given that a larger share of household income is from earnings and transfers for the poorer income groups, we expect the wealth effects to be more salient for higher income groups. In fact, we do find evidence of such effects on the stock price and the interest rate, as presented in Figure A3.

Our results showing a strong response of consumption to these shocks, compared to wage income, is also reminiscent of the positive effect of unanticipated inflation on household saving observed in Deaton (1977). As an explanation, Deaton (1977) offers the fundamental insight 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 re-

[47] Agricultural households are identified as agricultural laborers, small farmers, and organized farmers.

[48] This is consistent with a larger effect of global oil price rise on durable & service (as opposed to non-durable) consumption and larger price effects of global oil price increase on durable and service components of CPI in Figure A10. Priya and Sharma (2024) also find that the (average) effects of an increase in CPI (fuel) are larger on durable consumption using CPHS data.

sult on this front also connects to the unconditional stylized facts from the emerging market business cycle literature. For instance, Uribe and Schmitt-Grohe (2017) document that consumption growth is clearly more volatile than income growth for emerging market economies.[49]

Role of expenditure share heterogeneity Here we discuss the literature on consumption basket heterogeneity and resulting inflation inequality, surveyed in Jaravel (2021), to assess its role in understanding our results. We have documented a common pattern of dynamic heterogeneous responses across various consumption categories to both global food and oil price shocks. On average, as shown in Table A1, food shares vary across income groups while fuel shares do not. But variation in these steady-state shares by themselves cannot explain the dynamics of consumption responses, though the implied heterogeneity in income-group specific price indices can play a role in affecting overall purchasing power of given nominal wages.

To understand in detail the role of share heterogeneity, we refer to Equation (4.10) and make three observations. First, changes in relative prices (food relative to non-durable, or non-durable relative to overall CPI) can lead to heterogeneous consumption effects due to heterogeneity in shares of food or non-durable consumption across income groups. However, relying on such heterogeneity *alone* will imply different patterns of heterogeneous responses for cross-category consumption, contradicting our evidence in Figure A5. Since we observe the *same* dynamic pattern of heterogeneous responses across different consumption categories, heterogeneity in earnings response is a more plausible mechanism for explaining our results.

Second, income-group specific price indices can imply differential fall in real earnings even if nominal earnings do not change. This is the often discussed channel through which purchasing power of a given nominal wage income can be affected differentially, for the same underlying shock, across income groups. It is straightforward to show that a higher share of food in the consumption basket can lead to a larger fall in total consumption for poorer income groups with increase in food price, as they have a higher share of food in their basket, but that it goes together with a smaller fall in food consumption. Thus, this channel cannot explain the common estimated dynamics of heterogeneous responses across various consumption categories.

Finally, the literature on inflation inequality documents that poorer income groups generally experience a higher rate of inflation, particularly if overall inflation is driven by rise in food prices. Poorer income groups are however, more likely to have a net nominal debt position, as in our data in Table A1. The combination of higher rate of inflation and a net nominal debt position would imply a less negative impact on the poor due to a rise in food prices, which is the often discussed channel through which debtors benefit from unanticipated inflation. This

[49] 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 or HP filtered quarterly national income accounts data (1996:Q2 to 2019:Q4).

is contrary to the heterogeneous consumption effects of a rise in food prices.

In sum, in the absence of any income response, share heterogeneity and resulting differences in price indices and inflation rates experienced by different income groups cannot qualitatively explain the pattern of common heterogeneity for all consumption categories for a given external price shock. However, differences in consumption basket across income groups amplify the pattern of heterogeneity in total consumption responses across income groups.[50]

5.3 Sensitivity Analysis

How robust are the key results on distributional implications of global price shocks? We discuss four sensitivity exercises below. First, we have demonstrated that addressing omitted variable bias problem due to the influence of global demand shocks is crucial for the pattern of heterogeneous consumption responses. Another endogeneity concern could arise specifically with regard to global food prices due to India being a major exporter of rice such that local shocks that affect rice production in India, for example, can influence both global food prices and Indian consumption. Moreover, India's public distribution system ensures that poorer households can purchase cereals (mainly rice and wheat) at subsidized prices. In order to address both the endogeneity problem and the role of the public distribution system, we re-estimate the panel IV local projection Equation (3.1) for real food consumption *excluding cereals*, suitably adjusting the corresponding price deflator. The results are presented in the Appendix in Figure A16. It shows that the pattern of heterogeneity in response to global food price shocks is unchanged.

Second, we use alternate IVs for global food price changes. With the objective of removing the impact of global demand shocks from global food prices, we consider two alternates: residualizing changes in the food price index by only our estimated common factor, or by the economic activity shock of Baumeister and Hamilton (2019). The results are presented in Figure A17. Both the alternate IV strategies confirm the regressive nature of global food price increase.

Third, our baseline results presented in Figures 3 and 4 do not include household specific fixed effects. The panel local projections are estimated on log changes in household level consumption, which absorbs the household specific intercept term, but different demographic groups may experience different trend growth in consumption. In order to allow for differential trend growth rates of consumption across different demographics, we re-estimate the household panel local projection of Equation (3.1) including fixed effects for household's caste, religion, education, residence in a big city, and age. The results are presented in Figures A18 and A19, and the pattern of heterogeneity is unchanged. This is also re-assuring from the perspective of our IV strategy having successfully isolated exogenous variation.

[50] If households residing in different regions experience different rates of inflation and that income groups differ in the region they reside (see, Table A2), role of inflation inequality is already incorporated in our empirical exercise.

Finally, we explore sensitivity to alternative definitions of income groups, as presented in Appendix E.3.2. Figure A20 presents both our baseline results and these alternative cases. This comprehensive set of exercises lead us to conclude that the facts about the distributional effects of global commodity price shocks on Indian household consumption are robust.

6 Conclusion

In this paper, we study the distributional implications of increases in global food and oil prices by utilizing panel data on Indian consumption and income. We show that while both sector-specific shocks lead to stagflationary macroeconomic dynamics, they differ in terms of distributional consequences. Consumption of lower income deciles is affected more by an exogenous increase in food prices, while consumption of both tails of the income distribution is affected similarly by an exogenous increase in fuel prices. We also find that these heterogeneous consumption responses 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. We provide a novel way to identify 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. For a rise in global food prices, we document a strong stagflationary impact, a monetary policy contraction, and regressive distributional implications. The distributional effects on consumption that we have documented suggest that in EMEs, monetary policy may need to react to global shocks in food prices, despite the flexibility of prices in this sector, echoing the insights of Olivi et al. (2023). If fiscal policy plays a role in addressing the distributional concerns, can the optimal monetary policy prescriptions of canonical open economy sticky price models (such as Clarida, Galı, and Gertler (2002)), which suggests looking-through external shocks from flexible price sectors, be restored? In future research, we plan to address such questions in heterogeneous agent economies explicitly allowing for role of monetary-fiscal policy mix (similar to Schaab and Tan (2023)) in addressing both efficiency and distributional concerns in the presence of a necessary consumption good.

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

Disclaimer: This research presents views of the authors and not that of the Federal Reserve Board or the Federal Reserve System.

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 232,000 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 monthly consumption and income 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 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 which includes cooking fuel, electricity, transport and communication, and intoxicants), durable consumption (appliances, furniture, jewelry, clothing, electronics, toys, cosmetics), and service consumption (entertainment, highway tolls, beauty services, fitness services, restaurants etc).

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

We also winsorize our constructed variables at the 1 percent level. We then deflate our total consumption, income and earnings measures by the Consumer Price Index (CPI) - Combined series (2012 base) available at a monthly frequency from The Ministry of Statistics and Programme Implementation (MoSPI), Government of India.

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 light and excludes the fuel used in transportation; the index for transportation is available under the "miscellaneous (transportation and communication)" category.[51] 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:

$$CPI(FL+TC)_{s,r,t} = \frac{W(FL)_{s,r}CPI(FL)_{s,r,t} + W(TC)_{s,r}CPI(TC)_{s,r,t}}{W(FL)_{s,r} + W(TC)_{s,r}}$$

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

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

$$CPI(NonDur.)_{s,r,t} = \frac{W(Food)_{s,r}CPI(Food)_{s,r,t}+W(FL)_{s,r}CPI(FL)_{s,r,t}+W(TC)_{s,r}CPI(TC)_{s,r,t}+W(Pan)_{s,r}CPI(Pan)_{s,r,t}}{W(Food)_{s,r}+W(FL)_{s,r}+W(TC)_{s,r}+W(Pan)_{s,r}}$$

Macro data

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. The Global Price of Food Index is an index of 28 different food commodity prices, where the weights are global import shares.

[51] 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.

Appendix B Summary Statistics by Income

Table A1: Summary Statistics by Income Decile

Decile	No. of Hhs	Income	Earnings	Consumption	Non-dur. Share	Food Share	Fuel Share
1	33,830.51	827.37	504.42	2,520.58	0.78	0.62	0.24
2	5,644.08	3,943.66	3,191.57	3,908.62	0.79	0.65	0.21
3	8,093.39	4,899.28	4,238.48	4,295.64	0.79	0.64	0.22
4	10,576.03	5,899.26	5,218.08	4,716.47	0.78	0.63	0.23
5	12,287.31	6,923.61	6,101.26	5,145.57	0.77	0.61	0.24
6	12,892.10	8,177.10	6,997.05	5,543.09	0.77	0.60	0.25
7	14,493.92	9,834.17	8,274.90	5,944.41	0.76	0.59	0.26
8	16,485.14	12,095.56	9,660.60	6,532.69	0.75	0.58	0.27
9	19,543.08	16,126.54	12,189.33	7,344.10	0.75	0.56	0.29
10	29,928.75	32,483.79	21,010.59	9,434.76	0.73	0.52	0.32

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: Summary Statistics by Baseline Income Groups

	Lowest	*Low*	*Lower middle*	*Upper middle*	*High*
	Consumption				
$SD(\Delta log(C_{i,t})$	0.242	0.205	0.216	0.233	0.248
$SD(\Delta log(C_{i,N,t})$	0.205	0.170	0.172	0.178	0.182
Non-durable (% of C)	91.04	90.78	89.62	88.73	87.09
Food (% of non-durable)	69.72	72.53	69.61	66.01	61.32
	Labor Market Indicators				
$SD(\Delta log(earnings))$	0.576	0.274	0.233	0.268	0.4
Earnings (% of income)	34.77	84.21	86.69	78.34	67.05
Informal occupation (%)	82.51	89	82.8	72.4	52
Formal occupation (%)	15.99	6.12	9.03	15.75	30.91
Self-employed/business (%)	1.49	4.76	8.25	11.87	13.01
	Region				
Urban	58	53	64	73	81
Rural	42	47	36	27	19
	Education Category				
Upto 7th Std	48	67	57	46	25
Upto 12th Std	35	29	36	39	38
$\geq$ College Graduate	16	4	7	15	38
	Religion & Caste				
Hindu	85	87	85	84	85
SC	17	28	25	20	12
ST	7	9	6	4	3
	Age of Household Head				
25-49 years	40	55	53	37	24
> 49 years	60	45	47	63	76

Notes: This table presents summary statistics of key dependent variables and socio-economic variables by baseline income groups. The statistics are calculated by adjusting for sampling weights and non-response factors provided by the Center for Monitoring Indian Economy. We categorise the available occupation data. Informal occupations include agricultural laborers, home-based worker, small farmer, small trader/ hawker/ businessman without fixed premises, legislator/ social workers/ activists and wage laborer. Formal occupations include 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.

Appendix C Instrumental Variables for Global Price Changes

C.1 Estimation of the Food Price Shock IV

Table A3: 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 price IV, we first estimate a dynamic factor model with one common factor and a food-specific factor in a panel of 37 non-energy commodity prices (see, Table A3), which comprises 13 industrial inputs and metals and 24 food prices. We use monthly data from 1990-2022. The dynamic factor model can be described as:

$$r_{c,t} = B_0^c F_t + B_1^c F_{t-1} + .. + B_P^c F_{t-P} + \zeta_{C,t}$$

where $r_{c,t}$ is the log difference in the commodity price c, F_t is a vector of two factors, $B_k^c, k = 0 : P$, is a 1×2 vector of factor loadings for commodity c at lag k, and $\zeta_{c,t}$ is the idiosyncratic component. The factor loadings reflect the degree to which variation in commodity returns can be explained by each factor. The first factor (F_t^{common}) is the common factor affecting all commodities in the sample, the second factor is a food factor (F_t^{food}) affecting only the 24 food commodity prices. The unexplained idiosyncratic errors, $\zeta_{c,t}$, are assumed to be normally distributed, but possibly serially correlated. They follow Q-order autoregressions,

$$\zeta_{c,t} = \phi_1^c \zeta_{c,t-1} + \phi_2^c \zeta_{c,t-2} + .. + \phi_Q^c \zeta_{c,t-Q} + \eta_{c,t}$$

where $\phi_j^c, j = 1 : Q$ are autocorrelation coefficients. All the innovations, $\eta_{c,t}$, and the factors are assumed to be zero mean, contemporaneously uncorrelated normal random variables:

$$\eta_{c,t} \sim N(0, \sigma_c^2), F_t \sim N(0, \Sigma).$$

Here, Σ is a diagonal matrix with variance of the factors, F_t^{common} and F_t^{food}, as the diagonal entries. However, the factors affect the commodity prices with P lags.[52] Also, the idiosyncratic errors are orthogonal to the factors. The time paths of the factors, $\{F_t\}$, the factor loadings B_k^c, the autocorrelation coefficients ϕ_j^c, the error variances σ_c^2, and the factor variances, $\sigma^2_{F_t^{common}}$ and $\sigma^2_{F_t^{food}}$ are jointly estimated.

Estimation of the dynamic factor model requires further identification and normalization assumptions. Identification denotes exclusion restrictions with the aim of interpreting the factors as representing shocks of different nature. The main exclusion restriction we impose is that while the common factor, F_t^{common}, potentially affects all commodity prices, the food factor, F_t^{food}, only affects the 24 food commodity prices included in our estimation. Hence, $B_c^k(1,2) = 0$, for all c belonging to the industrial metals group and $\forall k$. 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 contemporaneous common factor, $B_c^0(1,1) \geq 0 \forall c$. This implies that all commodity prices comove with the unobserved common factor–an improvement in global demand leads to an increase in all commodity prices and vice-versa.

We 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 et al. (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. Our main focus is estimating the common factor. We have conducted robustness analysis where we normalized factor loadings for copper instead of iron ore, given the role of copper prices in predicting global business cycles. We also estimated an extended model incorporating crude oil prices along with the non-energy prices in Table A3.[53]

[52] An alternative assumption would be that the factors affect commodity prices only contemporaneously, but the factors have autoregressive representation. While these two assumptions are equivalent theoretically, the assumption made here, lags in factor loadings and no autoregression in factors, allows for a simpler estimation technique following Justiniano (2004). The alternative formulation is employed by Kose, Otrok, and Whiteman (2003) and Kose, Otrok, and Whiteman (2008) for estimating global business cycle and by Delle Chiaie, Ferrara, and Giannone (2022) for estimating a global factor in commodity prices.

[53] We have also used alternative normalizations of the food factor, setting factor loadings for other food items to unity. The results are remarkably similar. Normalizing poultry is the baseline case since it is an important

We cast the dynamic factor model in the state space form and estimate it using Bayesian methods using Markov Chain Monte Carlo (MCMC). The state space model is described in detail in Justiniano (2004). We follow an extensive literature on Bayesian estimation of dynamic factor models (see, for example, Bernanke, Boivin, and Eliasz (2005), Kim and Nelson (2017), Kose et al. (2003), Kose et al. (2008)) which can easily accommodate restrictions on how the factors affect subsets of series that lie at the heart of our interpretation of the factors.

The estimation procedure is based on the following observation: if the factors were observable, under a conjugate prior, the models would be a set of regressions with Gaussian autoregressive errors; that simple structure can, in turn, be used to determine the conditional normal distribution of the factors given the data and the parameters of the model. This conditional distribution can, then, easily be used to generate random samples, which can serve as proxy series for the unobserved factors. As the full set of conditional distribution is known – parameters given data and factors and factors given data and parameters – it is possible to generate samples from the joint posterior distribution for the unknown parameters and the unobserved factors using sequential sampling of the full set of conditional distributions in a Gibbs sampling method. The process is iterated for 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.

In our implementation, the lag in factor loadings (P) and the length of idiosyncratic autoregressive polynomial (Q) are both 1. We follow Kose et al. (2008) to specify the prior distributions. The prior on all the factor loading coefficients and the autoregressive parameters is $N(0,1)$. The prior assumptions on the factor loadings reflect the expectation that on average, the factors do not affect commodity returns. We use a diffuse Inverted Gamma prior for the error variances and the factor variances. 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 with these two factors to construct our food commodity shock that we use as an instrument in the household panel local projections.

A statistical factor based approach allows us to circumvent non-availability of high frequency production data for food commodities, the problem of aggregation and also reliance on few major crops (such as rice and wheat) which could be problematic in the context of India. However, it is imperative to understand what drives our estimated factors.

Our identification of the common factor relies on comovement of this factor with non-

part of the food consumption basket in India (the most commonly consumed meat), and unlike other commonly consumed items such as rice and wheat, is not subject to domestic price controls. Rice and wheat are subject to various price controls within the Indian economy in the form of public distribution system for consumers and minimum support price for farmers. This is also why we do not use the harvest shock constructed in De Winne and Peersman (2016) because it relies on four major crops including rice and wheat.

energy commodity prices, the aim being to interpret it as an indicator of global demand. Crude oil price is very responsive to global business cycles. Baumeister and Hamilton (2019) use oil price, quantity, inventory and world IP data in a Bayesian VAR with sign restrictions to identify oil supply, oil demand, inventory and economic activity shocks. If commodity prices truly co-move with global demand, we expect positive comovement between the estimated common factor (note our baseline estimation doesn't use any oil price data) and the economic activity shock of Baumeister and Hamilton (2019). In Figure A1, we plot our common factor and the economic activity shock of Baumeister and Hamilton (2019).[54] Our common factor co-moves with the economic activity shock capturing major downturns in the global economy (such as the Global Financial crisis). The contemporaneous correlation is 0.23.[55] Delle Chiaie et al. (2022) find a similar strong positive correlation between world industrial production and the global factor estimated from a panel of commodity prices.

How to interpret the food-specific factor? Unlike the sign restrictions to identify the common factor, we do not impose sign restrictions on the factor loadings of the food factor (apart from the exclusion restriction, which implies that this factor only affects the 24 food prices in our panel). However, in our baseline estimation and in various robustness exercises we perform with respect to normalization, the factor loadings for the food factor are overwhelmingly positive and statistically significant.[56] That can arise due to the food-specific factor capturing global demand for food (for example, due to faster growth in poorer economies in our sample), or global weather shocks leading to correlated negative supply shocks across all 24 food commodities, without affecting industrial metal commodities. Contemporaneous correlation between the first principal component of various dimensions of weather shocks in De Winne and Peersman (2021) and our estimated food factor is negative but very low (-0.03).[57] This leads us to conclude that the food factor mostly captures food-specific demand.[58]

[54] Our estimated factor and the economic activity shock have different scales. We rescale common factor estimates in 2007 for ease of visualization.

[55] To check the dynamic correlation pattern, we estimate a bivariate VAR with 12 lags and the economic activity shock as the first variable, to show that the common factor responds in a positive and significant way to the economic activity shock for all 12 months after the initial impulse. The forecast error variance of the common factor explained by the economic activity shock varies between 4-14% over 12 months.

[56] Only 4 out of 24 food commodity prices have weakly negative factor loadings for the food factor.

[57] The various dimensions of global weather shock in De Winne and Peersman (2021) are: temperature, temperature squared, precipitation, and precipitation squared. To check the dynamic correlation pattern, we estimate a bivariate VAR with 12 lags and the first principal component of the weather shocks as the first variable, to show that the food factor responds in a negative but insignificant way to the weather shock for 10 out of 12 months after the impulse. The forecast error variance of the food factor explained by the weather shock is nearly zero for first 5 months and rises to about 6-7% after 10-11 months.

[58] We provide additional support for this hypothesis in the Sensitivity Analysis section (Figure A17) where instead of residualizing the global food price index by the estimated food and common factors, we residualize only with respect to the common factor, or only with respect to the economic activity shock of Baumeister and Hamilton (2019). Our IV results when residualizing with respect to both factors lead to more negative effects, which strongly

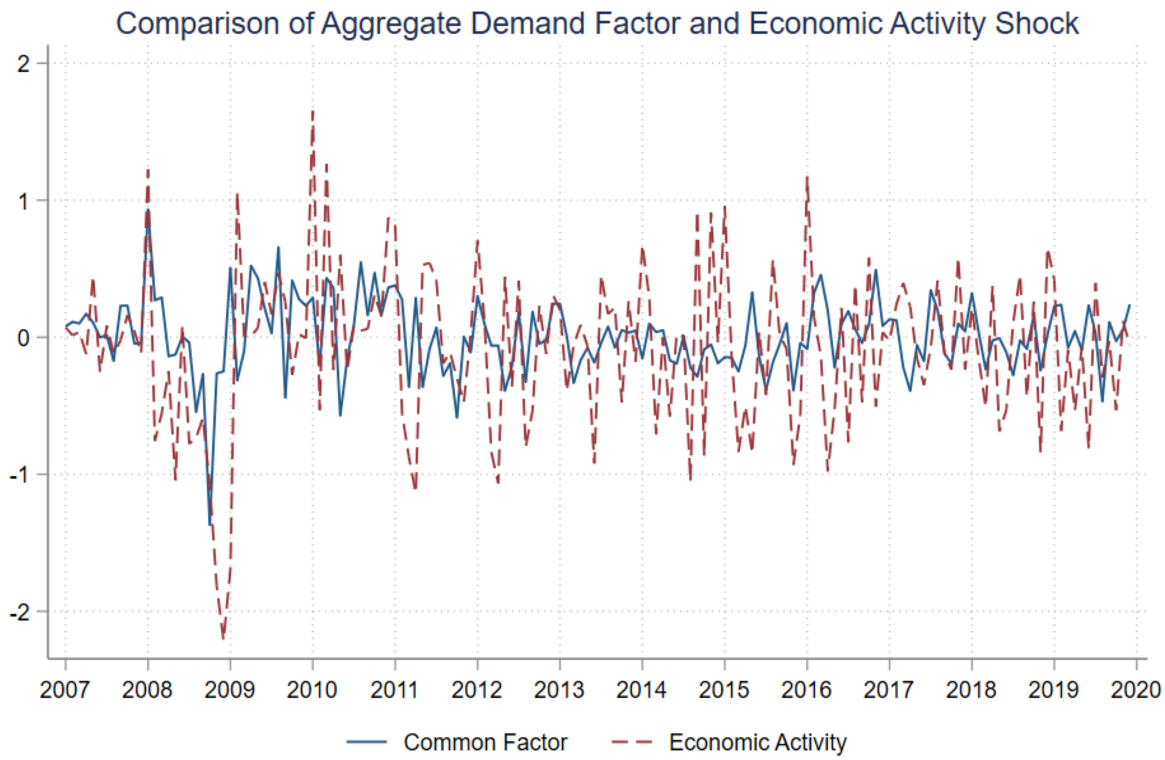

Figure A1: Comparison of Aggregate Demand Factor and Economic Activity Shock

Notes: This figure plots the time series of the estimated economic activity shock from Baumeister and Hamilton (2019) and the common factor estimated from the dynamic factor model as described in Online Appendix C. Both series are normalized to have the same scale in 2007 January.

After we residualize the (changes in log) global food price index by the estimated common factor and the food factor, what remains is largely food component specific idiosyncratic supply shocks and potentially some speculative component (because these are globally traded commodity prices). We use this residualized changes in global food price index as our IV in household panel local projections.

C.2 IVs for Global Price Changes: Time Series and Macro Effects

We described above in detail how we construct the IV for global good price change. For the global oil price change, our IV is the supply shock from Baumeister and Hamilton (2019). Figure A2 presents global food and oil price changes with the respective IVs, which we take to micro data as our measure of sector-specific external shocks.

suggests that it removes more variation coming from demand.

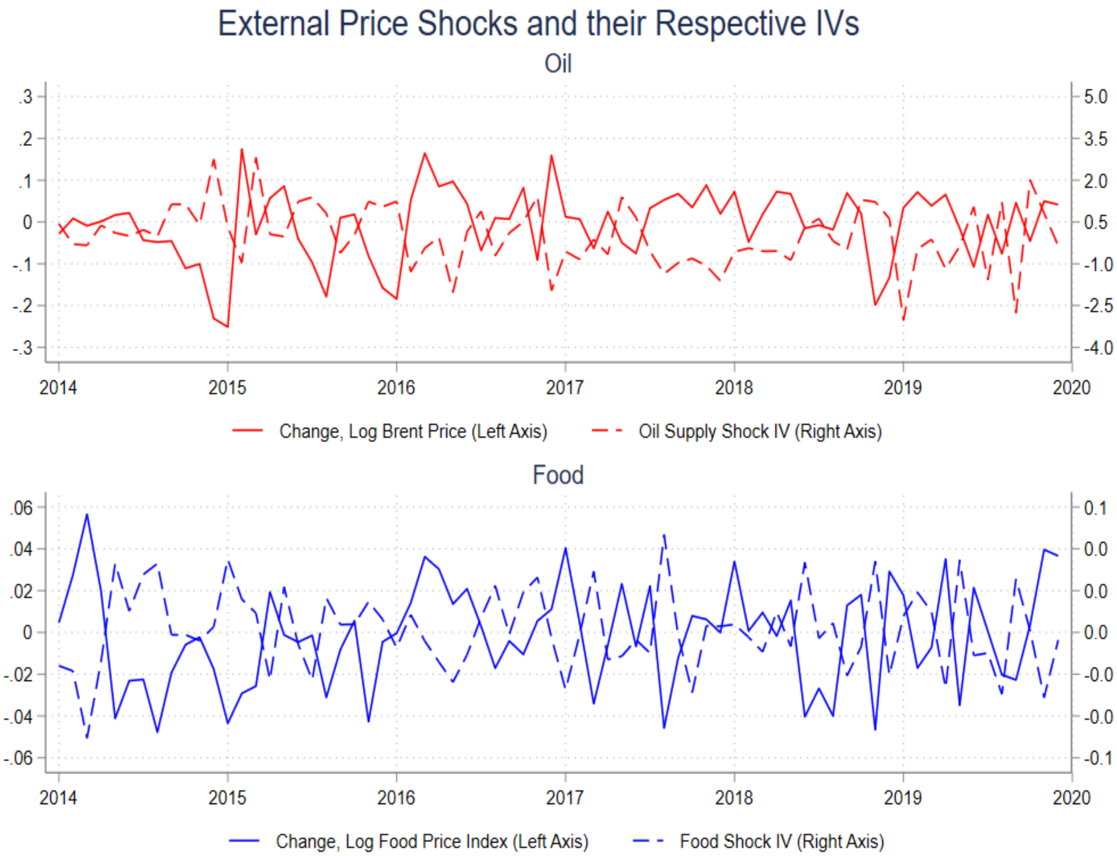

Figure A2: Oil and Food Price Shocks and the Respective Instrumental Variables

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 Appendix C.

In Figure A3 we demonstrate how an adverse food supply shock, measured using our method, leads to a stagflationary impact on the Indian macroeconomy with falling real economic activity (proxied by monthly real GDP interpolated using industrial production), rising consumer prices (proxied by monthly GDP deflator interpolated using CPI), rising short term interest rate, and falling local stock market. Our specification is a Bayesian 4- variable VAR with 12 lags where the food supply shock is the exogenous shock. For comparison, in Figure A4 we present macroeconomic effects of the adverse oil supply shock of Baumeister and Hamilton (2019) estimated using the same method, which shows that the macroeconomic effects are similar .[59]

[59]Both sets of VAR-based IRFs are scaled such that the food or oil supply shock has unit impact on the log level of global food and oil prices respectively.

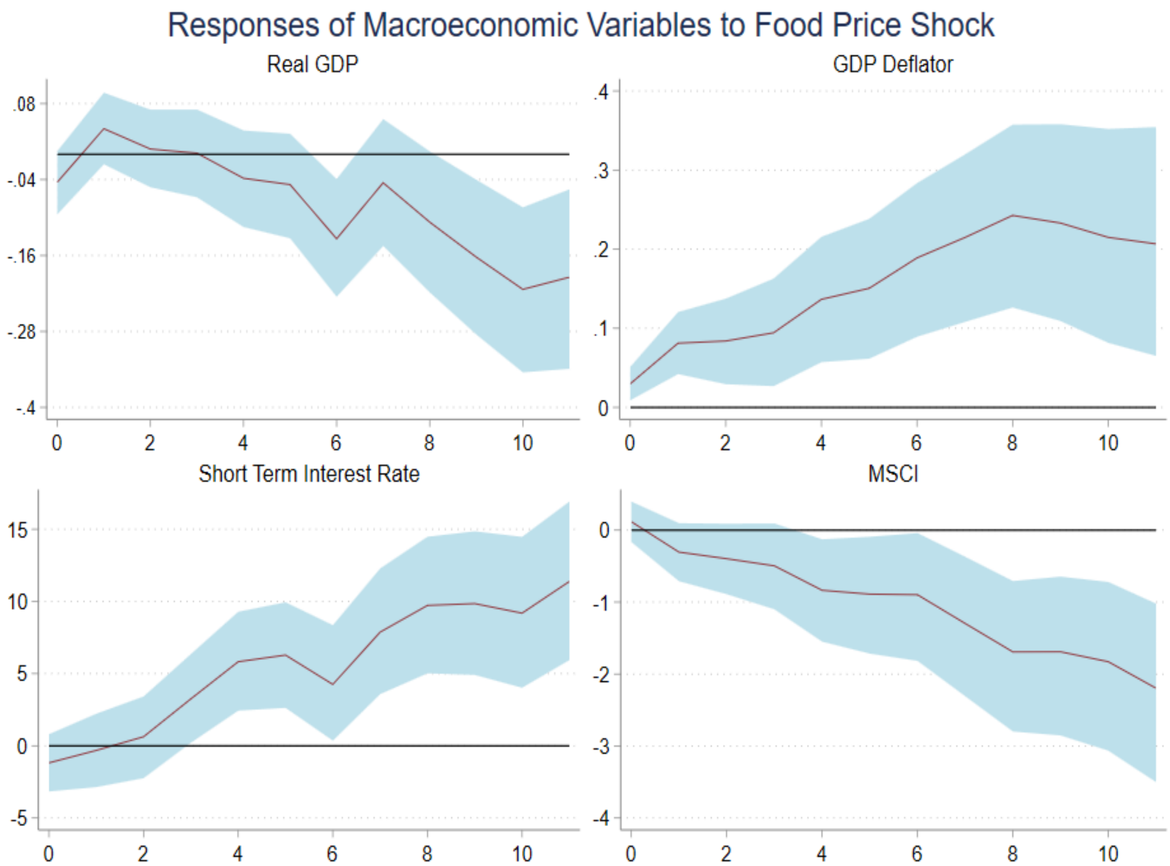

Figure A3: Macroeconomic Effects of Food Price Shocks

Notes: This figure plots the impulse response of Indian Real GDP, GDP deflator, 3-moth interest rate, and local stock market index to an adverse (positive) food supply shock that raises log of global food price index by one unit on impact. The impulse responses are estimated from a Structural VAR with four endogeneous variables and the food supply shock as an external shock, allowing for 12 lags of endogenous variables and external shock. The food supply instrument is constructed using a dynamic factor model as described in Appendix C. Stock market and interest rate data are collected from the Global Economic Monitor of the World Bank, while the real GDP, GDP deflator (and IP and CPI used in interpolation) are collected from Haver Analytics. Sample used: 2000-2019. Dummies included: GFC, Taper Tantrum and India's demonetization policy.

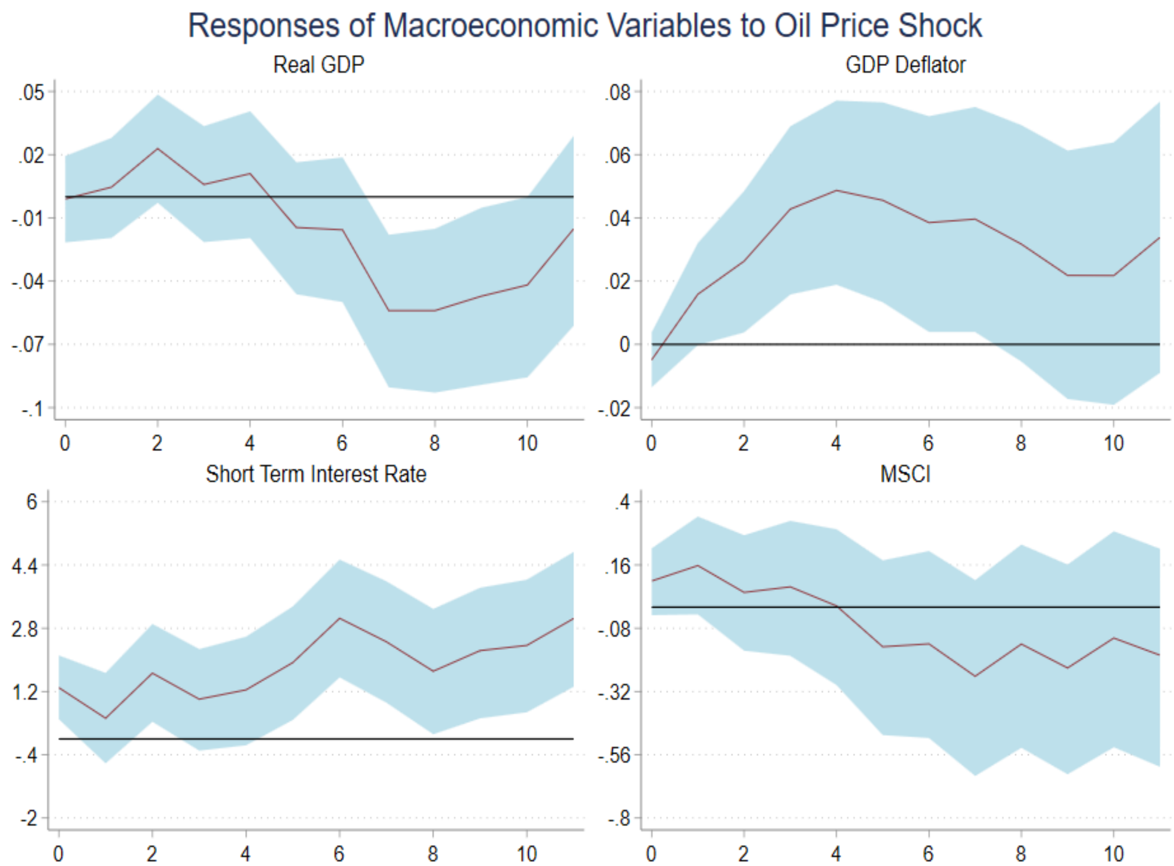

Figure A4: Macroeconomic Effects of Oil Price Shocks

Notes: This figure plots the impulse response of Indian Real GDP, GDP deflator, 3-moth interest rate, and local stock market index to an adverse (negative) oil supply shock of Baumeister and Hamilton (2019) that raises log of Brent crude oil price by one unit on impact. The impulse responses are estimated from a Structural VAR with four endogeneous variables and the oil supply shock as an external shock, allowing for 12 lags of endogenous variables and external shock. Stock market and interest rate data are collected from the Global Economic Monitor of the World Bank, while the real GDP, GDP deflator (and IP and CPI used in interpolation) are collected from Haver Analytics. Sample used: 2000-2019. Dummies included: GFC, Taper Tantrum and India's demonetization policy.

Appendix D Details on Specifications and Results

Table A4: 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
- Aggregate world condition controls (interacted with household income group dummies)
  - World Industrial Production (Baumeister and Hamilton (2019))
  - 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.

Table A5: 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	3,761.7	3,759.1
	Panel B : Global Oil Price Shock & Oil Supply IV	
First stage F-stats	856.8	838.6

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.1 Across Category Consumption Responses

In Figure A5 we show across-category consumption responses to the external price shocks.

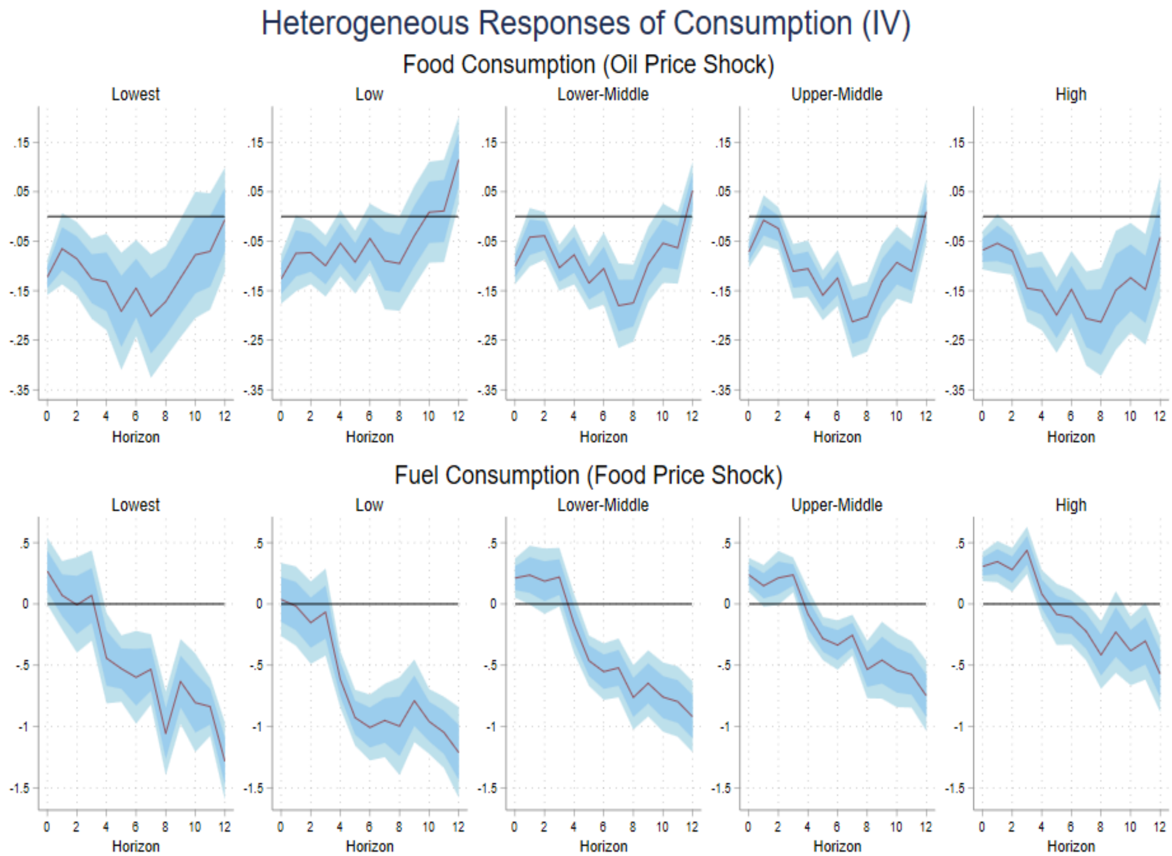

Figure A5: Response of Cross-Category Consumption to External Price Shocks by Income Quintiles (IV)

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

D.2 Non-joint Estimation

In Figure A6, we present results relative to the low-income group for both food and oil price shocks when the estimation of Equation (3.1) is done separately for the two shocks.

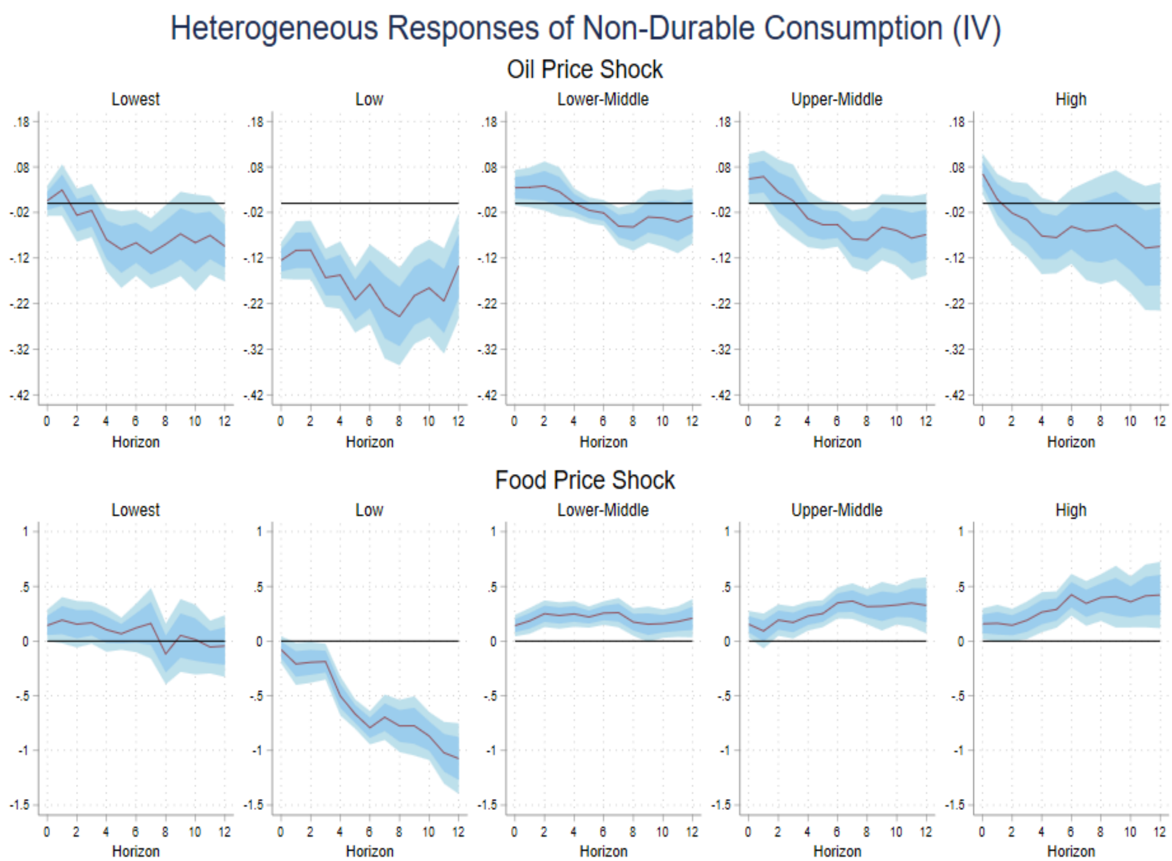

Figure A6: Relative (to low income group) Response of Non-durable Consumption to External Food and Oil Price Shocks by Income Quintiles (IV)

Notes: Cumulative IRFs on the basis of equation (3.1) where the external shock is log changes in the global food or oil price, which is instrumented by the corresponding supply shock and the dependent variable is log changes in household non-durable consumption. Column 2, for the low income group, shows the total effects for this baseline group, while the rest of the columns show the relative effect compared to the low income group. The light blue region is the 90% confidence interval and the dark blue region is the 68% confidence interval.

D.3 OLS and IV Comparison for Food Price Shocks

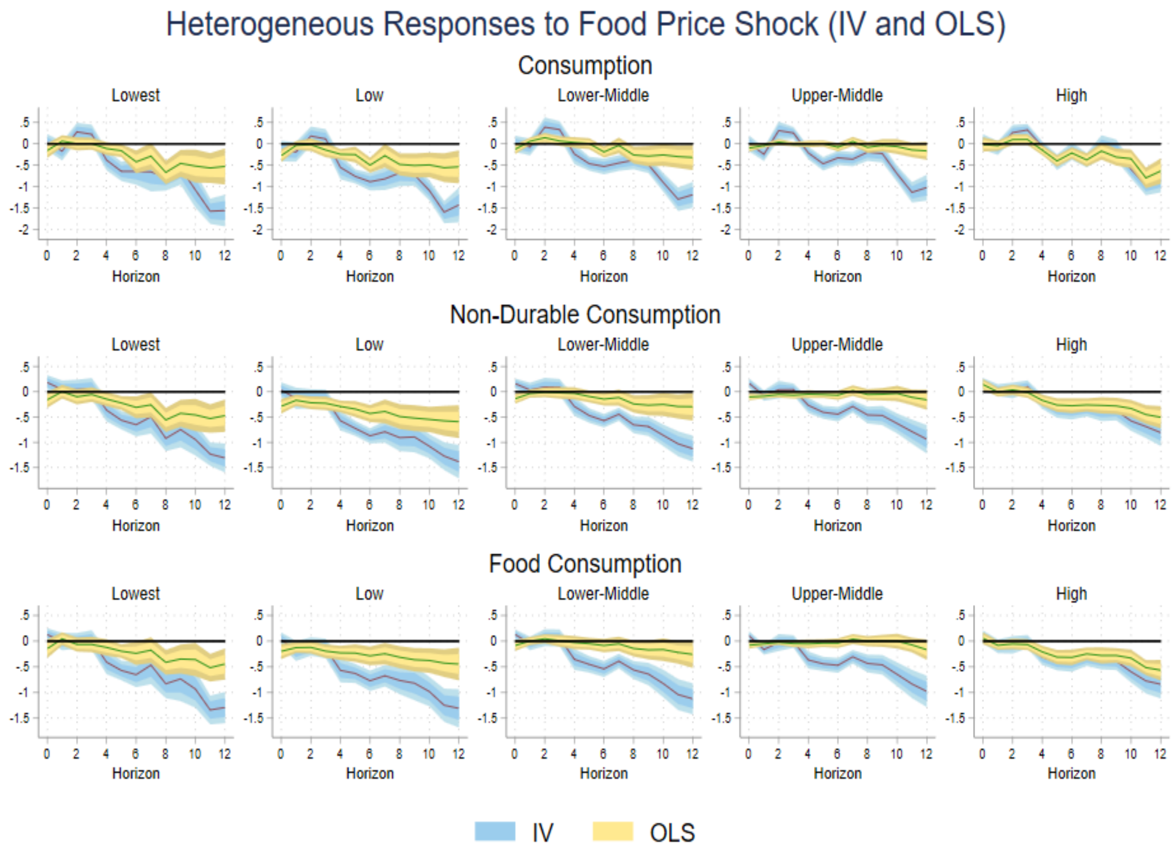

Figure A7: Response of Consumption to External Food Price Shocks by Income Quintiles

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 food 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 Prices

Table A6: 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 (Baumeister and Hamilton (2019))
  - 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.

Table A7: F-statistics for Panel Local Projection IV Regressions of State-Region 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	2,384.7
	Panel B : Global Oil Price Shock & Oil Supply IV		
First stage F-stats	1,848.2	1,876.0	1,255.8

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.4.1 OLS results on regional price effects of external shocks

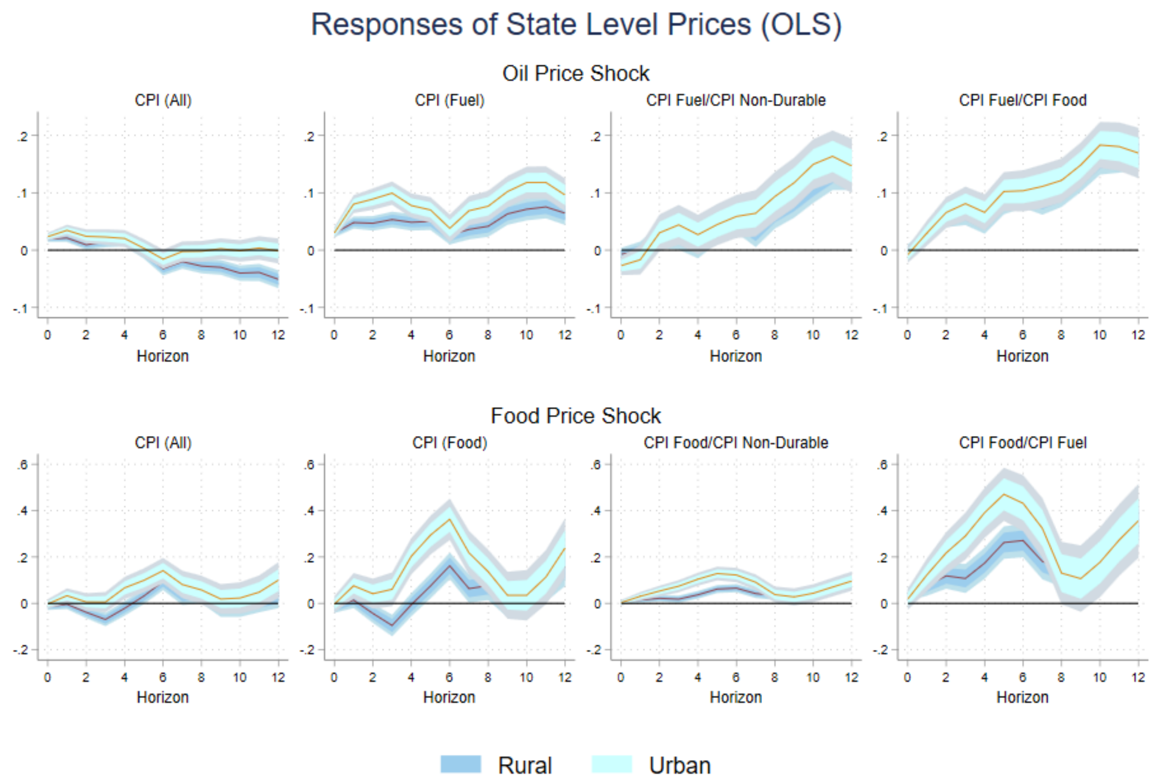

Figure A8: Response of State Level Prices to External Oil and Food Price Shocks (OLS)

Notes: Cumulative IRFs on the basis of equation (4.12) 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.4.2 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 the results on expenditure share effects. In Figure A9 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 A9 presents in a more dis-aggregated form the results that we presented before for food to fuel CPI ratio. 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.

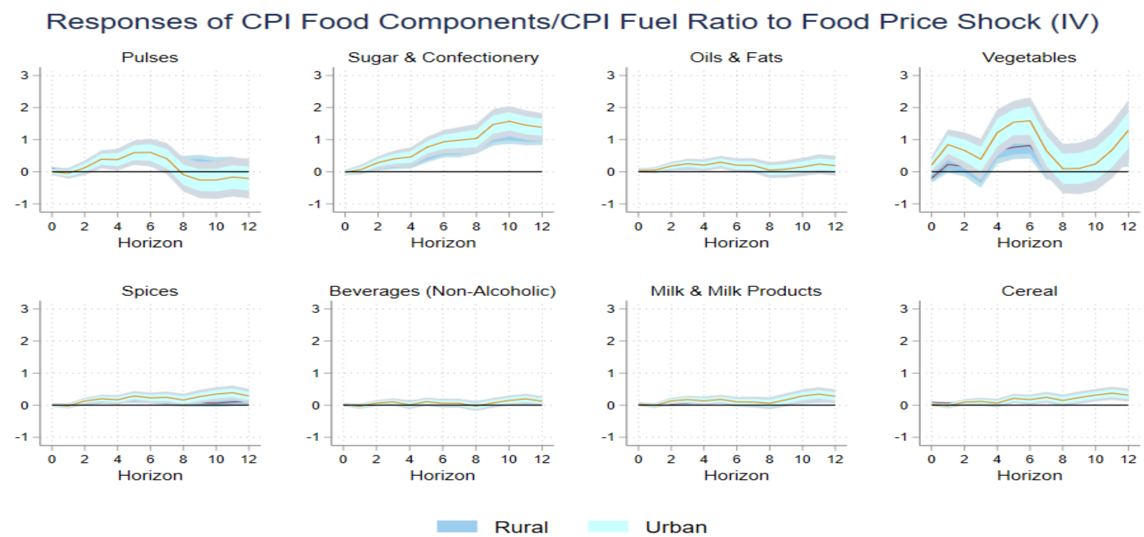

Figure A9: Response of State Level Relative Prices to External Food Price Shocks (IV)

Notes: Cumulative IRFs on the basis of equation (4.12) 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.

D.5 Expenditure Switching of Non-durables

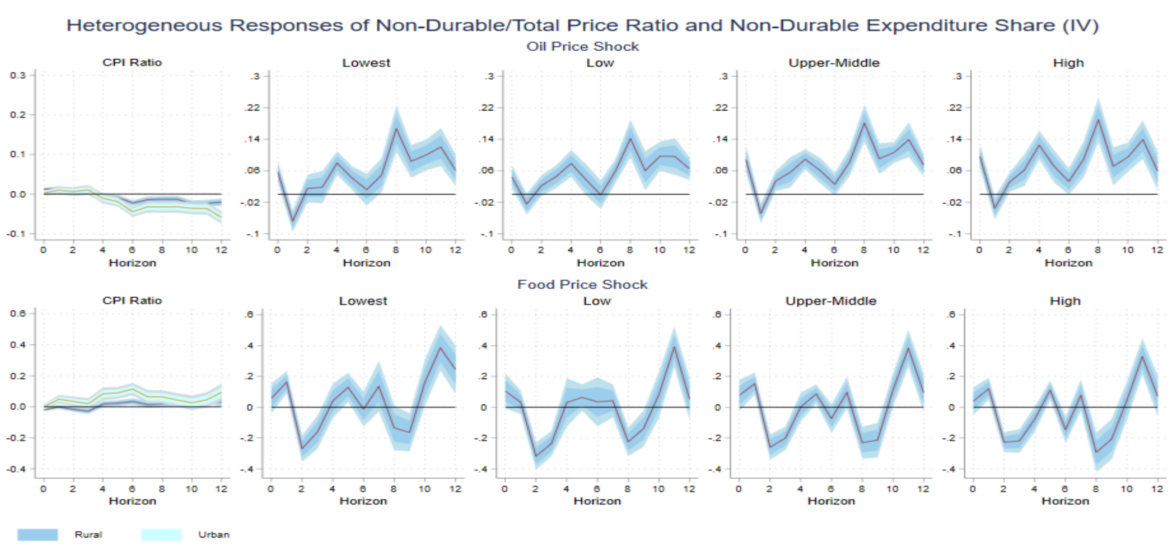

Figure A10: Response of Non-durable to Total Price Ratio and Non-durable Expenditure Share to External Oil and Food Price Shocks (IV)

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.

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.[60] In addition, the response of the non-durable expenditure shares are very similar across various income groups, suggesting that relative price movements are the main determinant, as captured by a homothetic CES aggregator.

D.6 Responses of Detailed Food Categories to Fuel Expenditure Ratios

Here 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. Testable Prediction 2 had summarized that relative expenditure on food components increasing in response to the food price shock would be a *sufficient* proof for non-homotheticity, as the relative price of these food components increases (Figure A9) and real non-durable consumption falls (Figure 3).

Figure A11 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 A9). 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 A11 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.[61] 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 2.

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

[61] To preserve space, we only reported four income groups in Figure A11.

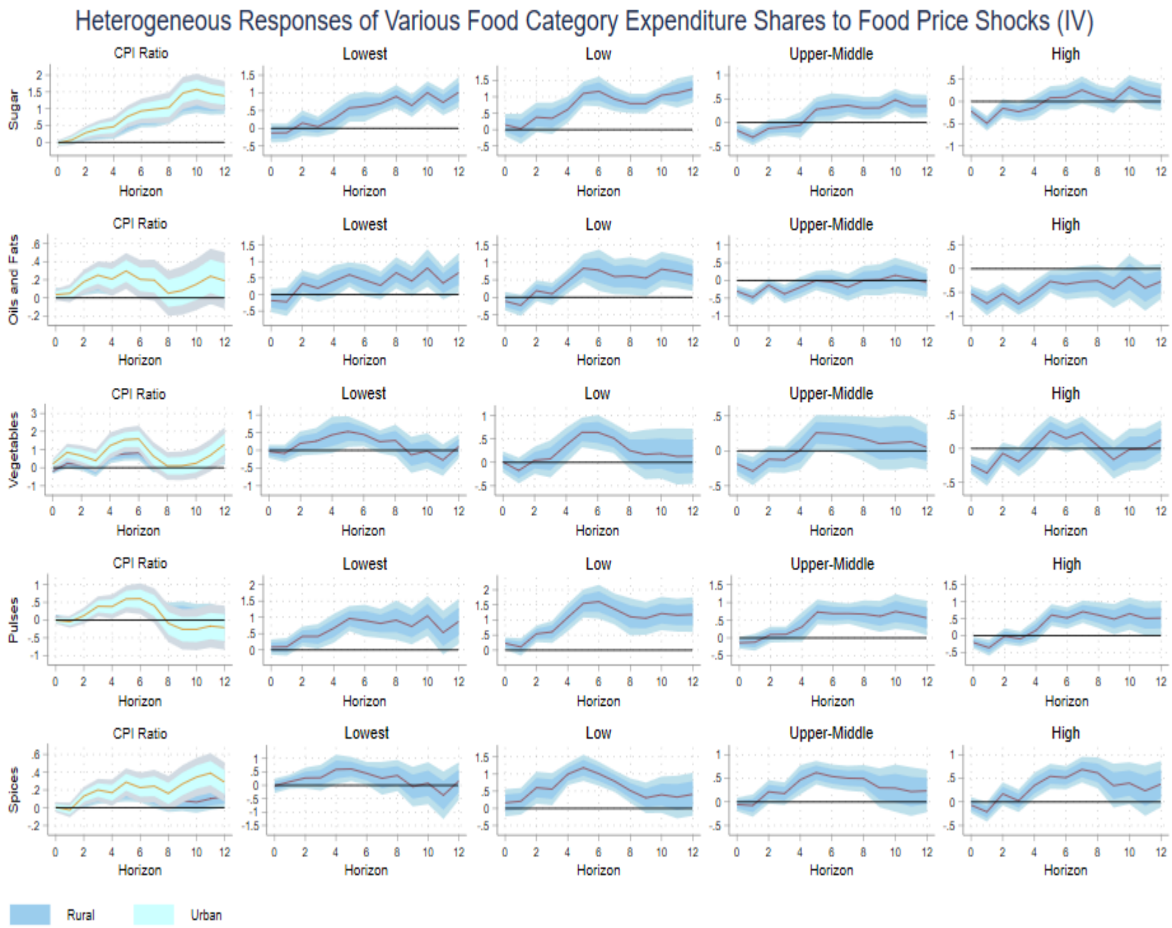

Figure A11: Response of Various Food Categories Expenditure Shares to External Food Price Shocks by Income Quintiles(IV)

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.

Appendix E Additional Results

E.1 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 from underlying household level panel. 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:

$$Cineq_{s,t+h} - Cineq_{s,t-1} = c + \beta_0^{h,\text{food}} ext_t^{\text{food}} + \beta_0^{h,\text{oil}} ext_t^{\text{oil}} + \sum_{j=1}^{J} \alpha_j^h (Cineq_{s,t-j} - Cineq_{s,t-j-1}) + \sum_{k=1}^{K} \beta_k^h ext_{t-k} + \sum_{d=0}^{D} \delta^h D_{t-d} + \gamma_h X_t + \theta_s + \delta_t + \epsilon_{s,t+h} \tag{E.1}$$

where $Cineq_{s,t}$ denotes various measures of state-region 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-region level price regression specification in equation (4.12). 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 by the corresponding supply shocks.

How does regional consumption inequality evolve dynamically in response to external food and oil price changes? Figure A12 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 A13 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.[62]

[62] For example, consistent with larger effect of global oil price increase especially on total consumption of higher income groups (as opposed to non-durable consumption), we see a decline in total consumption inequality in Figure A13.

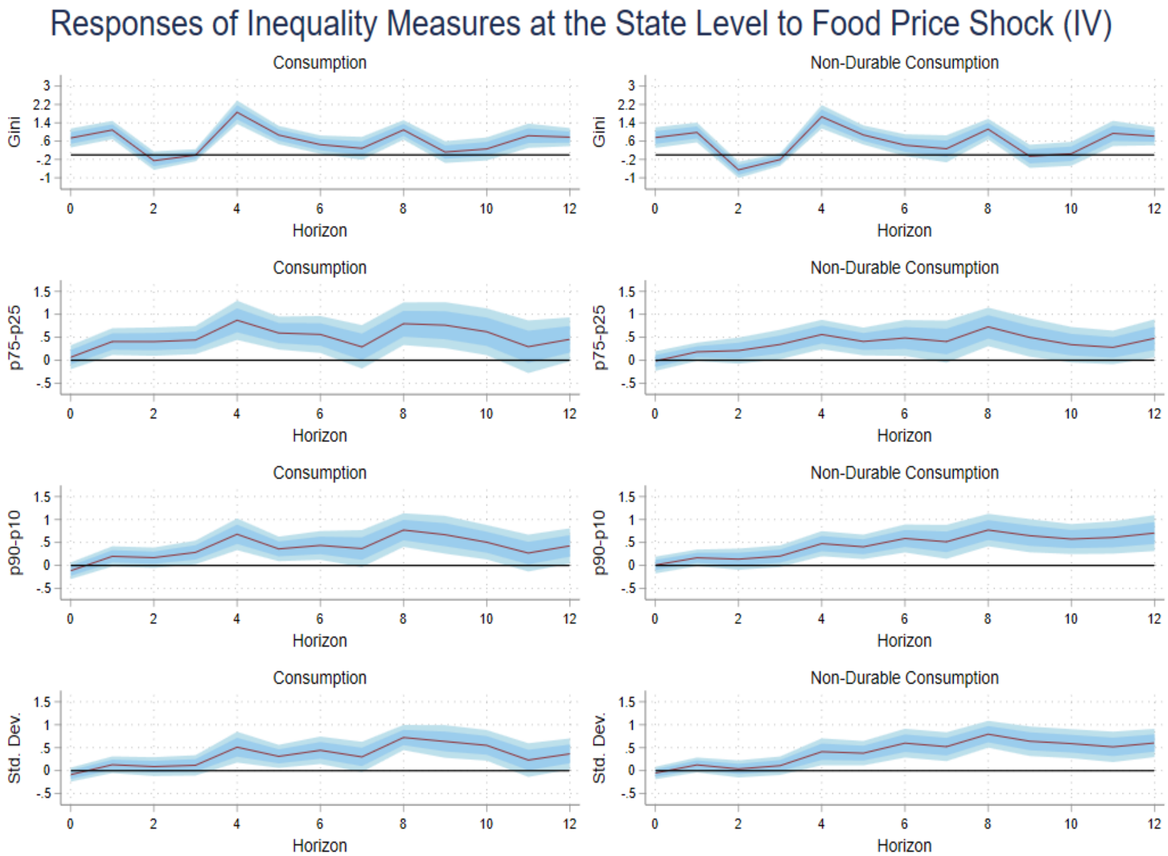

Figure A12: Response of Regional Inequality to External Food Price Shocks (IV)

Notes: Cumulative IRFs on the basis of equation (E.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.

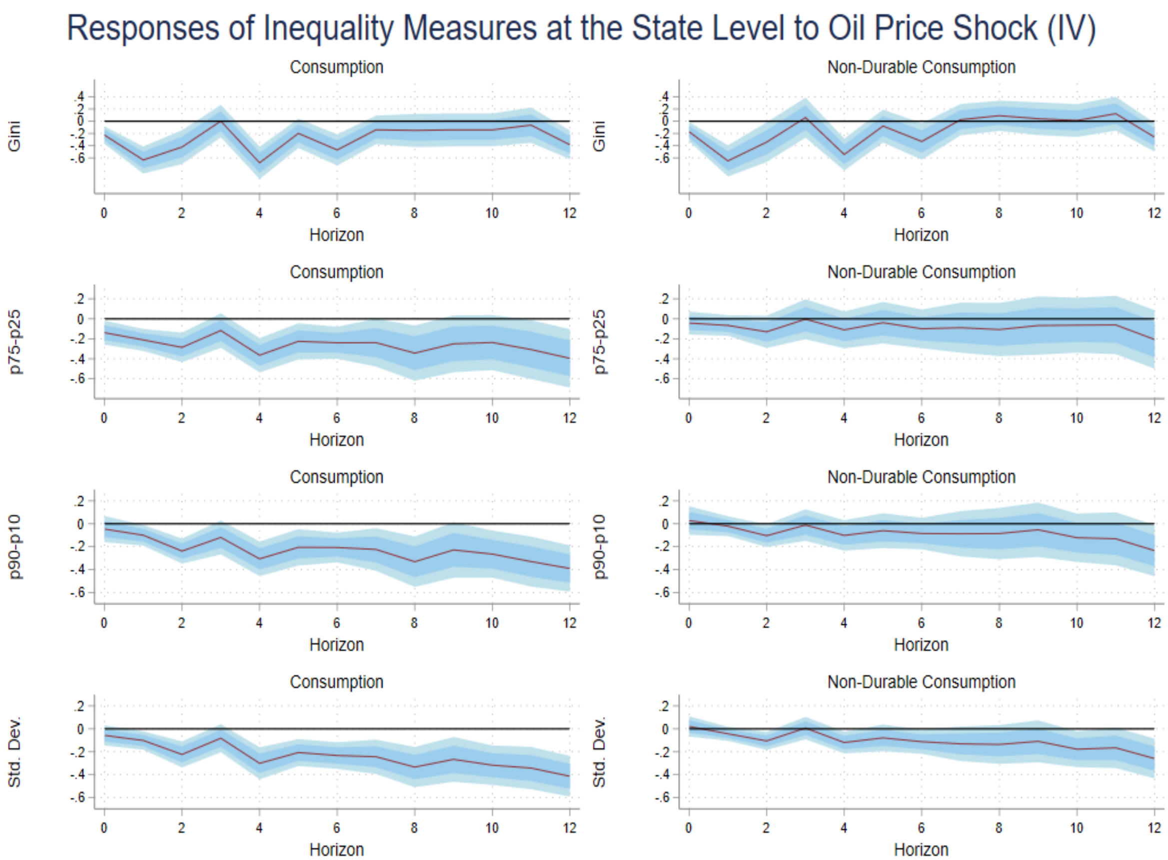

Figure A13: Response of Regional Inequality to External Oil Price Shocks (IV)

Notes: Cumulative IRFs on the basis of equation (E.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.

E.2 Impact of Global Food Price Shocks on the Agriculture Sector

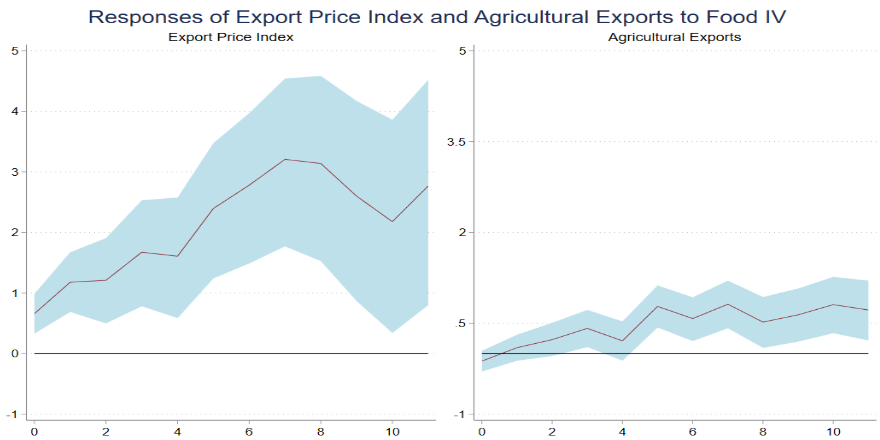

Figure A14: Response of Export Price Index and Agricultural Exports to Food IV

Notes: This figure plots the impulse response of India's export price index and agricultural exports to an adverse (positive) food supply shock that raises log of global food price index by one unit on impact. The impulse responses are estimated from a Structural VAR with two endogeneous variables and the food supply shock as an external shock, allowing for 12 lags of endogenous variables and external shock. The food supply instrument is constructed using a dynamic factor model as described in Appendix C. The export price index data is collected from IMF and the product level monthly (available from 2011) trade data is collected from COMTRADE. Sample used: 2011-2019. Dummies included: Taper Tantrum and India's demonetization policy.

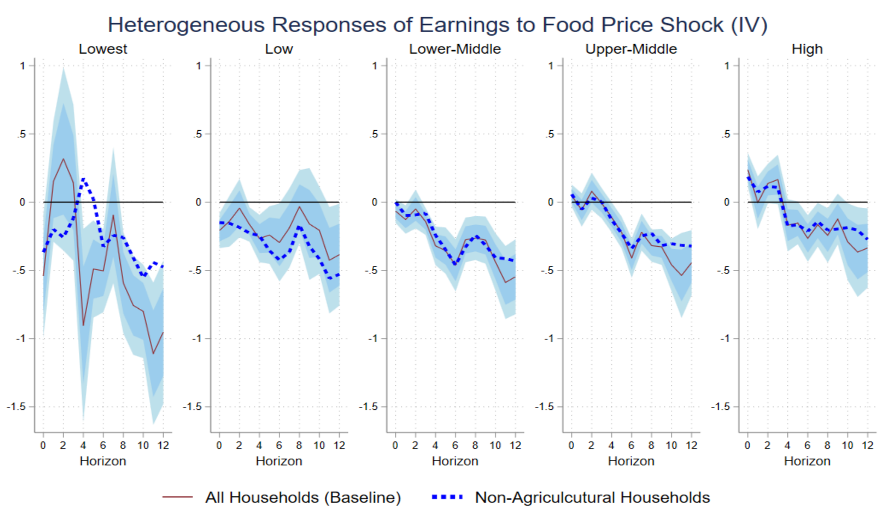

Figure A15: Response of Earnings of Non-Agri Households to External Food Price Shocks by Income Quintiles

Notes: Cumulative IRFs on the basis of equation (3.1) where the external shock is log changes in the global food price, which is instrumented by a global food supply shock and the dependent variable is log changes in household (real) earnings. We present our baseline estimates from Figure 7 with error band and the dashed line refers to mean responses for the robustness exercise where we drop agricultural households from our sample. The light blue region is the 90% confidence interval and the dark blue region is the 68% confidence interval.

E.3 Sensitivity of Key Consumption Heterogeneity Results

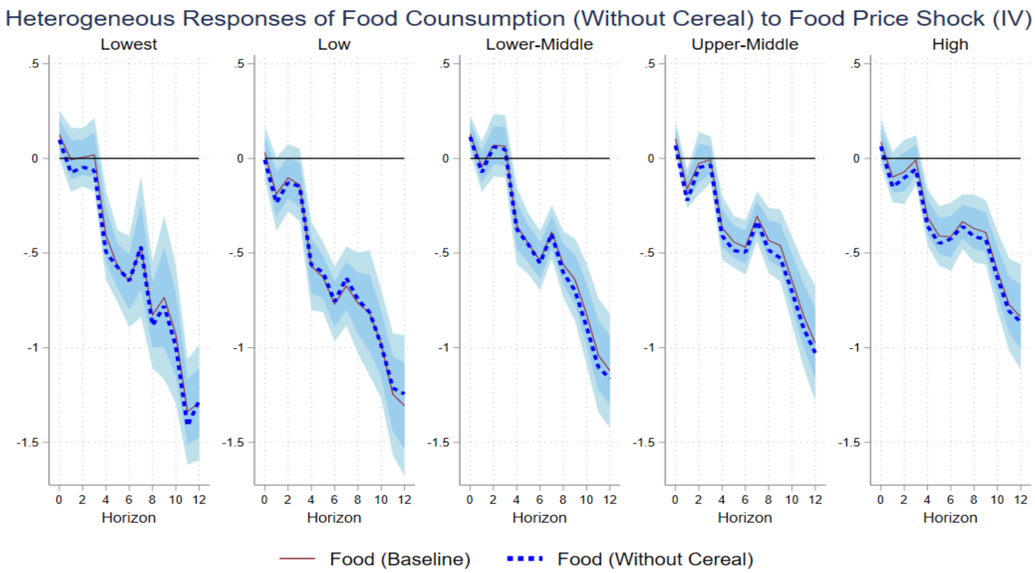

Figure A16: Response of Non-Durable Consumption (without cereal) to External Food Price Shocks by Income Quintiles

Notes: Cumulative IRFs on the basis of equation (3.1) where the external shock is log changes in the global food price, which is instrumented by a global food supply shock and the dependent variable is log changes in household (real) food consumption. We present our baseline estimates from Figure 3 with error band and the dashed line refers to mean responses for the robustness exercise where we drop cereals from food consumption and suitably adjust the state-region specific prices to deflate. The light blue region is the 90% confidence interval and the dark blue region is the 68% confidence interval.

Figure A16 shows that the adverse impact of a rise in global food prices on household food consumption is largely similar to Figure 3. The adverse impact is slightly larger in magnitude potentially reflecting the role of public distribution system in protecting cereals consumption.

The two alternate instruments used in Figure A17 are global food price change residualized by: (a) only our estimated common factor and (b) economic activity shock of Baumeister and Hamilton (2019), while in the baseline we residualize with respect to both common and food factor, as described in Appendix C. Note that both of the alternate instruments used in Figure A17 imply the same regressive nature of an increase in global food price increase, but the negative impact is smaller in magnitude compared to our baseline instrument. This larger negative impact on consumption after removing the food factor from the global price variation (on top of removing the common demand factor) is consistent with interpreting the food factor as a global demand factor specific to food commodities.[63]

[63] If the food factor mainly captured correlated global weather events, we expect an opposite sign from the omitted variable bias. Also, note that the three IVs imply very similar magnitude of impact first four months after the shock but differ dynamically.

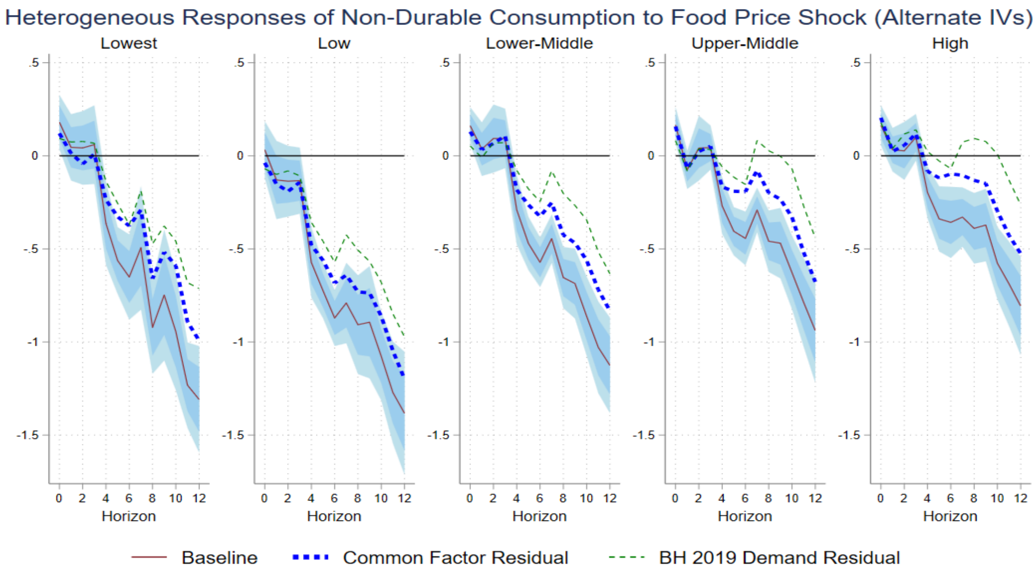

Figure A17: Response of Non-Durable Consumption to External Food Price Shocks (alternate IVs) by Income Quintiles

Notes: Cumulative IRFs on the basis of equation (3.1) where the external shock is log changes in the global food price, which is instrumented by a global food supply shock and the dependent variable is log changes in household (real) non-durable consumption. We present our baseline estimates from Figure 3 with error band and the two dashed line refer to mean responses for the robustness exercises where we use alternate instruments for the global food price shock. The light blue region is the 90% confidence interval and the dark blue region is the 68% confidence interval.

E.3.1 Role of household fixed effects

We include a set of household characteristic specific fixed effects in our baseline panel local projections described in equation 3.1 and present the results in Figures A18 and A19.[64] Our conclusions regarding distributional effects of global price shocks on household consumption remain unchanged relative to Figures 3 and 4.

[64] We include fixed effects for caste, religion, education groups, big city and age bins. We define a total of eleven age groups 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. We define education groups 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 educated and above. Summary statistics for different household characteristics are presented in Appendix B in Table A2.

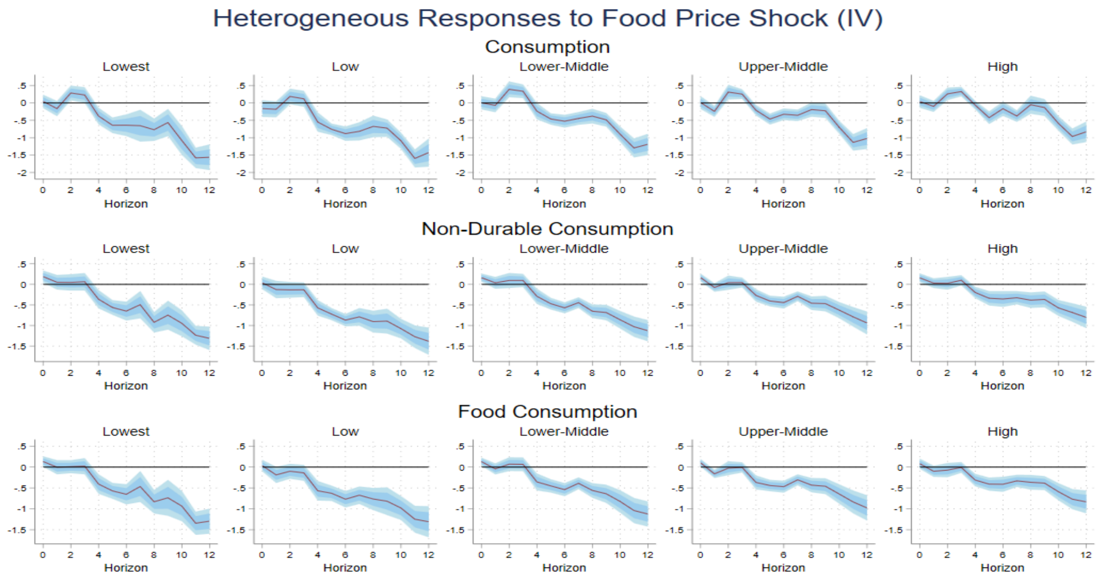

Figure A18: Response of Consumption to External Food Price Shocks by Income Quintiles (IV) after allowing for demographic specific fixed effects

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. These regressions include a rich set of household fixed effects. The light blue region is the 90% confidence interval and the dark blue region is the 68% confidence interval.

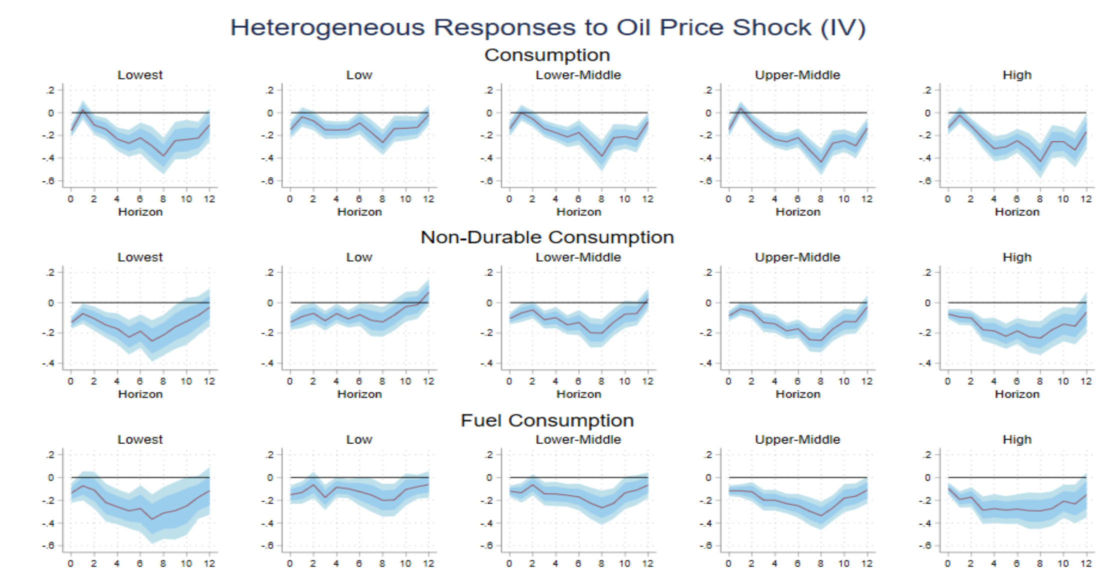

Figure A19: Response of Consumption to External Oil Price Shocks by Income Quintiles (IV) after allowing for demographic specific fixed effects

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. These regressions include a rich set of household fixed effects. The light blue region is the 90% confidence interval and the dark blue region is the 68% confidence interval.

E.3.2 Alternate definitions of income groups

In our final robustness exercise, 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, households are grouped according to cut-offs based on total household real income in the initial period. While the definition of the groups is on the basis of the initial income distribution, households can and do transition to a different income group over time depending on current income. We next report two important sensitivity analyses of our baseline results where we change the definition of income groups.

In the first sensitivity analysis, 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)). To account for this, we group households into five income groups according to the per capita income deciles and estimate the heterogeneous consumption responses according to equation (3.1).

Table A8: 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.

In the second sensitivity analysis, 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 A8. While more than 80% of households remain in the same income group over time (as captured by the diagonal entries of Table A8), 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.

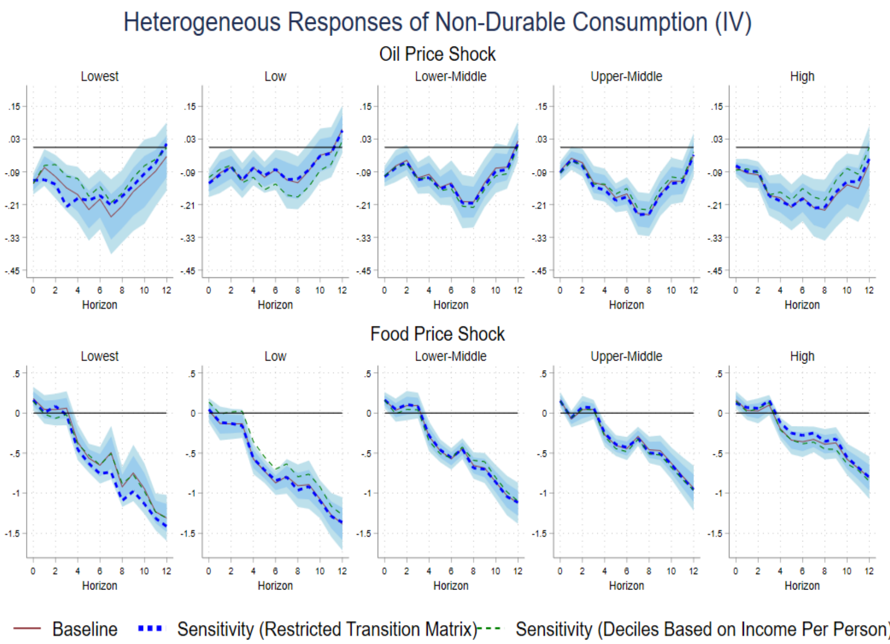

Figure A20: Response of Non-Durable Consumption (sensitivity to alternate income groups) to External Oil and Food Price Shocks by Income Quintiles

Notes: Cumulative IRFs on the basis of equation (3.1) where the external shock is log changes in the global food or oil price, which is instrumented by the corresponding supply shocks and the dependent variable is log changes in household (real) non-durable consumption. We present our baseline estimates from Figures 3 and 4 with error bands and the dashed lines refer to mean responses for the robustness exercise where we use alternate definitions of income groups. The light blue region is the 90% confidence interval and the dark blue region is the 68% confidence interval.

The results for both sensitivity analysis are presented in Figure A20. These results again are similar in nature to the baseline results of Figures 3 and 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.