Food, Fuel, and Facts: Distributional Effects of External Shocks*

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Abstract

In this paper we investigate the distributional implications of rising global food and oil prices using rich consumption and income panel data from India. We show that these external price shocks pass-through to domestic prices. We document that consumption inequality rises for the entire horizon of one year following a positive shock to global food and fuel prices. Using a household panel local projection method, we estimate heterogeneous consumption effects along the income distribution. We find robust evidence that lower income deciles are hit harder by rise in food prices, whereas rise in fuel prices hit both the lower and the middle income deciles. For both shocks, however, consumption of top income deciles is largely unscathed. The effects of external price shocks on inequality are quantitatively large and economically meaningful.

JEL classification: F41, F62, O11

Keywords: External shocks; Food prices; Gas prices; Inequality; Household heterogeneity; Dynamic effects; India

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1 Introduction

There has been a rapid increase in *global* oil and food prices recently. Such large external shocks have raised major concerns worldwide, but especially so in emerging market economies, whose economy tend to be vulnerable to global shocks. Effects on both inflation and real macroeconomic outcomes, and how to negotiate them, have therefore been at the forefront of policy makers' agenda.

While the relationship between such global shocks, especially oil prices, and the macroeconomy, have been studied, little is known about the *distributional* implications of such shocks.[1] As a result, polarised opinions on how such shocks affect inequality often appear in the popular media, which has been exacerbated recently with the rapid increase in food and oil prices.

In this paper, we address whether increases in global food and fuel prices increase consumption inequality in India using a rich household panel data. Our dataset is a monthly panel data on Indian households from 2014-2019. To answer our research question, we take two approaches. First, we construct aggregate consumption inequality measures and estimate dynamic effects of global oil and food price shocks on inequality. Second, we use a panel regression specification and estimate how dynamic consumption effects of global oil and food price shocks differ along the income distribution.[2]

Our two main results follow. First, consumption inequality rises for the entire horizon of one year following a positive shock to global food and fuel prices. This holds for various measures of consumption, such as total consumption, non-durable consumption, and service consumption, and for all measures of inequality, such as Gini and inter quartile range.

Second, effects on consumption are clearly heterogeneous along the income distribution. Lower income deciles are hit harder by rise in food prices. Rise in fuel prices hit both the lower and the middle income deciles. For both shocks, consumption of top income deciles is largely unscathed. Moreover, we show that the effects are quantitatively large and economically meaningful.

Our paper is related to several strands of the literature. The two-way relationship between global oil prices and the US macroeconomy, and the implications for US monetary policy, has been studied extensively in Hamilton (1983), Hamilton (2003), Barsky and Kilian (2004), and Kilian (2009). We build on this body of work by estimating the distributional effects of global oil and food prices, a topic in which empirical evidence is scarce.

[1] In fact, for emerging market economies, even the aggregate effects of both global food and fuel price shocks has not been investigated rigorously.

[2] We estimate dynamic effects using a local projection method, where global food and fuel price change serve as an external shock to the Indian economy.

Our paper is also closely related to two other strands of the literature, that has assessed distributional effects of domestic monetary policy shocks. For instance, Coibion, Gorodnichenko, Kueng, and Silvia (2017) study effects on inequality of US monetary policy shocks while Holm, Paul, and Tischbirek (2021) study heterogeneous effects along the liquid asset distribution of households of Norwegian monetary policy shocks. We also build on this body of work in terms of a focus on distributional implications of aggregate shcoks and empirical methods, but by focusing on an external shock in the context of an emerging market, using detailed panel data at a monthly frequency.

Finally, our paper has a common theme with the literature that has emphasized how external or global shock impinge heavily on emerging market economies and are a source of business cycle dynamics. For instance, Neumeyer and Perri (2005) and Uribe and Yue (2006) emphasize the role of global interest rate or spread shocks while Fernandez-Villaverde, Guerron-Quintana, Rubio-Ramirez, and Uribe (2011) and Bhattarai, Chatterjee, and Park (2020) emphasize the role of global volatility or uncertainty shocks. The external shocks we study are different, global food and oil price shocks, and moreover, our empirical focus is on the distributional implications of such shocks in India. In particular, we show how the transmission of such shocks to consumption in India is heterogeneous along the income distribution of households.

2 Data and Stylized Facts

2.1 Data Description

Our data is from the Consumer Pyramid Household Survey (CPHS) dataset, a survey conducted by the Centre for Monitoring the Indian Economy (CMIE). The CPHS has surveyed over 236,000 unique households since 2014, and is the most comprehensive longitudinal consumption data available for India.

The dataset is unique in including both income data and detailed information about consumption in a single longitudinal data set. Moreover,it is available at the monthly frequency, which allows an analysis on effects of external shocks such as global food and oil prices in a straight-forward way, without having to impute data due to frequency mismatch between the shock series and the consumption data.

Consumption expenditure comprises 153 categories, from Jan 2014- Dec 2019. We work with a balanced panel of 75366 observations at the household level–we only keep households that have reported monthly income and consumption variables for all time periods considered.

We construct consumption and expenditure closely matching the categories constructed by Coibion, Gorodnichenko, Kueng, and Silvia (2017), for clear comparison with previous work. Consumption is the sum of non-durable consumption (food, fuel, intoxicants), durable consumption (appliances, furniture, jewelry, clothing, electronics, toys, cosmetics), and service consumption (electricity, entertainment, public transport, airfare, highway tolls, beauty services, fitness services, restaurants etc). Expenditure is the sum of consumption and expenses on loan payments, health expenditure and education spending and other miscellaneous expenses. We deflate nominal income and consumption by the CPI - Combined series (2012 base). We also winsorize our constructed variables at the 1 percent level.

We provide further details on the data in the Appendix in Section 5.1 and some relevant summary statistics in Section 5.2.

2.2 Stylized Facts

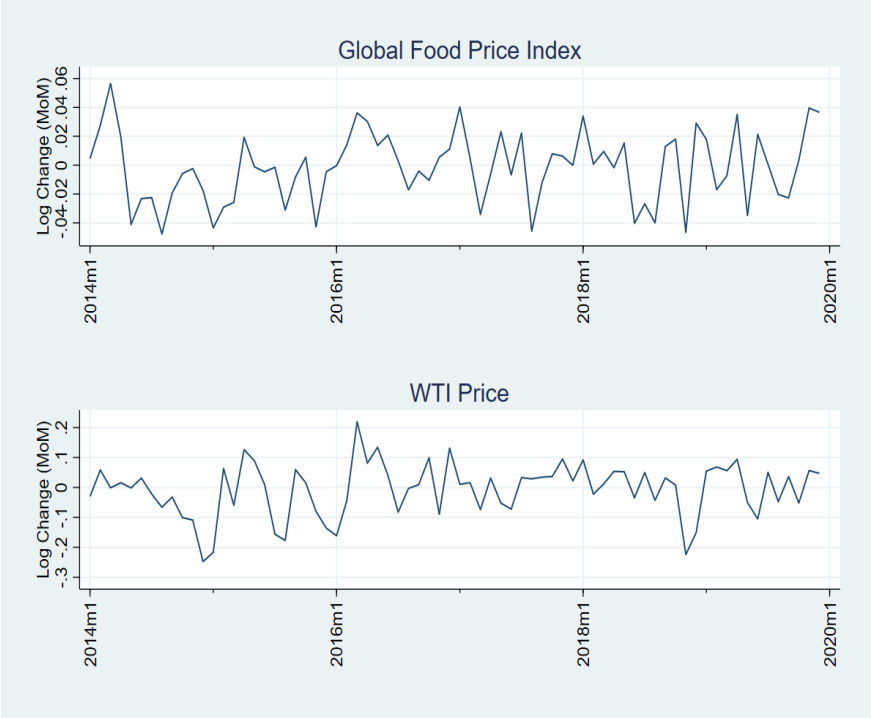

Figure 1: Changes in Global Food and Fuel Prices

We use FAO's Food Price Index (FPI) and WTI crude oil prices for our food and oil prices.

We plot the log changes in global food and oil prices in Figure 1. These are our measures of external good and oil price shocks for the Indian economy. As expected, average of the shocks are close to zero while the standard deviation is approximately 3% for food price and

nearly 10% for oil price, confirming a higher oil price volatility. AR(1) coefficient of the estimated shocks processes are very low, indicating that these shocks are largely transitory in nature. Finally, the two shocks are positively correlated but not very highly so[3], hence implying independent sources of variation.

Before proceeding to use the rich micro data to construct various measures of inequality, we first investigate whether external price shocks pass-through to domestic prices that consumers face. We use state level monthly CPI data for various components from MOSPI. We then estimate the dynamic responses of domestic prices, that is, various components of state level monthly CPI, to these global shocks in a panel local projection framework:

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

Here, $p_{s,t+h}$ is the log CPI (overall and various sub components) for state s at horizon h after the shock to external prices at time t; ext stands for different measures of the global price shock and $J = 3, K = 3$ are respectively the AR and MA coefficients in the specification. Moreover, D is the dummy for demonetization, which is allowed to have lagged effects up to 3 lags. X here are controls for aggregate world conditions captured by the world industrial production as a proxy for aggregate demand (Kilian) and US monetary policy stance as captured by the shadow federal funds rate and global uncertainty as proxied by the VIX index. We include fixed effects for month and year and state, and the impulse response coefficients are clustered at the state level. We present the cumulative impulse responses on the basis of equation (2.2) in Figure 2, where the top panel captures the effect of an increase in global food price and the bottom panel captures the effect of an increase in global oil price.

[3]Correlation of the two series is .2.

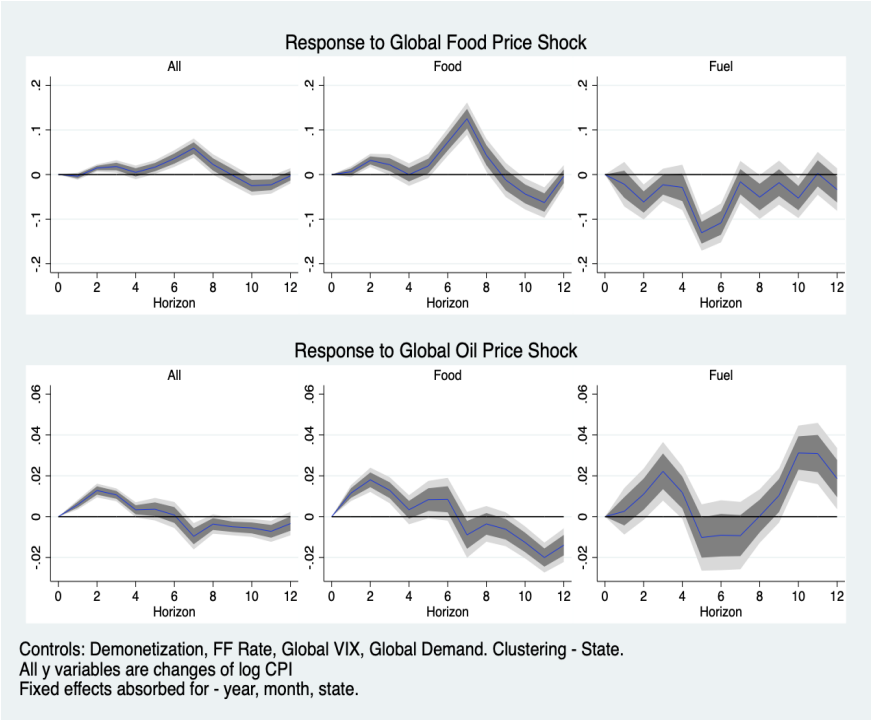

Figure 2: Response of Domestic Inflation to Global Price Shocks

Clearly, general CPI and food prices in India respond positively and significantly to an increase a global food price, whereas prices of fuel does not register a positive response. Relative to general CPI, food becomes more expensive domestically with a positive shock to global food prices. Moreover, this effect on domestic food prices persists over nearly 10 moths following the initial shock to global food prices, which is transitory in nature as we emphasized above.

Response of domestic inflation to global oil price shock shows a different dynamics: while overall CPI and domestic fuel prices rise initially, there is possibly some automatic stabilizer in place via excises taxes which dampen this price response after 4-6 months. Interestingly, domestic food prices also rise with an increase in global oil prices and the elasticity is almost as high as the elasticity of domestic oil price itself.

These results confirm that external price shocks have strong impact on different components of Indian inflation, changing both the general cost of living (as captured by overall CPI) as well as relative prices. This, certainly, has implications for consumer behaviour. In this paper, we are particularly interested to learn whether these external price shocks impact consumption inequality.

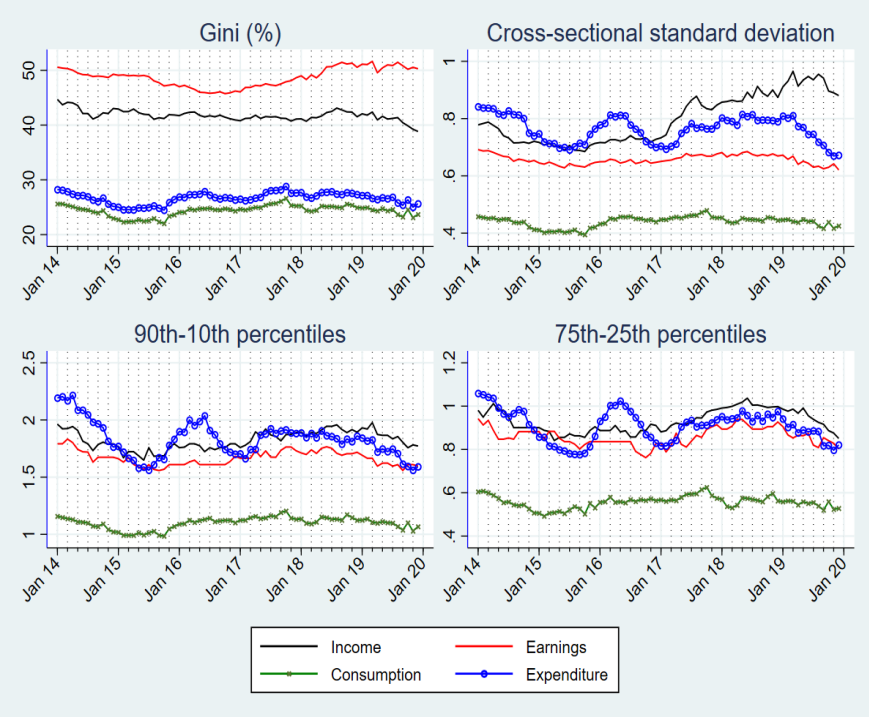

Figure 3: Changes in Inequality

Figure 3 shows the dynamics of inequality for income, earnings, consumption and expenditure in India. We report several widely used inequality measures. A few points to note: first, income and earnings show higher inequality than consumption, as is commonly established in the literature for other countries as well; second, expenditure shows higher degrees of inequality than consumption.

Table 1: Inequality: Summary Statistics

Panel A: Levels of Inequality Measures				
	Gini	SD	90th-10th	75th-25th
Income Inequality	0.519	0.799	1.824	0.930
Earnings Inequality	0.575	0.657	1.667	0.859
Consumption Inequality	0.375	0.440	1.100	0.556
Expenditure Inequality	0.394	0.764	1.830	0.908
Panel B: Second Moments of Inequality Measures				
	Gini	SD	90th-10th	75th-25th
Income Inequality	0.004	0.007	0.007	0.003
Earnings Inequality	0.003	0.000	0.004	0.002
Consumption Inequality	0.006	0.000	0.003	0.001
Expenditure Inequality	0.006	0.002	0.024	0.005

We present summary statistics for different measures of inequality in Table 1. As expected, broadly, income, earnings and expenditure are all more unequal than consumption. Moreover, overall, the unconditional volatility of these various measures of inequality is relatively low as the panel B of Table 1 reveals.

The conditional correlation of various measures of inequality with lagged values of global food and oil price shocks however, are mostly positive and much larger in magnitude, as shown in Table 2. The largest positive correlations are observed between consumption inequality and the two shock measures.[4]

[4]This is consistent with the observation in Coibion, Gorodnichenko, Kueng, and Silvia (2017) on the correlation between inequality and monetary policy shock in the US

Table 2: Inequality: Correlation with Shocks

Panel A: Correlations With Global Food Price Shock				
	Gini	SD	90th-10th	75th-25th
Income Inequality	0.108	0.097	0.153	0.063
Earnings Inequality	0.058	0.098	0.077	-0.062
Consumption Inequality	0.234	0.232	0.215	0.229
Expenditure Inequality	0.132	0.087	0.144	0.193
Panel B: Correlations With WTI Crude Oil Price Shock				
	Gini	SD	90th-10th	75th-25th
Income Inequality	0.137	0.134	0.118	0.134
Earnings Inequality	0.047	0.098	0.090	-0.023
Consumption Inequality	0.285	0.296	0.269	0.230
Expenditure Inequality	0.102	0.086	0.076	0.107

Response of consumption to shocks is the most relevant metric to evaluate welfare effects of any external shocks. Our raw data reveals a strong correlation between consumption inequality and the external shocks. Does this "smell test" pass an econometric examination? We turn to this question next.

3 Results

We follow two approaches to empirically identify the distributional effects of external shocks in a dynamic setting. We use detailed monthly panel data on Indian households for 2014-2019. First, we construct aggregate consumption inequality measures from the underlying micro data and estimate dynamic effects of global oil and food price shocks on inequality. Second, in a household panel framework, we estimate how dynamic consumption effects of global oil and food price shocks differ along the income distribution.

3.1 Effects on Inequality

In the first empirical exercise, we closely follow Coibion, Gorodnichenko, Kueng, and Silvia (2017) to estimate the response of inequality to external price shocks at different horizons h

using local projection methods:

$$x_{t+h} = c + \sum_{j=1}^{J} \alpha_j^h x_{t-j} + \sum_{k=0}^{K} \beta_k^h ext_{t-k} + \sum_{d=0}^{D} \delta^h D_{t-k} + \gamma_h X_t + \epsilon_{t+h}.$$

Here, x denotes different measures of inequality; ext stands different measures of the price shock and $J = 3, K = 3$ are respectively the AR and MA coefficients in the specification. More, D is the dummy for demonetization which is allowed to have lagged effects up to 3 lags). X here are controls for aggregate world conditions captured by the world industrial production as a proxy for aggregate demand (Kilian) and US monetary policy stance as captured by the shadow federal funds rate. We include fixed effects for month and year.

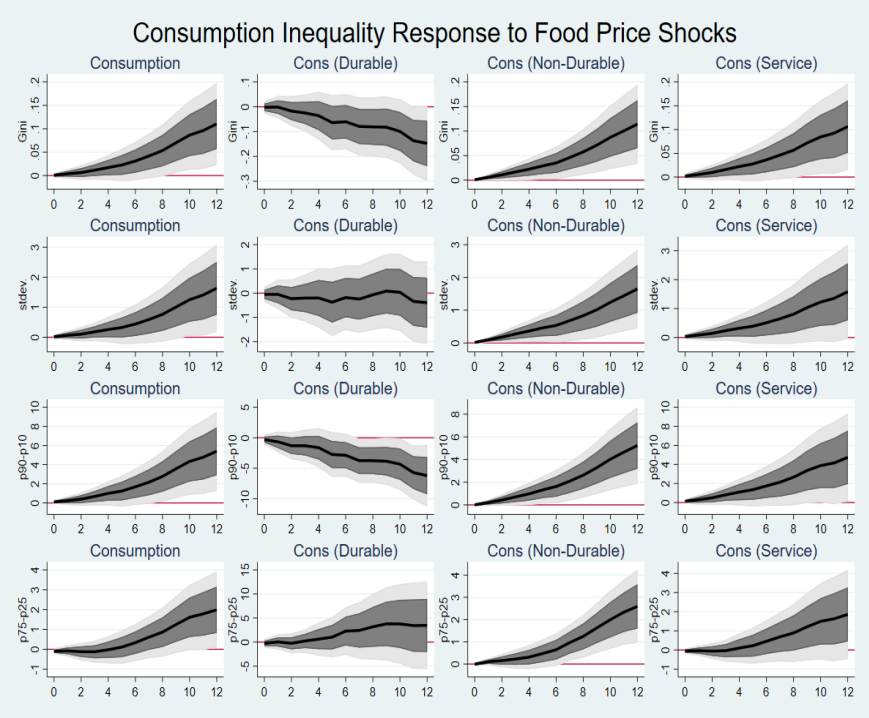

Figure 4: Response of Consumption Inequality to Food Price Shocks

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

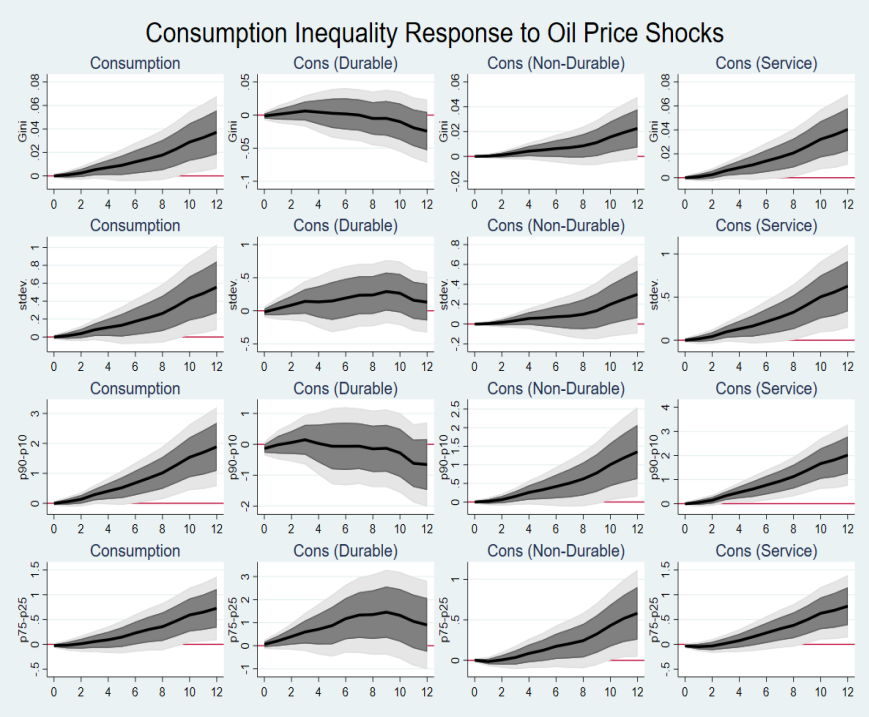

Figure 5: Response of Consumption Inequality to Oil Price Shocks

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

Figures 4 and 5 show the cumulative impulse responses of inequality to global food and oil price shocks respectively. In both cases, overall consumption, nondurable consumption, and services consumption show an increase in quality even a year after the initial shock. This result holds for all of the various measures of inequality considered. Durable consumption, on the other hand, shows a mixed response.

3.2 Heterogeneous Consumption Effects Along the Income Distribution

Next, we investigate heterogeneity in consumption response along the income distribution to further corroborate and understand the distributional implications of external shocks. To capture dynamic effects, we estimate a panel local projection model using household level consumption data:

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

Here, c_i is total consumption for household i; ext stands for different measures of the

external shock and D is the demonetization dummy. As before, $J = 3, K = 3, D = 3$. The most important aspect of this specification is that we allow the consumption effects to differ by initial income of the household. That is, g denotes decile on the basis of initial income and the effects of external shocks are thus, allowed to vary along the income deciles. X are the usual macroeconomic controls. Moreover, in these household panel regressions, we include additional fixed effects such as state by time fixed effects and fixed effects for different socioeconomic groups (caste, religion, education group, big city). The standard errors are clustered at the household level. We report cumulative impulse responses below.

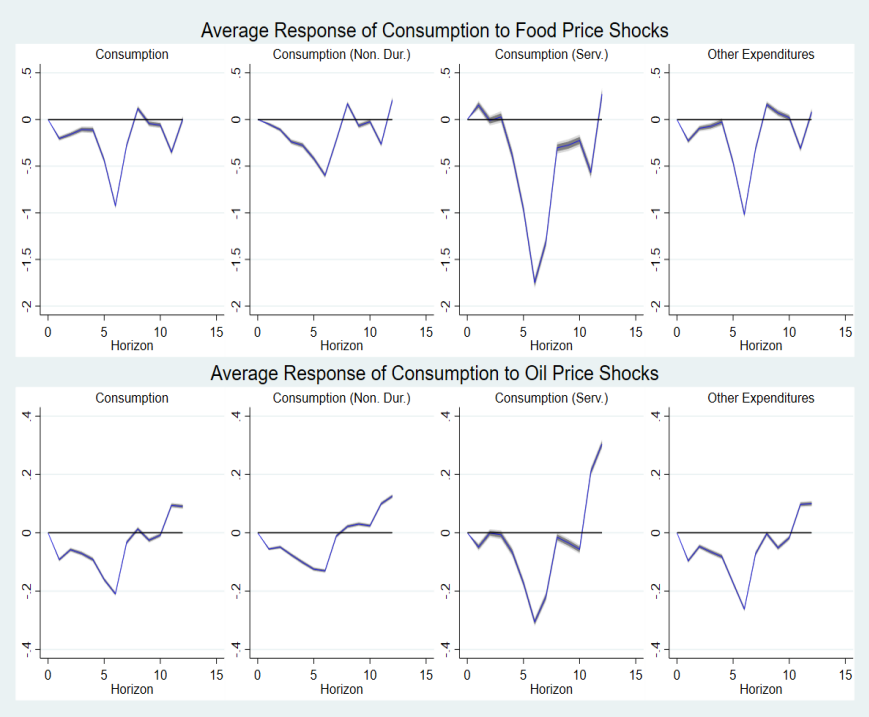

Figure 6: Average Response of Consumption to External Shocks

Cumulative IRFs on the basis of equation (3.2) setting β^g same for all deciles g.

Figure 6 plots the average response of consumption to external shocks where we estimate equation (3.2) without allowing the regression coefficients to differ by deciles. This gives a benchmark for the key results we show below. The top panel of the figure shows the responses to the global food price shock and the bottom panel to the oil price shock. In both cases, we observe a decline in consumption over a period of 10 months after the shock and a slight rebound towards the end of the horizon. Also, interestingly non-durable consumption, which includes expenses on food and fuel, actually has a lower elasticity compared to other categories of consumption such as service consumption and other expenditures.

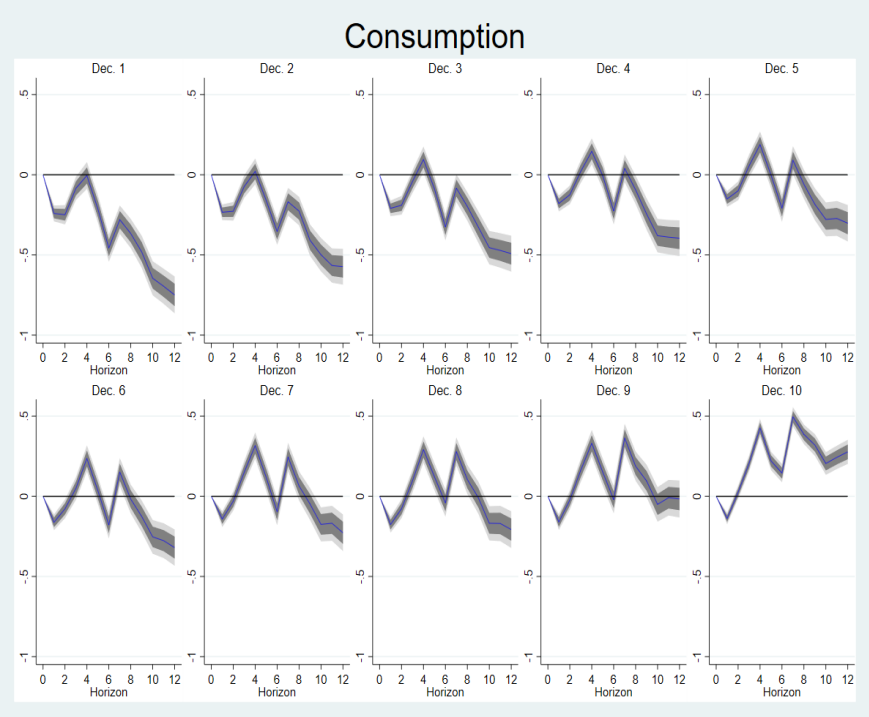

Figure 7: Response of Consumption to Food Price Shocks by Income Deciles

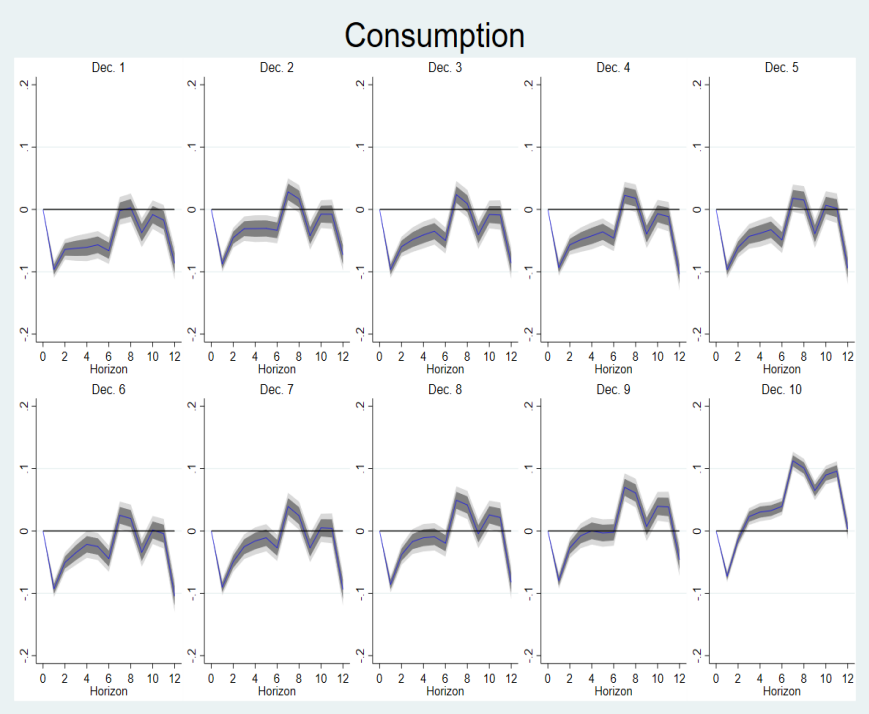

Figure 8: Response of Consumption to Oil Price Shocks by Income Deciles

Figures 7 and 8 present the key results of the paper: How does dynamic response of consumption to global food and oil price shocks vary by ex-ante income deciles? Broadly speaking, in Figure 7, we observe a monotonically larger negative impact of food price shock on consumption of lower income deciles, whereas in Figure 8, we see that the bottom seven deciles seem to suffer an equivalent degree of consumption loss with rising oil prices. In both cases, however, the effects on the top income deciles are both small and transitory– their consumption largely recovers three months after impact. These observations lead us to conclude that lower income deciles are hit harder by rise in food prices, whereas rise in fuel prices hit both the lower and the middle income deciles. For both shocks, consumption of top income deciles is largely unscathed.

To illustrate these empirical patterns more succinctly, we present three sets of summary statistics on the basis of the estimated impulse responses presented in Figures 7 and 8. Figure 9 shows the maximum negative response of consumption to food and oil price increases by income deciles. The figure clearly illustrates that the effect of food price shock is progressively larger on the lower income deciles, whereas the maximum effect of oil price is largely uniform.

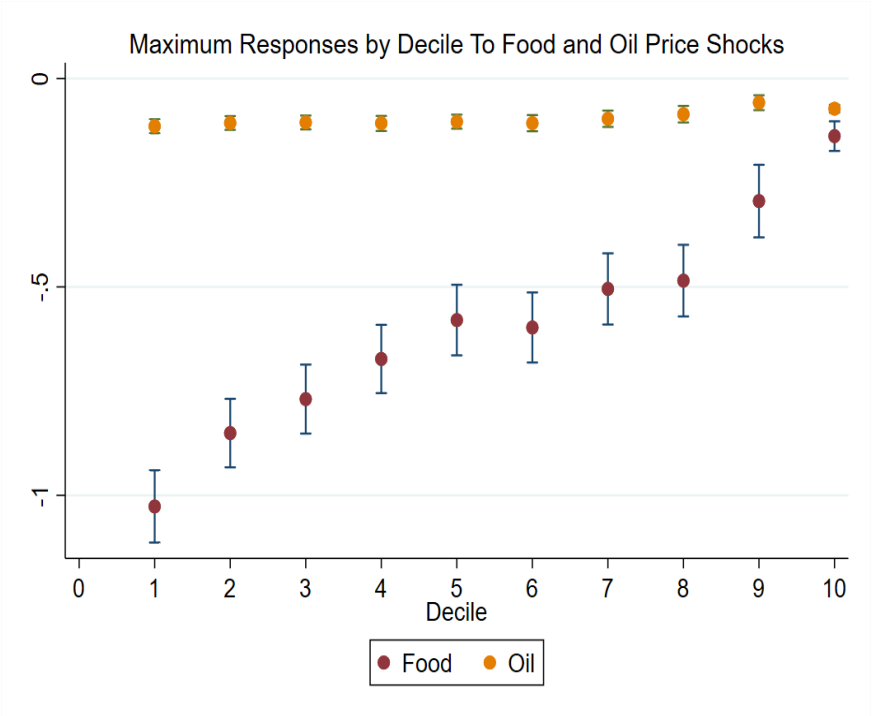

Figure 9: Max Response of Consumption to Food and Fuel Price Shocks by Income Deciles

Figure 10: Response (at 6 month) of Consumption to Food and Fuel Price Shocks by Income Deciles

Figure 10 shows the response of consumption to food and oil price increases by income deciles at a six-month horizon. This figure further corroborates our conclusion above, while additionally illustrating the transient impact on consumption of the top income earners. For both shocks, by the end of six months, consumption of top income deciles have recovered. As before, the impact on consumption (at six-month) is progressively larger on lower income deciles for food price increases, whereas for oil price, the impact is more uniform across deciles except at the very top of the income distribution. The consumption elasticities to the food price shock are larger in magnitude in general, but the impact of oil price increase is more broad-based.

Figure 11: Response of Consumption (after a year) to Food and Fuel Price Shocks by Income Deciles

We next present results at the 1-year horizon in Figure 11. The figure further confirms our conclusions above as the results are similar to those at the 6-month horizon.

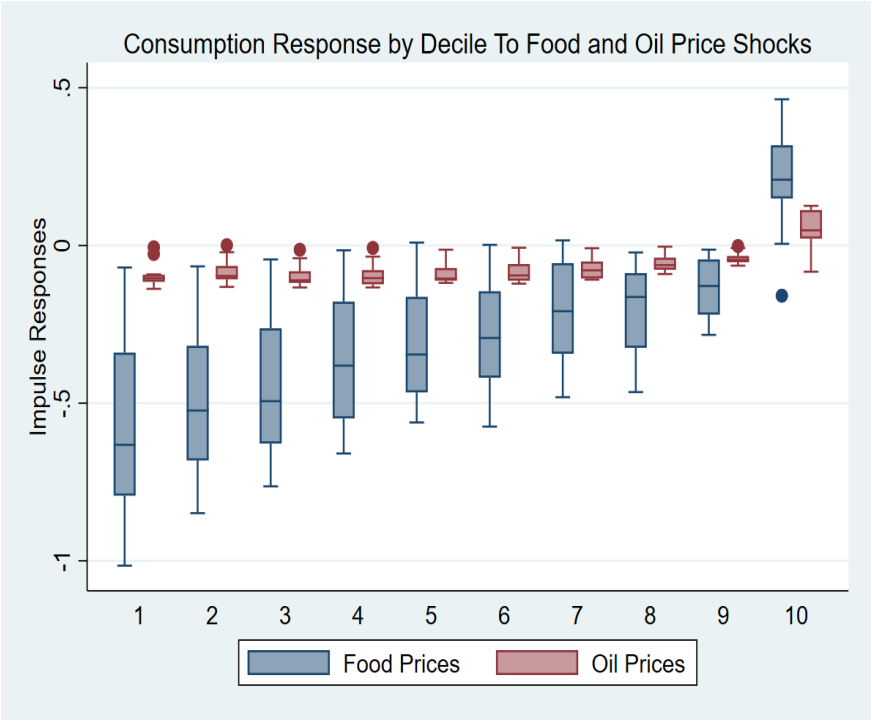

Figure 12: Response of Consumption (after a year) to Food and Fuel Price Shocks by Income Deciles

A box and whisker plot is presented in Figure 12 to illustrate that the monotonic impact of food price increase and the non-monotonic impact of oil price increase on consumption is not specific to any horizon. Over the entire horizon of the estimated impulse responses, poorer income groups suffer a larger consumption loss due to rise in food prices, whereas middle-income groups tend to suffer comparatively more from an increase in oil prices.

In order to understand the economic magnitude of the impact, we multiply the elasticities reported in Figures 10 and 11 by the typical size of the shock (3% in the case of food price changes and 10% in the case of oil price changes) and the average consumption of the corresponding income deciles. These results are reported in Table 3. We see that a 3% rise in global food price reduces consumption by roughly 2 to 3 % over the six month to one year horizon for the poorest (1st decile) decile. The effect is roughly half in magnitude for the median income earner (those in the 50th decile), whereas the top income earners report a small consumption increase at both horizons. For a 10% rise in oil price, the magnitude of the impact is smaller, roughly 1%, but it is roughly the same impact for the poorest and the middle income deciles. Again, consumption of the top income earners seems to be largely unaffected, as there is a small positive effect.

Table 3: Consumption Response to a typical shock

	3 % Rise in Global Food Price Shock		**10 % Rise in Global Oil Price Shock**	
Income Decile	Impact at 6 month	Impact at 12 month	Impact at 6 month	Impact at 12 month
1st Decile	-1.8	-3.1	-1.0	-.9
5th Decile	-1.06	-1.73	-.89	-.97
10th Decile	.43	.83	.39	.02

We provide further details on heterogeneous effects on various categories of consumption in the Appendix in Section 5.3. Moreover, we provide results on heterogeneous effects on income and earnings in Section 5.4.

4 Conclusion

In this paper we investigate the distributional implications of rising global food and oil prices using rich consumption and income panel data from India. We document that consumption inequality rises for the entire horizon of one year following a positive shock to global food and fuel prices. Using a household panel local projection method, we estimate heterogeneous consumption effects along the income distribution. We find robust evidence that lower income deciles are hit harder by rise in food prices, whereas rise in fuel prices hit both the lower and the middle income deciles. For both shocks, however, consumption of top income deciles is largely unscathed. The effects of external price shocks on inequality are quantitatively large and economically meaningful.

In future work, we plan to use the richness of our consumption data to construct different proxies for poor, middle-class and rich to further confirm our findings. We also plan to analyse the transmission of external shocks via exchange rate, stock prices, and relative sectoral price changes and how that affects consumption of different income deciles with different expenditure shares.

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5 Appendix

5.1 Data Description

Survey Data

We use data from the Consumer Pyramid Household Survey (CPHS) dataset, a survey conducted by the Centre for Monitoring the Indian Economy (CMIE). The CPHS has surveyed over 236,000 unique households since it began in 2014, and is the most comprehensive longitudinal consumption data available for India. The CPHS is itself divided into 4 distinct datasets: Consumption Pyraminds, Income Pyramids, People of India Survey and Aspirational India survey. We use the data from the Consumption and Income Pyramid surveys to construct our variables, and data from the People of India survey for our control variables about demographics. Our analysis spans data from January 2014 to December 2019. We work with a balanced panel of observations at the household level - we only keep households that have reported monthly income and consumption variables for all time periods considered.

Level variables

We construct income, earnings, consumption and expenditure categories closely following the definitions given by Coibion and Gorodnichenko (2017). We first construct income as the sum of household income from rent, wages, self-production, private transfers, government transfers, business profits, sale of assets, lotteries and gambling, pension, dividends, interest and deposite provident fund and insurance. These categories are an exhaustive list of all income sources collected in the CPHS survey. We also construct several further sub-categories of incomes for our analysis. We construct income without government transfers, which is the sum of all income sources (as listed above) minus the income from government transfers. Similarly, we construct a measure of income without any transfers - excluding private and government transfers from the above list.

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

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

We construct consumption and expenditure closely matching the categories constructed by Coibion and Gorodnichenko (2017). The consumption variable we construct is the sum of non-durable consumption (food, fuel, intoxicants), durable consumption (appliances, fur-

niture, jewelry, clothing, electronics, toys, cosmetics), and service consumption (electricity, entertainment, public transport, airfare, highway tolls, beauty services, fitness services, restaurants etc). The expenditure variable is the sum of consumption variable and expenses on loan payments, health expenditure and education spending and other miscellaneous expenses. We then deflate all our income and consumption measures by the Consumer Price Index (CPI) - Combined series (2012 base). We also winsorize our constructed variables at the 1 percent level.

Inequality variables

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

External shock measure

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

5.2 Summary Statistics of Income and Consumption by Income Deciles

Table 4: Annual Income Data Description by Deciles

	Mean	p25	Median	p75	SD
1st Decile	38,390.82	33,200.52	41,420.40	46,730.78	11,003.23
2nd Decile	58,308.15	54,773.83	58,323.06	61,858.21	4,160.67
3rd Decile	72,606.82	68,956.67	72,617.73	76,185.65	4,110.67
4th Decile	86,646.85	82,956.35	86,491.81	90,262.37	4,197.31
5th Decile	103,392.13	98,763.11	103,155.70	107,961.42	5,413.72
6th Decile	124,661.92	118,707.89	124,328.91	130,539.01	6,856.51
7th Decile	152,211.00	144,274.98	151,929.90	159,718.58	9,213.13
8th Decile	193,386.92	180,658.88	192,910.99	205,470.08	14,639.24
9th Decile	261,045.38	238,595.69	258,175.47	281,905.20	25,874.08
10th Decile	455,564.91	353,413.14	410,754.95	522,396.05	131,073.38

Table 5: Monthly Consumption Data Description by Deciles

	Mean	p25	Median	p75	SD
1st Decile	3,880.38	3,585.82	3,917.12	4,398.98	602.77
2nd Decile	4,644.51	4,276.77	4,646.69	5,069.99	457.41
3rd Decile	5,009.53	4,671.71	4,998.23	5,330.10	372.98
4th Decile	5,284.37	5,045.72	5,214.42	5,559.49	300.17
5th Decile	5,576.03	5,323.30	5,545.89	5,801.40	290.77
6th Decile	5,929.24	5,725.44	5,967.60	6,118.86	279.80
7th Decile	6,313.19	6,095.11	6,368.57	6,546.68	316.83
8th Decile	6,777.18	6,502.99	6,778.23	7,043.89	387.73
9th Decile	7,443.68	7,164.51	7,404.41	7,675.00	528.69
10th Decile	8,940.13	8,408.52	8,845.50	9,268.35	938.10

Table 6: Average Consumption Composition by Deciles

	Non-durable	Service	Expenditure	Durable
1st Decile	0.78	0.10	1.12	0.12
2nd Decile	0.77	0.10	1.12	0.13
3rd Decile	0.77	0.10	1.13	0.13
4th Decile	0.76	0.11	1.13	0.13
5th Decile	0.76	0.11	1.13	0.13
6th Decile	0.76	0.11	1.14	0.13
7th Decile	0.75	0.11	1.14	0.13
8th Decile	0.74	0.11	1.15	0.13
9th Decile	0.74	0.12	1.16	0.13
10th Decile	0.72	0.13	1.19	0.15

5.3 Response of Different Components of Consumption

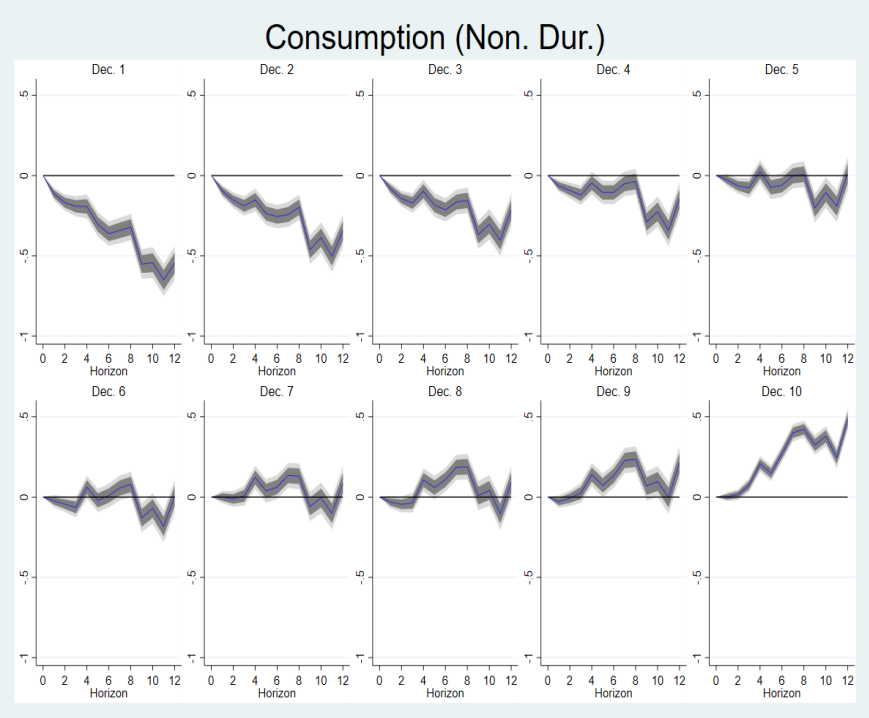

Figure 13: Response of Nondurable Consumption to Food Price Shocks by Income Deciles

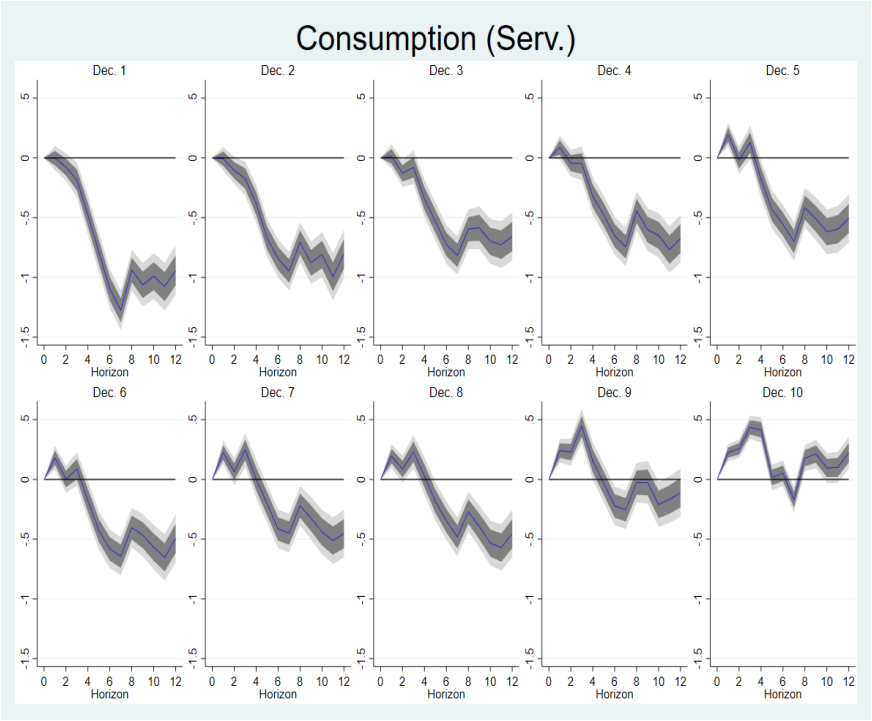

Figure 14: Response of Service Consumption to Food Price Shocks by Income Deciles

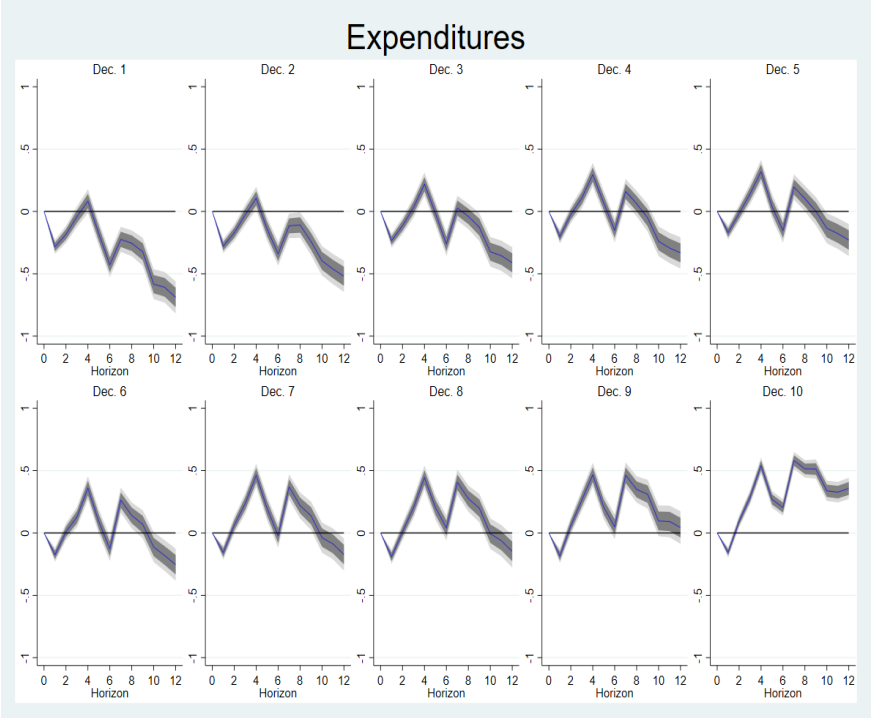

Figure 15: Response of Other Expenditures to Food Price Shocks by Income Deciles

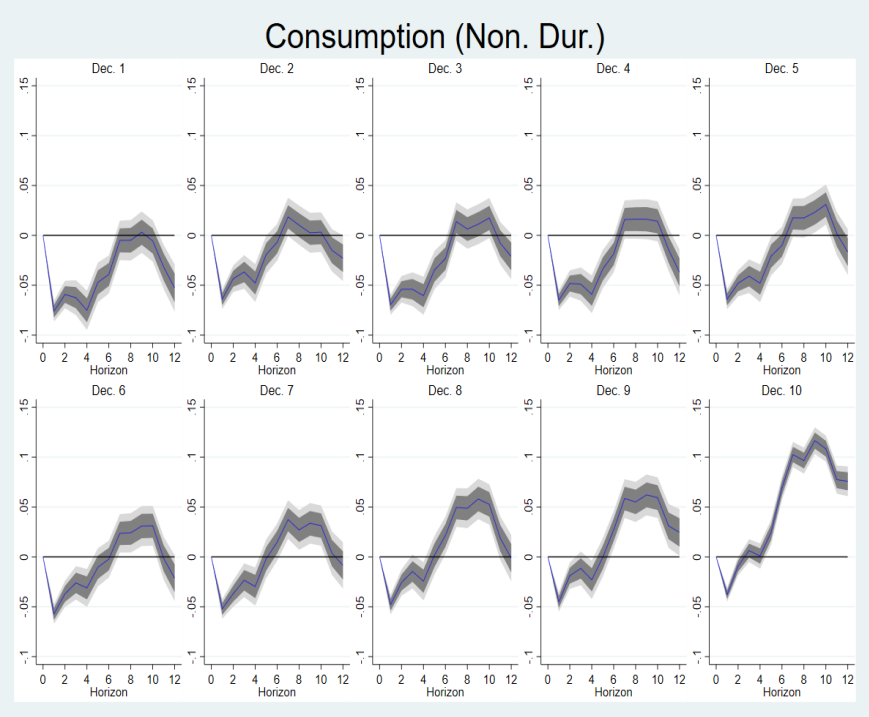

Figure 16: Response of Nondurable Consumption to Oil Price Shocks by Income Deciles

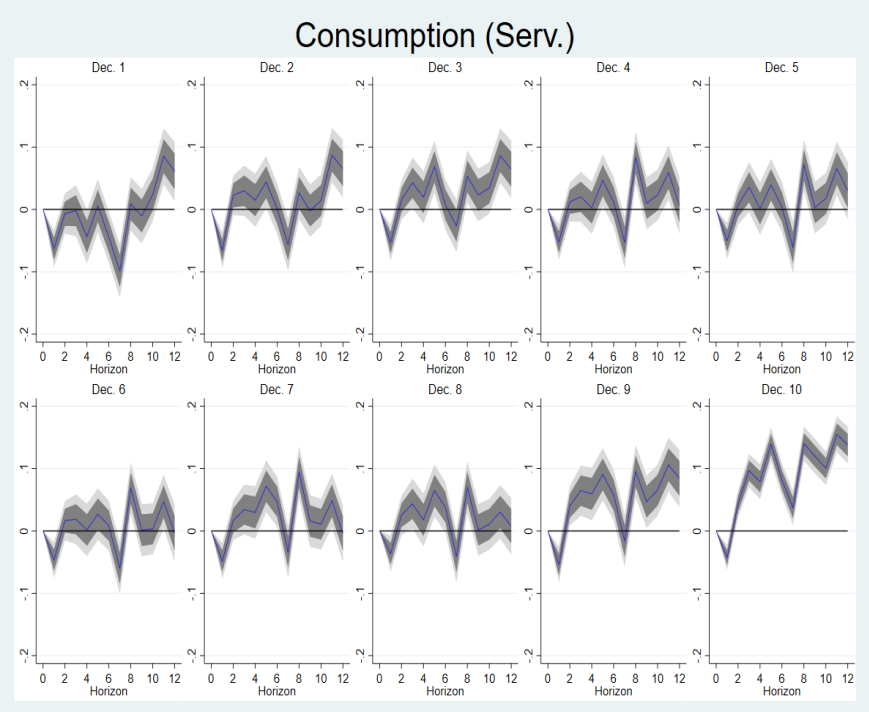

Figure 17: Response of Service Consumption to Oil Price Shocks by Income Deciles

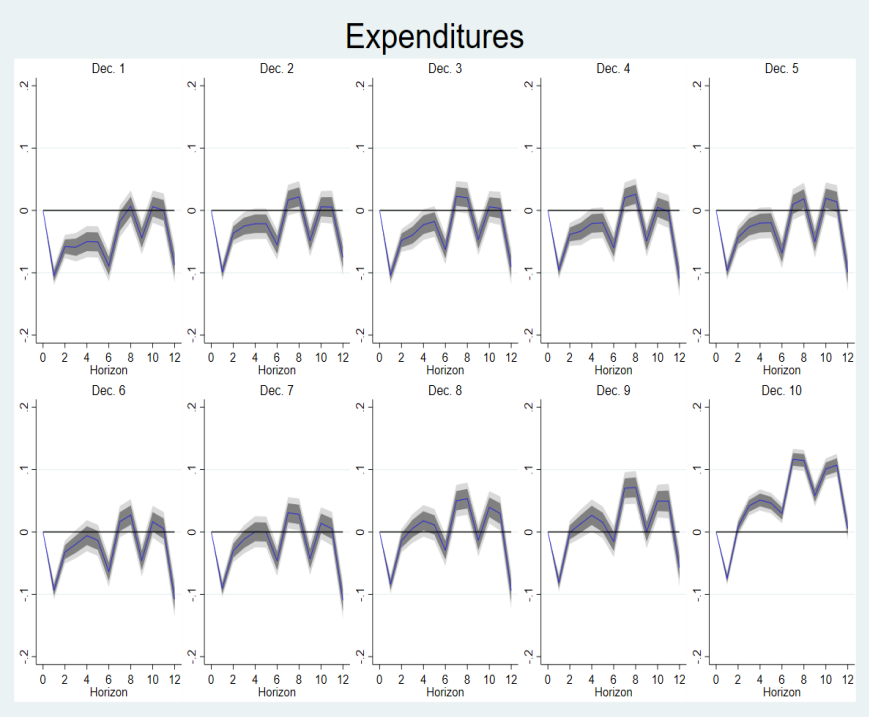

Figure 18: Response of Other Expenditures to Oil Price Shocks by Income Deciles

5.4 Response of Income and Earnings

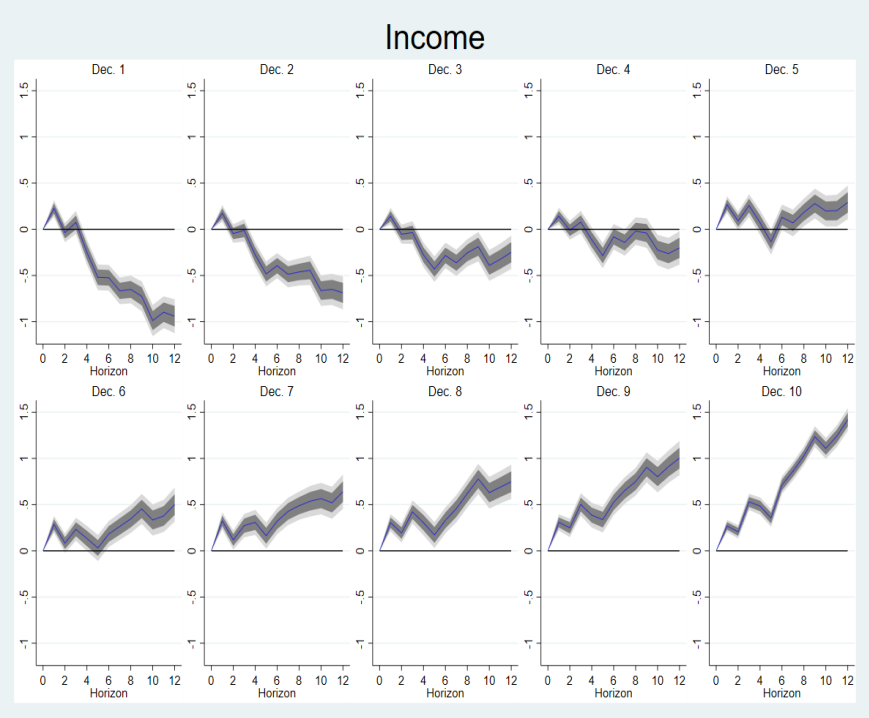

Figure 19: Response of Income to Food Price Shocks by Income Deciles

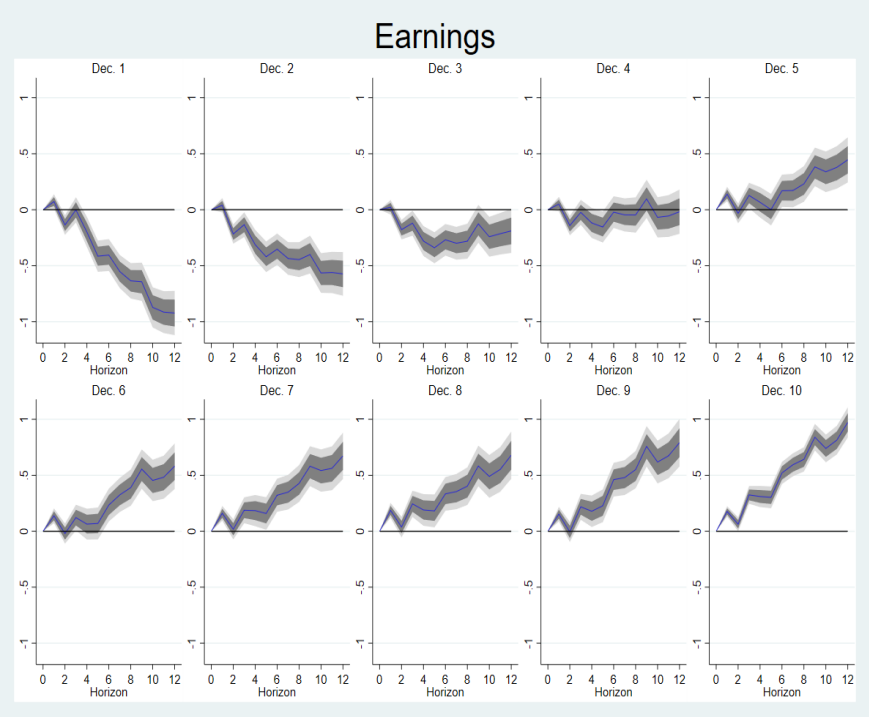

Figure 20: Response of Earnings to Food Price Shocks by Income Deciles

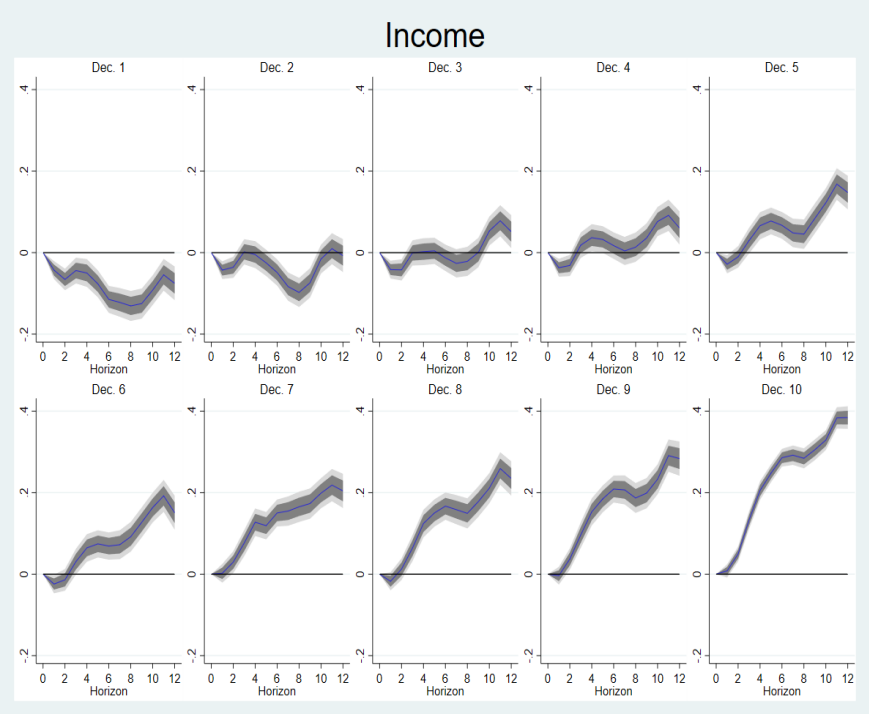

Figure 21: Response of Income to Oil Price Shocks by Income Deciles

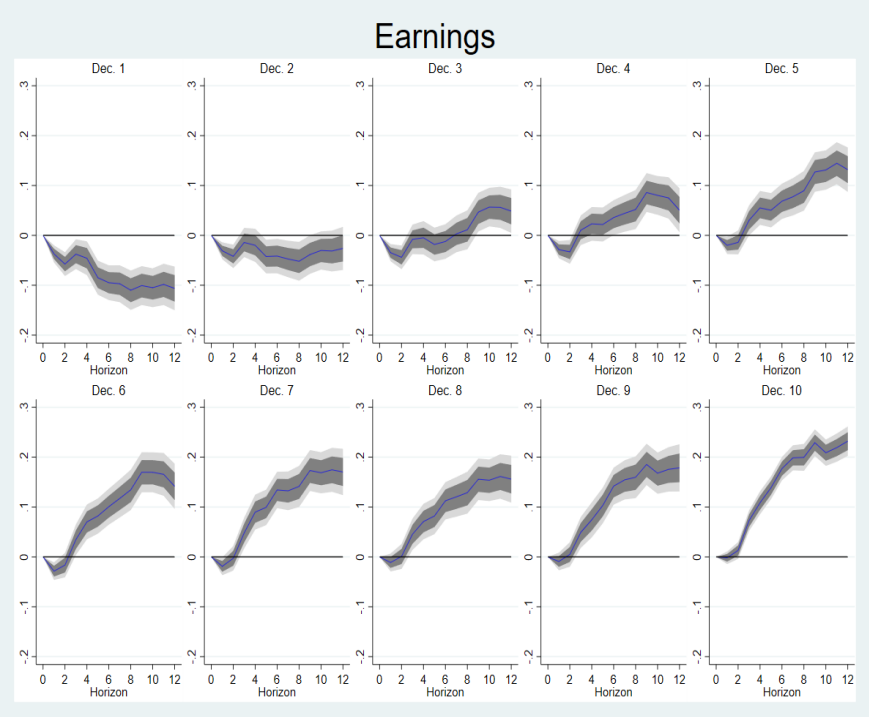

Figure 22: Response of Earnings to Oil Price Shocks by Income Deciles