India's Pandemic Through the Lens of Consumption Expenditure

Capturing Welfare Effects

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Abstract

There is rich literature available on the employment and income effects of the pandemic in India. When it comes to the effects on consumption expenditure, the literature is sparse. Gupta et al. (2020b) find that the pre-pandemic rich experienced a higher drop in consumption during the first lockdown, and they recovered much slower. The pre-pandemic poor, on the other hand, experienced a small fall in consumption during the first lockdown, and recovered much quicker. This thesis uses the CMIE-CPHS to capture the welfare effects of the pandemic on consumption expenditure. It finds that poverty spiked around lockdown one, but reverted to its pre-pandemic levels in the months that followed. Using a trend and regression analysis, the thesis confirms the finding mentioned in Gupta et al. (2020b). It contributes to the literature by establishing that the drop in discretionary spending, that is dominated by richer quantiles drove the higher drop in overall MPCE for the rich.

Acknowledgements

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Contents

Chapter 1

Motivation

This chapter cites existing literature on the topic and establishes the gap where this thesis will contribute. After using literature to motivate the topic, it presents the main findings of the thesis, and lays out the structure of the thesis.

The Indian economic structure already had several existing stress points before the pandemic hit. Mehrotra and Parida (2019) have found employment to have declined by an unprecedented 9 million jobs (a 2 percent drop) between 2011-12 and 2017-18. The drop was fuelled mainly by the agricultural sector, which saw a decline of 11.5 percent in employment and by manufacturing sector, where employment fell by 5.7 percent. While employment declined in the period, the absolute number of people who were "not in the labour force, education and training" increased from about 84 million to over 100 million (Mehrotra & Parida, 2019). Besides unemployment, undernutrition (a proxy for food insecurity) was alarming in India. Based on the National Family Health Survey (4^{th} round) findings, the proportion of underweight children was 36 percent in India in 2015-16. Only two or three countries in the world have a higher proportion of underweight children (Drèze & Somanchi, 2021). India has also had a high degree of informality for several decades, with over 90 per cent of the entire workforce being informal[1](Mehrotra, 2019). Since a majority of informal jobs came from the unorganized sector, India had a significant percentage of precarious jobs even before the pandemic hit.

These existing stress points were exacerbated by the pandemic. Nutritional deficiencies, employment and income losses, and a tendency towards higher indebtedness and sale of assets for consumption smoothing were some immediate impacts. Various surveys highlighted a sharp increase in food insecurity. The Hunger Watch survey by the Right to Food Campaign found two-thirds of its 4000 respondents reporting that nutritional quality had worsened and quantity of food had reduced (in September-October 2020) compared to pre-lockdown. Another purposive survey (done between April-May 2020) used in Kesar et al. (2021) found that almost 80 percent of the responding households experienced a reduction in food intake after the lockdown. The situation was even worse amongst poorer groups. ActionAid found that 35% of surveyed informal, mainly migrant workers were eating fewer than two meals a day in May 2020 (Daniyal, 2021). Lahoti and Kesar (2021) have stated that 22 percent respondents of Azim Premji University Covid-19

[1] defined as those without any social insurance.

Phone Survey (henceforth APU CLIPS) had sold or pawned their assets to cover basic expenses during the lockdown. This points towards increased indebtedness in the surveyed vulnerable population. Employment and earnings losses have been documented at nationally representative levels since the first lockdown. Although employment seemed to show a V-shape recovery (the bottom of the V being approximately 23 to 21 percent unemployment in April-May 2020), Bertrand et al. (2020) have warned that it is risky to assume that employment has "recovered". Abraham et al. (2021) have tracked job trajectories, and found much higher informality in the recovered jobs in addition to earnings losses. Thus, the recovery has only been partial, with increased precarity. In addition, Kesar et al. (2021) suggests that large employment and earning losses due to the shock of the pandemic quickly translated into food and livelihood insecurity because of an inadequate social-safety net.

To summarize, the pandemic has had severe welfare implications on the Indian population, especially after the first lockdown in April 2020. While the literature cited above has captured employment and income effects of the pandemic adequately, there is a dearth of literature on the consumption side effects of the pandemic. It becomes pertinent to examine consumption expenditure to understand how the shock changed the poverty and inequality situation in the country. Hence, the central question of this thesis is 'what were the welfare effects of the pandemic on consumption expenditure?'

This thesis uses the Consumer Pyramids Household Survey, a large nationally representative repeated panel dataset to understand the welfare implications of the pandemic on consumption expenditure. It finds that poverty spiked after the first lockdown, but recovered to its pre-pandemic levels. After disaggregating monthly per capita consumption expenditure (MPCE) by dynamic deciles, the thesis finds that inequality remained the same during the first lockdown, but decreased thereafter. This is because the poorer quintiles had a quicker recovery in consumption than the richer quintiles. After disaggregating MPCE by static deciles, this thesis finds that the pre-pandemic rich had higher drops in consumption when compared with the pre-pandemic poor. This is consistent with Bussolo et al. (2021) and Gupta et al. (2020b), who have not provided a reason for this pattern. Using a regression framework, the non-intuitive trend is verified, and a hypothesis for the cause behind the trend is tested. The thesis finds that the drop in discretionary spending, that is chiefly carried out by richer deciles, causes the pre-pandemic rich to have a relatively higher drop in consumption and a slower recovery. This mechanism that explains why the rich had a higher drop and a slower recovery is the contribution of the thesis to the literature.

The thesis is structured in the following manner. Chapter 2 familiarizes the reader with the dataset and establishes techniques of manipulating the data, that will be followed throughout the thesis. Chapter 3 presents some findings on the trends in consumption-based poverty and inequality during the pandemic. It also discusses the trends dis-aggregated by region, consumption quintiles, and by the category of spending to better understand the trends. Chapter 4 uses a regression framework to confirm the trends found in Chapter 3. It also explains an unusual finding that has been observed in the literature. Chapter 5 concludes.

Chapter 2

Exploring CMIE-CPHS

2.1 Introduction

The aim of this chapter is to familiarize the reader with CMIE-CPHS. An unbalanced panel made with 12 months of 2017's CPHS data was put through sanity checks to ensure that certain features/results of the data are justifiable using economic theory. This is a necessary step before analyzing the pandemic period and making any extrapolations. The other objective of this chapter is to identify robust techniques that can be used in the analysis of the pandemic period. For instance, through comparison, this chapter identifies the correct usage of survey weights, levels of aggregation of data that give different results, and whether different recall periods in the survey make a difference.

2.1.1 About CMIE-CPHS

CMIE-CPHS is a large sample survey that repeatedly surveys 1.4 to 1.8 lakh households every four months in India. Thus, each household gets interviewed thrice a year. In each interview, the household recalls and provides information for the previous four months. The questionnaire is very detailed- households provide the exact monthly expenditure on food, clothing and footwear, bills and rent, education, health, transport, appliances, recreation and some more. Moreover, these are just the aggregate consumption heads. For instance, even within expenses on the aggregate 'food' category, there is information on how much was spent on cereals and pulses, edible oils, dry spices, meat and eggs, fruits and so forth. The aggregate variables in CPHS are of two types- monthly expenditure and adjusted monthly expenditure. The first category just asks the household to state the expenses for a particular expense head at a monthly level- this is noted in the 'monthly expenditure' category. For certain expense heads, where the information may be more accurate when also collected at the weekly level (e.g. fruits, edible oils), the expense on such items in the week that precedes the interview is noted. CMIE then uses an adjustment factor that makes use of both, the monthly and weekly heads to churn out an 'adjusted monthly expenditure'.

This dataset was chosen because it is the only large survey available in India to analyze the impacts of the pandemic on consumption expenditure. Another advantage of this dataset is that it provides monthly data. This is a high enough frequency to catch some peculiar effects of the pandemic and the lockdown, that lasted for a month or two.

2.2 Food-share of consumption

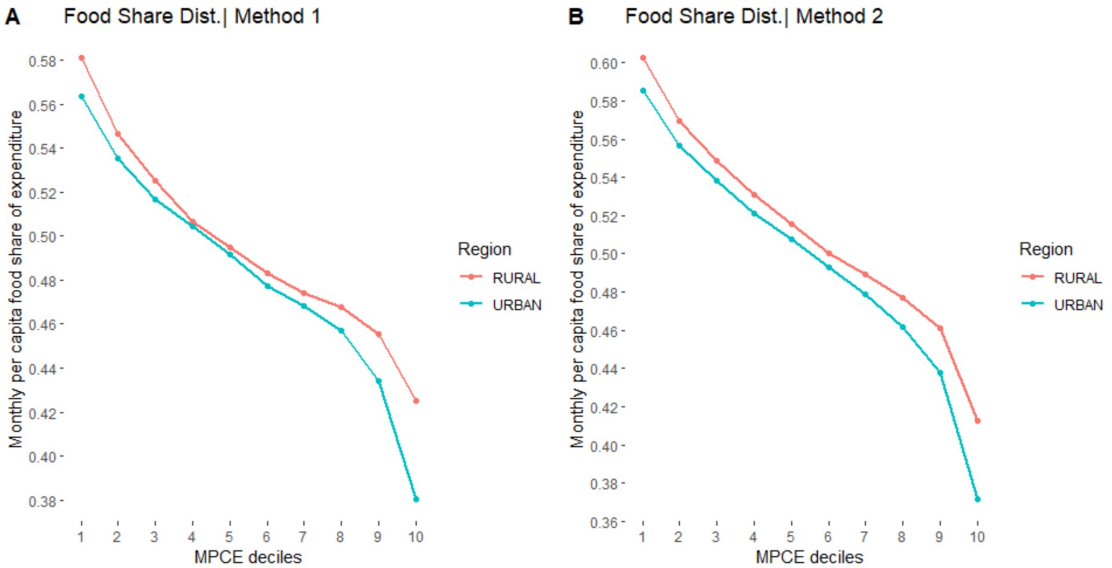

Figure 2.1: Food share of consumption declines as households get richer. Rural population has a higher food share of consumption. Data: January-December 2017, CMIE-CPHS.

The first sanity check for this dataset was verifying the behaviour of food share of consumption by deciles. As Figure 2.1 conveys, the richer households spend a smaller proportion of their consumption on food. The tenth decile's food share is roughly 20 percentage points lesser than that of the first decile. Moreover, rural households spend a higher proportion of their consumption on food as compared to urban households in every decile. Both the results are in line with standard microeconomic theory.

To obtain the two graphs in Figure 2.1 two slightly different methods were used. In Method 1, the following was done. Each household in the unbalanced panel had maximum 12 entries (from the year 2017). The annual unweighted means of monthly per-capita consumption expenditure (MPCE) and monthly per-capita food expenses were taken for each household[1]. Similarly, the (12-month) mean survey weight[2] was calculated for each household. Based on the distribution of mean MPCE, each household was assigned a decile rank. Then weighted means for MPCE and food expenses were taken, by region and by decile. Food share was a simple division of per-capita food by MPCE, done at the aggregate level. This is plotted in the left panel of Figure 2.1.

In Method 2, the following was done. For each month, the distribution of MPCE was taken and households were assigned decile ranks. It was possible for households to have a different decile rank in different months. Then month-wise MPCE and month-wise per-capita food expenses were calculated by taking weighted means of the respective variables after grouping for month, decile, and region. Using this, the annual average was

[1]CMIE-CPHS does not provide a numeric household variable. This variable was created based on the median value from the 'household size' variable. For instance, "8-10 members" was taken as 9 members in the household. The per-capita variables were created by dividing the household level monthly expense heads by the household size. It assumes that all members of the household consume the same amount.

[2]The household weight for the country was multiplied with the non-response factor to create accurate survey weights.

created separately for each region and decile. The food share was a simple division of the resulting two final variables. This was plotted on the right hand side of Figure 2.1.

While the analysis in this thesis will be done at the national level, it is noted that different states within India are likely to have varying experiences. An illustration of this can be seen in Figure 2.2, where weighted per-capita food shares of consumption are plotted by state. It is expected that richer states have a lower food share of consumption, but this doesn't necessarily reflect for each state in Figure 2.2. The key takeaway from this figure is that while most states on the chloropleth map are coloured in the same shade of orange, a more accurate analysis will account for the variance in results aggregated at the state level.

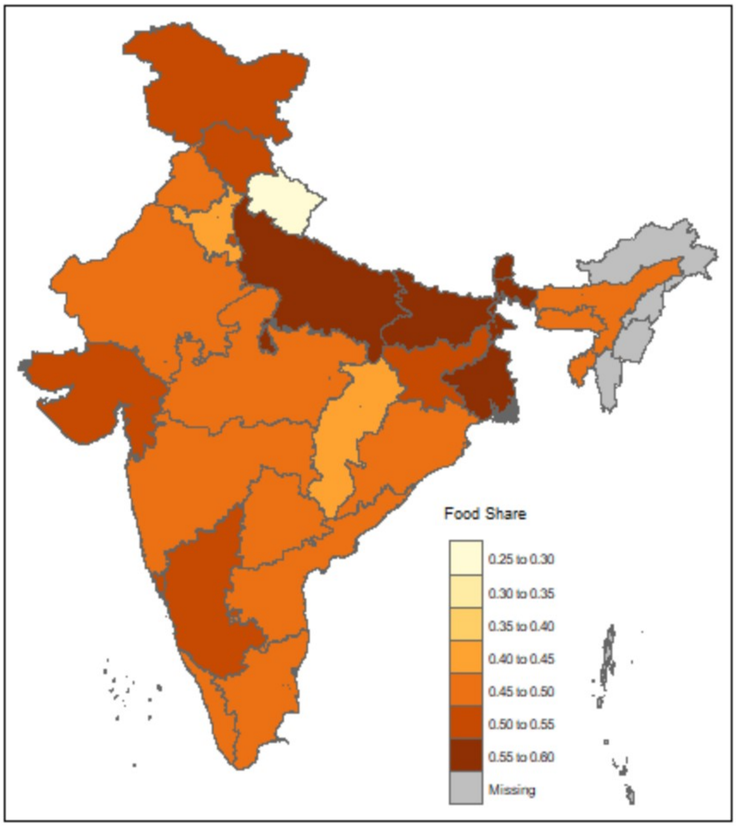

Figure 2.2: There is a variance in the weighted per-capita food share of consumption by states. Data: 2017, CMIE-CPHS.

2.3 MPCE by deciles

This section aims to identify the choices of weights and ways of aggregating data, that make a difference to the results. In a panel dataset, maintained in a long format, each household has maximum 12 entries (because only the 12 months of 2017 are used in this panel). Any operation done within households (e.g. 12-month mean MPCE of each household) is typically followed by a weighted operation- this raises the question of whether the 12-month mean of household weight should be taken, or a random month's weight is sufficient for the purpose (e.g the weight of the first month/last month). The section also aims to see whether recall periods yield different results. As previously mentioned, the surveyors ask respondents to provide information for the last four months in one sitting. It would be intuitive to expect that the data for the month immediately preceding the interview month would be most accurate. Hence, the section verifies if there are major differences in MPCE by deciles when different recall periods are used.

2.3.1 Choice of weights and levels of aggregation

As columns 1A, 1B, and 1C from Table 2.1 indicate, there is no visible difference in results when the mean of weights, or a random month's weight (first/last month's weight) is used. Based on this finding, future analysis in this thesis picks the first weight for each household (the method used in 1B).

Table 2.1: Comparison of weights in decile-specific MPCE (CMIE-CPHS, 2017)

Decile	RURAL			URBAN		
	(1A)	(1B)	(1C)	(1A)	(1B)	(1C)
1	1239	1241	1236	1312	1313	1310
2	1713	1712	1712	1720	1720	1721
3	2035	2034	2035	2042	2042	2042
4	2342	2341	2341	2344	2344	2344
5	2661	2662	2661	2668	2668	2668
6	3023	3025	3025	3032	3032	3032
7	3454	3457	3456	3463	3463	3463
8	4032	4036	4035	4045	4045	4045
9	4943	4944	4947	4958	4957	4958
10	7495	7532	7537	8067	8074	8076

Table 2.2 uses different methods of aggregating the data. The difference between column 2 and 3 is the amount of months in the data. While column 2 has upto 12 months of data for each household, column 3 has one random month per household. Visually, it looks like there is no change in the decile-wise MPCE numbers between columns 2 and 3. However, the method used in column 3 is avoided because households are known to increase their expenditure in certain months (e.g. festival months like September and October). Hence, it is possible that picking random months can exacerbate the noise in the data. Wherever a monthwise analysis takes place in the thesis, the method used in column 2 is used.

Table 2.2: Decile-wise MPCE, Aggregated differently

Decile	RURAL			URBAN		
	(1A)	(2)	(3)	(1A)	(2)	(3)
1	1239	1132	1123	1312	1185	1175
2	1713	1589	1590	1720	1605	1597
3	2035	1925	1915	2042	1930	1920
4	2342	2243	2231	2344	2247	2236
5	2661	2584	2567	2668	2588	2574
6	3023	2975	2956	3032	2981	2959
7	3454	3447	3423	3463	3454	3435
8	4032	4071	4050	4045	4085	4061
9	4943	5068	5034	4958	5077	5038
10	7495	8253	8249	8067	8606	8723

Each column explained:

1A: For each household ID, a column with the simple mean of the adjusted total expenditure for all 12 months was created. Another column with the simple mean of the weights for all 12 months was created. A weighted average of MPCE was found for each household ID. Households were then grouped by decile rank and region to generate this summary.

1B: For each household ID, a column with the simple mean of the adjusted total expenditure for all 12 months was created. Another column for weight was created, which picked the first weight corresponding to a particular household ID. A weighted average of MPCE was found for each household ID. Households were then grouped by decile rank and region to generate this summary.

1C: For each household ID, a column with the simple mean of the adjusted total expenditure for all 12 months was created. Another column for weight was created, which picked the last weight corresponding to a particular household ID. A weighted average of MPCE was found for each household ID. Households were then grouped by decile rank and region to generate this summary.

2: There were 12 entries for each household ID to begin with. A column for decile rank was added. Household IDs were grouped by month, decile rank and by region. A column for weighted monthwise-MPCE was added. This generated 20 entries for each month (10 deciles into 2 regions), a total of 240 entries. To get annual averages, grouping was done again by regions and deciles and the summary was generated.

3: For every household ID, 11 months were dropped and a random month was kept. The weighted average of MCPE was made using the weight for the corresponding month. Households were then grouped by decile rank and region to generate this summary.

2.3.2 Grouping and Recall Periods

The creation of decile is done based on the type of analysis. Deciles disaggregated by region are used where we are exploring numbers separately for each region. Using national-level deciles doesn't make sense here because the distribution of consumption expenditure for rural and urban India is known to be different. Due to higher costs of living and higher-paying sources of income, urban consumption distribution will be shifted to the right with reference to the rural distribution of consumption. Thus, in future analysis, whenever figures like MPCE are dis-aggregated by region and presented, the deciles are also separately constructed for each region. In general, decile creation is in line with the aggregation of data (national/by-state/by-region).

Table 2.3 highlights that there are no large differences in results when different recall periods are used (see columns 1 and 2). In this analysis, each household could have a maximum of 3 observations (from the 12 observations in year 2017) because either the months that immediately preceded the interview or the months that were four months away from the interview month were kept for analysis. For the results shown in the "Last Month" column, only those months that immediately preceded the interview months were kept in the dataset. For the results shown in the "Fourth Month" column, only the months in which the households provided data that was four months before the interview month were kept. The table shows that the recall periods do not add high levels of inaccuracy in the data. From here on, all recall periods are used to generate averages.

Table 2.3: Comparison of last month and fourth month recall

Decile	RURAL		URBAN	
	Last Month	Fourth Month	Last Month	Fourth Month
1	1014	1033	1373	1416
2	1347	1369	1841	1892
3	1582	1607	2199	2235
4	1810	1833	2535	2563
5	2055	2067	2893	2911
6	2327	2333	3295	3300
7	2665	2652	3791	3784
8	3119	3073	4452	4429
9	3819	3735	5467	5470
10	6085	5966	8802	9079

2.4 Conclusion

There were several small but important takeaways from this chapter, that are useful for later analysis. Firstly, while the analysis in this thesis will be at the country level, it is important to account for differences in states (wherever possible). Next, the choice of weights (mean household weight/ first/ last month's weight) does not make a major difference to results. Thus, as a standard practice, the first weight of each household will be picked whenever required. Further, when results are presented separately for rural and urban India, and if deciles were created in the process, they will be created separately for each region. Lastly, there are no large differences in results that are arising due to recall periods. Hence, all recall periods are assumed to have the same level of accuracy.

Chapter 3

Trend Analysis: Poverty and Inequality in the Pandemic

3.1 Chapter Summary

Much of the analysis of the pandemic's economic impacts have been in terms of labour market effects (especially unemployment) and income losses. This chapter examines the welfare shock of the pandemic on poverty and inequality using data on consumption from a large nationally representative repeated panel dataset (CMIE-CPHS). The key finding is that bottom four rural and five urban deciles fell below poverty line during March-May 2020. As a result, there was a sharp rise in poverty. Roughly 40 percent of the rural population and 50 percent of the urban population fell below poverty line in April 2020. The inequality story (gauged by the trend in MPCE disaggregated by dynamic deciles) suggests a no drop in consumption inequality during the lockdown months, followed by a fall in inequality. While this seems counter-intuitive, it is justified by a higher relative drop in the consumption expenditures of the top deciles. This lowered consumption inequality does not imply a better welfare outcome because it is not arising out of any structural changes. The pandemic has disproportionately cut the overall discretionary spending, something the top deciles dominate, which materialized into reduced consumption inequality.

3.2 Introduction

After India had its first lockdown that started on 24th March 2020, a consumption expenditure shock was foreseeable. This expectation is intuitive because of enforced mobility restrictions, closure of shops selling non-essential goods, reduced incomes- putting a downward pressure on consumption, and voluntary slowdown of expenditure to avoid exposure to the virus. Several months into the pandemic, we have reliable literature on the labour market and income effects of the pandemic. For instance, after a heightened unemployment rate of 21 to 23 percent in April-May 2020 and a suggestive "V-shape recovery" in the following months, Bertrand et al. (2020) warned of an incomplete recovery. Abraham et al. (2021) have refined that to show that the recovered jobs come with earning losses and increased precarity through more informal contracts. On the income side of the story, Gupta et al. (2020a) find that the "shock is either neutral or progressive across household income". This is based on the finding that the relative fall in income was higher for richer quartiles in rural India, while it was almost equal for all quartiles in urban India during April 2020.

While the trends in poverty based on consumption expenditure have remained largely unexplored, a recent working paper by Gupta et al. (2020b) has shed light on inequality and trends in poverty. This chapter enriches the existing literature on the welfare impacts of the pandemic in India by using Gupta et al. (2020b) as a reference. The chapter re-highlights the trend in poverty using a different method, analyses consumption-inequality and comments on its deceptively progressive outcome.

3.3 Data and Methods

This chapter uses the Centre for Monitoring Indian Economy's (CMIE) Consumer Pyramids Households Survey (CPHS) to carry out the secondary data analysis. The CPHS is a nationally representative[1] dataset which surveys households once every four months. CPHS started its sample survey in 2014 and continues till date. An advantage of using this dataset is that it interviews the same households over the years. While Somanchi (2021) finds large, possibly non-random attrition in the CPHS data, this chapter only analyzes roughly two years of data- enough to create a large unbalanced panel despite attrition.

The key variables used in this analysis are (real) Monthly Per-capita Consumption Expenditure (MPCE), decile rank, and the poverty threshold. Firstly, CMIE provides the total monthly expenditure at the household level. This number was divided by the household size to obtain MPCE within households. Since CMIE reports the nominal values of expenditure for each month, these were converted to real values by rebasing each month's MPCE with January 2020's prices (done separately, by state, for rural and urban households using CPI-R and CPI-U). Thus, real MPCE was obtained, with January 2020 as the reference month.

Using the real MPCE, two types of decile ranks were assigned to each household. One was a dynamic decile rank, while the other was a static decile rank. The dynamic decile rank was constructed by first creating a distribution of real MPCE for each month, and then binning these households into ten groups (deciles). Under dynamic deciles, households were essentially allowed to change their decile rank in every month based on their real MPCE. The assignment of a dynamic decile rank is useful because it provides a snapshot of data in each month. This is useful to examine the trend in inequality and poverty over the months. As the section on poverty will elaborate, there were some stark changes in the proportion of population below poverty line during the lockdown months- dynamic decile rank was insightful here.

Static deciles are used for comparison with the pre-pandemic year. It is worthwhile to find out that given, a household belongs to a particular decile in the pre-pandemic year, what is its relative real expenditure during a pandemic month. Static deciles were created by keeping only those households that were responsive between April 2019 and March 2020 for the analysis. This created an unbalanced panel, where every household

[1]Whether the CPHS is nationally representative is being debated. See Somanchi (2021). However, CPHS is the only large-scale survey available to study the welfare impacts of the pandemic.

was present in at least one month of the pre-pandemic year. Then, the pre-pandemic year's mean real MPCE for each household was calculated. Given the distribution of the pre-pandemic year's mean real MPCE for all households, households were binned into ten groups. Thus, static deciles were created- each household was assigned a permanent decile rank.

3.4 Findings

3.4.1 Poverty

Whenever one wants to quantify poverty in a country, the choice of picking an arbitrary poverty line is a tough one. This paper uses the Rangarajan line, updated with the mean consumer price index of all states in January 2020. The resulting urban poverty line stands at rupees 2080/person/month, while the rural poverty line stands at rupees 1497/person/month. For context, the World Bank's \$1.9/person/day extreme poverty threshold amounts to rupees 1255/person/month in PPP terms[2] .

Before we examine the trend in the proportion of below poverty line (BPL) population, we will examine the trend in absolute real MPCE of households. Figure 3.1 displays the absolute real MPCE values for the bottom six rural deciles, while Figure 3.2 displays the MPCE values for the bottom six urban deciles. While in the pre-pandemic scenario only one decile was below poverty line, four rural deciles went below poverty (Figure 3.1) during the lockdown months. In urban India, the impact was more stark- five deciles went below poverty (Figure 3.2) during the lockdown months.

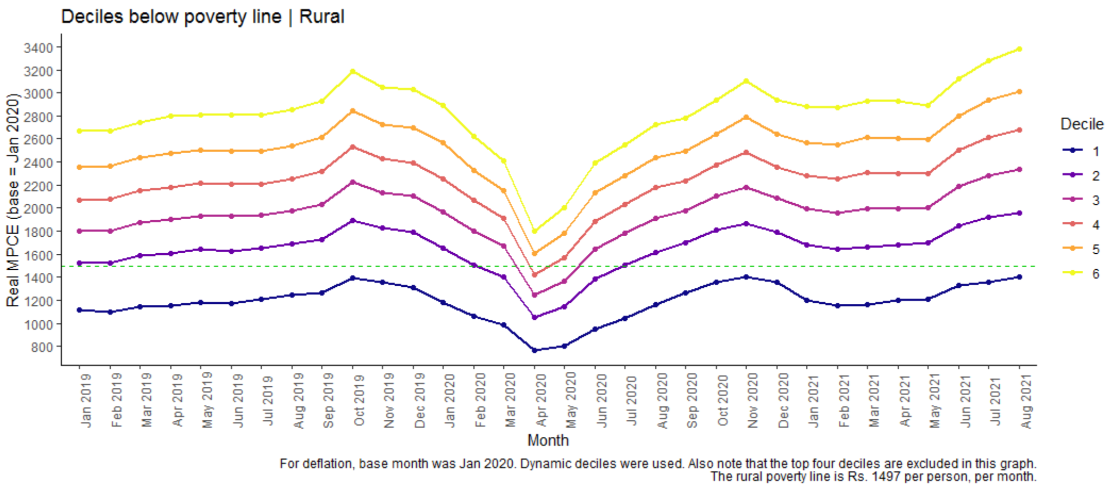

Figure 3.1: Four rural deciles went below poverty during the lockdown months.

[2]The quick calculation can be done by multiplying \$1.9 into 30 days into 22.01 (\$ PPP for India- source)

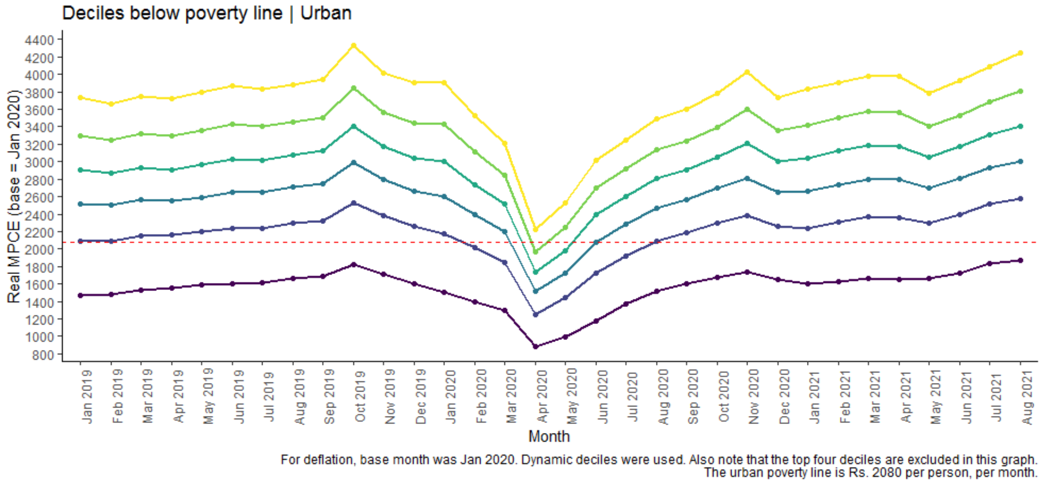

Figure 3.2: Five urban deciles went below poverty in the lockdown months.

Figures 3.1 and 3.2 combined, foreshadow the impact of the pandemic and the lockdown on headcount poverty. From being close to 15 percent and 14 percent in urban and rural India respectively in January 2019, headcount poverty peaked to 50 percent and 40 percent in urban and rural India respectively (Figure 3.3). Gupta et al. (2020b) also find a sharp rise in income poverty around the first lockdown, that remains slightly above the pre-pandemic level aftwewards. They use three income-based poverty measures (the World Bank $1.9 threshold, National Minimum Wage- income of 1909 and 2256 per capita month in rural and urban areas, and the poverty line set by the seventh Central Pay Commission-income of 4,660 per capita per month). Their results mostly remain the same in all methods.

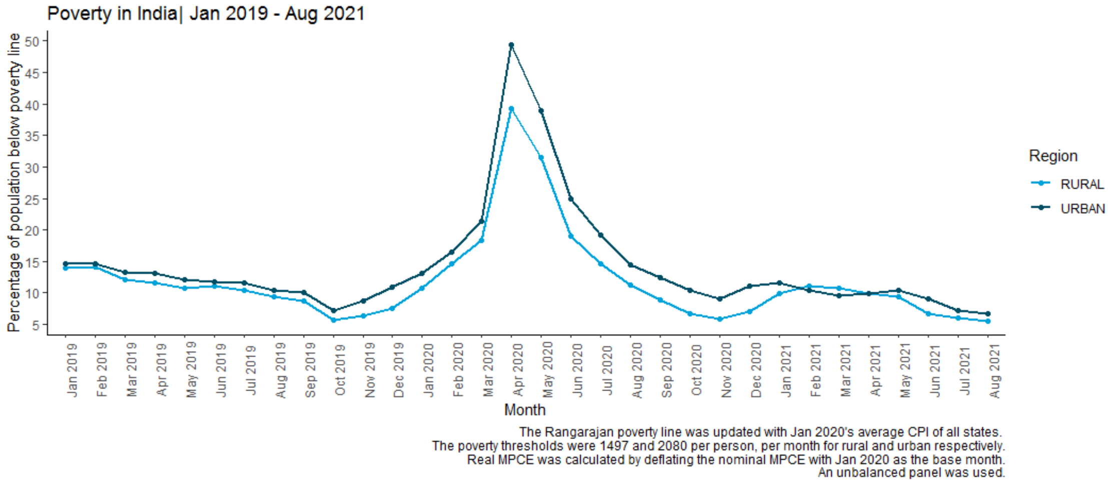

Figure 3.3: Sharp rise in headcount poverty during April 2020.

3.4.2 Inequality

This section gauges consumption-inequality during the pandemic by examining the trend in relative MPCE, disaggregated by dynamic deciles. As previously mentioned, allowing households to change deciles gives us a snapshot of consumption by each decile in each month. Inequality, here is not a precise number, but the visible difference in MPCE between the tenth and first decile. Figures 3.4 and 3.5 show that there was a homogeneous drop in MPCE during April 2020. Since all deciles dropped consumption by the same proportion, there was no change in inequality during the first lockdown. After that however, the poorer deciles recover faster than the richer deciles. This implies that consumption inequality declined in the post-lockdown period.

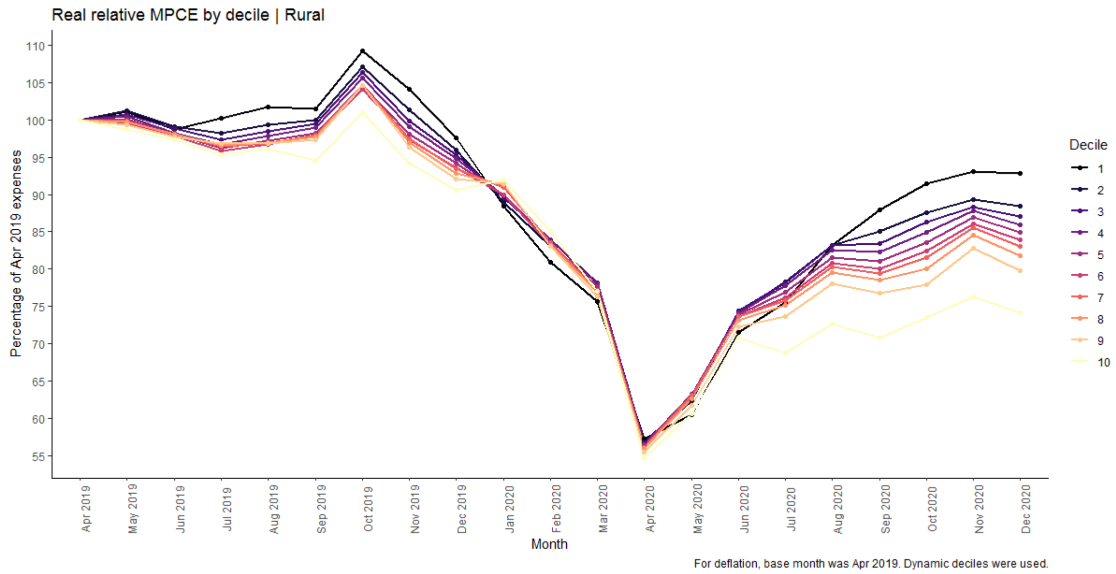

Figure 3.4: All deciles witnessed a similar drop in April 2020, but the poorer deciles recovered faster.

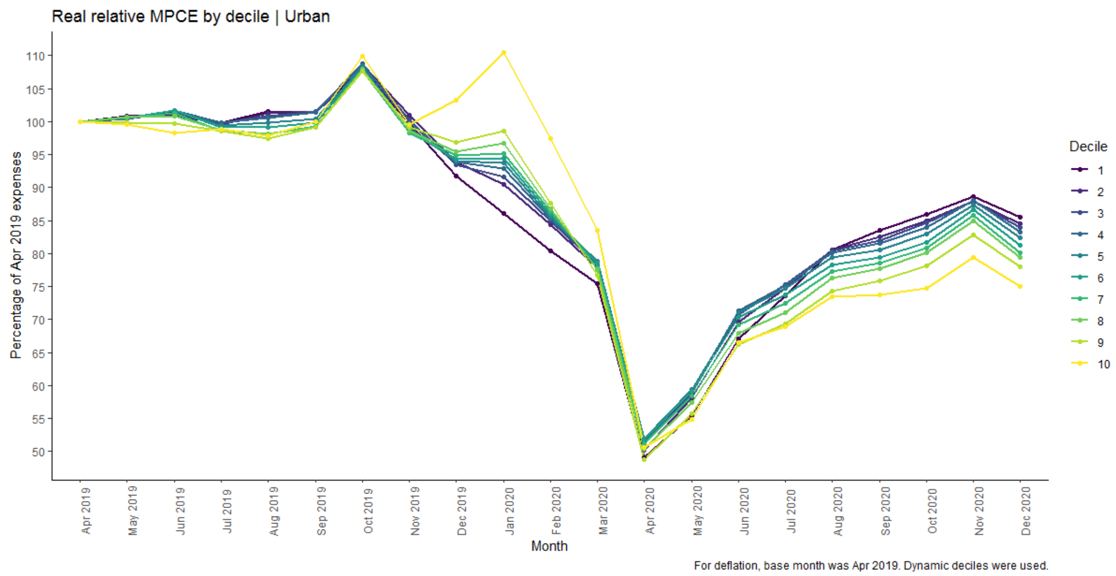

Figure 3.5: In urban India too, all deciles witnessed a similar drop in April 2020, but the poorer deciles recovered faster.

3.5 Analysis of Static Deciles

This section takes advantage of the panel aspect of CMIE-CPHS. We follow households to see what happened to their consumption based on how well-off they were before the pandemic. In other words, households are first assigned a static decile rank based on the distribution of average MPCEs for all households. This provides us with insights about mobility, that are different from the insights received from the dynamic decile analysis.

With static deciles, we find that there was a gradation in the drop in consumption during lockdown. The richer deciles had a higher fall in expenditure and had a low recovery in months that followed. While the 1st decile's consumption in April 2020 stood at roughly 75 percent of its expenditure in April 2019, the 10th decile's consumption was less than half of its April 2019 consumption (Figure 3.6). Moreover, while the lower deciles (poorer population) were able to recover its consumption quickly, that wasn't the case with richer deciles. The pattern of higher fall and lower recovery for richer deciles in the static decile analysis remains true in the urban subset as well. Dynamic deciles suggested that there was no change in inequality during lockdown. However, if we follow the pre-pandemic rich and the pre-pandemic poor, we get a counter-intuitive finding. It is unusual to see the pre-pandemic rich experiencing higher falls in consumption, and having a low recovery. However, bifurcating consumption into essential and discretionary spending may provide some explanations.

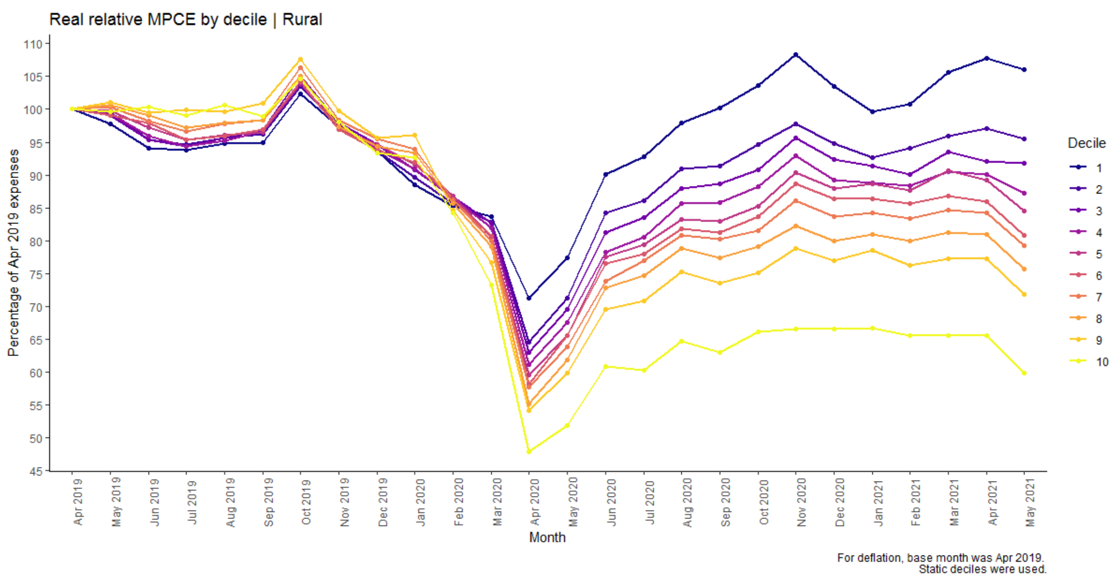

Figure 3.6: In rural India, compared to the expenditure in April-2019, consumption of richer deciles was affected more severely. Note that static deciles are used in this graph- they are decile ranks assigned to households based on their mean consumption in the pre-pandemic year.

For simplicity, the expenditure on food is considered as essential consumption expenditure, while all non-food consumption is assumed to be discretionary spending. Despite allowing for the inaccuracy in categorization of essential and non-essential goods, we find that the fall in expenses on non-food consumption is double that of the fall in food expenditure in April 2020 (Figure 3.7 and 3.8). It is known that richer deciles spend disproportionately higher on non-food/non-essential goods. A possible reason for the richer deciles experiencing higher drops in consumption may come from the fact that they are cutting down on discretionary spending (and that more the income, more the discretionary spending of a household). These trends call for a more rigorous verification of the suggested mechanism behind the counter-intuitive finding.

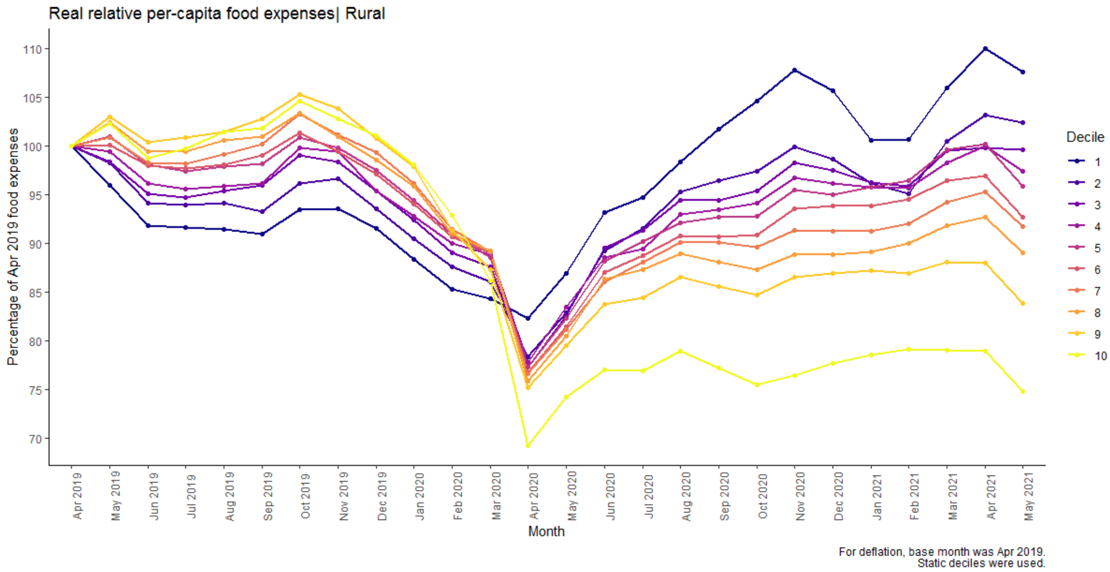

Figure 3.7: Essential expenditure was not driving the fall in real MPCE. Note that the richest decile still has the worst impact on food expenses- this is because CPHS has several 'non-essential' food items such as cake, chocolates, mithai, etc.

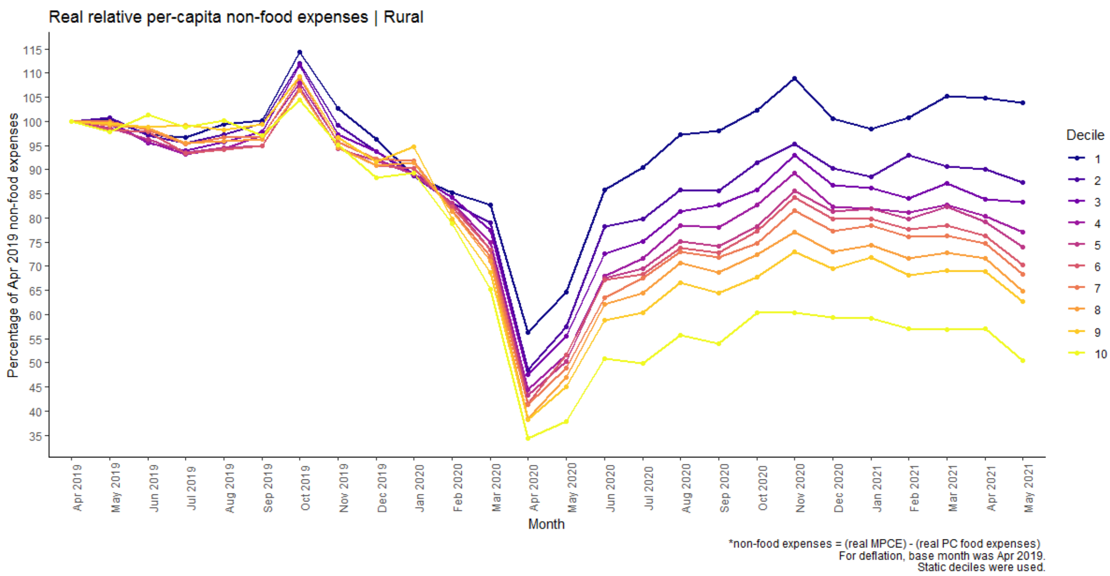

Figure 3.8: The drop in non-food expenditure is double that of the drop in food expenditure for the 10th decile (35 percent of April 2019 expenditure v/s 70 percent of April 2019 expenditure, respectively). The dip in discretionary spending by the top decile is the driver for fallen consumption inequality.

3.6 Conclusion

To conclude, India saw a sharp rise in poverty during April 2020, followed by recovery to pre-pandemic levels. The dynamic decile and the static decile analyses presented slightly different stories. The former suggested that there was no change in inequality during the lockdown (because all deciles had a proportionate fall in consumption), while inequality reduced in the following months (because the poorer deciles recovered quicker). Here too, the quicker recovery of poorer deciles is surprising. The later analysis suggested that the pre-pandemic rich witnessed higher drops in consumption even during lockdown. Similar to the previous case, the pre-pandemic poor recovered consumption quicker. This counter-intuitive finding could perhaps be explained by bifurcating consumption expenditure into essential and non-essential heads. If it is rigorously verified that the drop in the rich-household-dominated discretionary spending is driving the drop in consumption for the richer households, the counter-intuitive finding can be explained.

Chapter 4

Regression Analysis

4.1 Introduction

Certain findings from the previous chapter were counter-intuitive. Figure 3.6 shows that the richer deciles experienced a higher drop in consumption in April 2020, and a much slower, incomplete recovery in the following months. This ability of the poorer population to better smooth consumption expenditure has also been noted by Bussolo et al. (2021). They find that informal workers (who are expected to be in lower deciles) experienced a smaller drop in consumption expenditures as compared to formal sector workers (who would find themselves in the higher deciles). Moreover, Gupta et al. (2020b) have also found that richer quartiles experienced a higher drop in consumption expenditure after the first lockdown, and their recovery continues to be slower than poorer deciles. However, the authors have used this (static-decile) finding to conclude that inequality fell during the pandemic (static deciles can only be used to comment on mobility). In short, while the trends in consumption expenditure are counter-intuitive, they are consistent with the literature.

The first objective of this chapter is to rigorously verify the trend found in chapter 3 (richer population experienced a higher drop in consumption and recovered only partially). This is done using a regression framework. The other objective of this chapter is to provide a mechanism for the observed trend. By analyzing trends in consumption, chapter 3 suggested that the richer deciles experienced a higher drop in consumption because they significantly cut down on discretionary spending. The poorer deciles have little discretionary spending, hence their relative overall expenditure experienced only a small drop around the lockdown months. Consumption smoothing for essential goods typically happens quicker as the goods are required for survival. The recovery of the poor was faster because they spend a large proportion of their expenditure on essential goods. Gupta et al. (2020b), who have reported the same trend in consumption expenditure, do not provide any mechanisms for the trend of richer deciles having a worse impact and slower recovery. This chapter will contribute to the literature by demonstrating that rich were affected more and recovered slower after the first lockdown because while the poor recovered quicker by smoothing their essential expenditure, the rich continued to hold back on discretionary spending.

4.2 Empirical Strategies

In line with the first objective, two regression models were used to verify whether the richer population experienced a higher drop in consumption post-lockdown, and recovered only partially. Next, the hypothesis for the counter-intuitive trend was verified using a regression model. This was done by bifurcating all expenses into essential and non-essential categories. For each region (rural/urban), the essential subset, followed by the non-essential subset was run on the basic regression model. For robust results, the 'essentials' category first had a broader set of items (see Table A.5), followed by only four food items.

The basic regression model was as follows:

$$\Delta Consumption_{i,t} = [\beta_0] + \beta_1 month_t + \beta_2 percentile_i + \beta_3 (month_t \times percentile_i) + [\gamma S] + \varepsilon$$

In model 1, $\Delta Consumption_{i,t}$ was the change in total per-capita expenditure of month t relative to the mean consumption of the household i in 2019. In other words,

$$\Delta Consumption = \frac{HH\_expenses\_in\_month\_t - mean\_2019\_HH\_expenses}{mean\_2019\_HH\_expenses}$$

On the right hand side, month t is the month identifier. $percentile_i$ is the static percentile rank assigned to the household based on its mean per-capita expenditure in 2019. This basic regression model was run separately for the rural and urban subset. Based on the insights from Figure 2.2, the model was first run with state fixed effects (γS), and then without the fixed effects. In the iteration where state fixed effects were used, the static percentile ranks were created by state and region. In the iteration where there were no state fixed effects, the static percentile assignment was made only by region. The results were reported after clustering the standard errors at the household level.

In model 2, the right hand side remained the same as above, but the $\Delta Consumption_{i,t}$ was created differently. For each household, the per-capita consumption of each month was plotted from January 2018 till December 2019. A trend line was fitted on this distribution of two-year expenditure data for each household. Based on the slope of this line for the household, each month after December 2019 had a predicted value for per-capita expenditure. Thus, in this model:

$$\Delta Consumption = \frac{HH\_expenses\_in\_month\_t - predicted\_HH\_expenses_t}{predicted\_HH\_expenses_t}$$

Since the reference period for model 2 was January 2018 till December 2019, the static percentile ranks were created based on the distribution of the two-year mean per-capita expenditure of households. Similar to model 1, in the iteration where state fixed effects were used, the static percentile ranks were created by state and region. In the iteration where there were no state fixed effects, the static percentile assignment was made only by region. The results were reported after clustering the standard errors at the household level.

The regressions in both the models above were run on an unbalanced panel. In such a panel, households are allowed to drop out of the sample/not respond for few months, and new households can enter the sample. On the other hand, a balanced panel ensures that only those households that have provided data for all twelve months of 2019 remain in the sample. The advantage of using a balanced panel is that it reduces noise in the data. The disadvantage is that a significant chunk of the sample (over fourty percent) gets dropped while creating a balanced panel. For robustness, the regressions were also run on a balanced panel. The coefficients were not majorly affected when the balanced panel was used. Hence, the reported results use unbalanced panels to benefit from the larger sample size.

For regressions where the data was bifurcated into essentials and non-essentials, the first, basic model was used. Instead of change in consumption relative to the 2019 mean consumption as the dependent variable, change in essentials (non-essentials) relative to 2019's mean expenses on essentials (non-essentials) was used. In other words, the dependent variable was the following:

$$\Delta Essential\_exp = \frac{HH\_essential\_exp\_in\_month\_t - mean\_2019\_HH\_essential\_exp}{mean\_2019\_HH\_essential\_exp}$$

Using an unbalanced panel, separate regressions were run for rural/urban regions and for essential/non-essential expenditure, as shown in the formula below:

$$\Delta Essential\_exp_{i,t} = [\beta_0] + \beta_1 month_t + \beta_2 percentile_i + \beta_3 (month_t \times percentile_i) + [\gamma S] + \varepsilon$$

4.3 Discussion of Results

The regression results are presented in the Appendix. Since there was an interaction term in the regression, the average marginal effects for the interaction term are presented in most tables. In these tables, the coefficients can be interpret directly. Only in A.2, the results are not presented with marginal effects. Here, to interpret the interaction term, the coefficient on the percentile variable needs to be added to each month*percentile interaction coefficient. That said, the month coefficient informs us about the magnitude of change in consumption for each month. This is used to verify whether there were large and significant drops in consumption in the lockdown months. The month*percentile interaction coefficient helps us identify whether the changes in consumption in a given month were progressive or regressive in nature. If the coefficient on the interaction term is negative and significant, it means that as we go higher from the median percentile (as we move towards richer percentiles), there is an increased drop in consumption. This would be termed as a progressive impact.

The results in A.1 and A.2 verify that the richer population experienced a higher drop in consumption post-lockdown. Appendix A.1 shows that the drop in consumption expenditure was the highest in April 2020, the month that immediately followed the first lockdown. The urban sector had higher negative coefficients than the rural sector in both models (with and without state fixed effects). More importantly, the month*percentile coefficients for all months in both models are negative and significant at the one percent level for rural and urban regions. The model confirms that as we climb up the percentile ladder (move towards richer percentiles), the fall in consumption expenditure is more. The month*percentile interaction coefficients gets more negative over time. It is also interesting to note that there is a pre-trend for the drop in consumption in February and March 2020 (these month coefficients are negative and significant). The unexplained pre-trend is also visible in the descriptive Figure3.6.

The results of model 2, that used predicted consumption values for each household instead of the mean expenses in the reference year are presented in A.2. Here as well, the month coefficient for April 2020 is negative and significant in both regions (rural and urban), and both with and without state fixed effects. The month*percentile interaction is negative and significant around the first lockdown months. In later months, the interaction coefficients are negative but not significant. This however, confirms that the richer percentiles experienced higher drops in consumption during the first lockdown.

The remaining regressions were run to test whether it was the drop in discretionary spending that was driving the counter-intuitive result that we have gotten so far (see A.3 and A.4 of the appendix). While the coefficient values on the month variables, and those on the month*percentile interaction for non-essential spending were expected, the interaction coefficient for the essential category presented surprising numbers. As previously mentioned, both A.3 and A.4 use the same regression model, but starkly different definitions of the 'essential' category. A.3 encompasses many items into the essential category (see Table A.5), while A.4 counts only four food variables as essential. Even with seemingly extreme compositions of the two essential bundles, the following results are consistent. (1) The drop in essential consumption is small (the values of the negative month coefficients are low in comparison with non-essential category) and significant for a few months around the first lockdown (April 2020) . On the other hand, the drop in non-essential consumption is much larger and significant, and it lasts for more months than the drop in essential goods. This was an expected result. (2) The month*percentile coefficient is negative and significant for all months of the non-essential category. This is also an expected result, because climbing up the percentile rank ladder takes us closer to richer households, who have higher discretionary spending to cut back. Nothing conclusive can be said about the month*percentile coefficient on the essential category, as it was surprisingly found to be negative and significant in most months.

4.4 Conclusion

Given the findings from the regression analysis, few inferences can be made to complete the narrative from the previous chapter. The first set of regressions confirmed that the richer households experienced higher drops in consumption expenditure after the first lockdown. Since the month*percentile coefficient was negative and significant in all months, it can be extended that the richer households also had an incomplete recovery. This is in agreement with the findings of Bussolo et al. (2021) and Gupta et al. (2020b). The second set of regressions (with the essential and non-essential categories) are broadly in agreement with the hypothesis that the richer percentiles experienced higher drops in consumption, and they recovered slower because of foregoing discretionary spending. The negative values on the month coefficients for non-essentials were significant and much larger when compared to their essential month counterpart. These negative month coefficients also lasted much longer for non-essential goods. The surprising result here is the negative and significant month*percentile coefficients in the essential category for several months in many iterations of the model- this remains unexplained. However, it is known that the levels between essential and non-essential spending are quite different. Since the level of non-essential spending is relatively much higher, which is also carried out by the richer population, it can still be argued that the drop in these drove down the consumption for the rich. The fact that richer households fared worse-off even in the essential category remains unexplained.

Chapter 5

Conclusion

The thesis started by exploring the dataset. It established some ground rules that were useful throughout the analysis. For instance, because the choice of weights (mean household weight/ first/ last month's weight) does not make a major difference to results, the first household weight of each household was used. Similarly, because recall periods (respondent's data on the first month or fourth month before the interview month) did not change results, all recall periods were assumed to have the same level of accuracy.

Then, a trend analysis of poverty and MPCE by dynamic and static deciles was presented. The main finding on poverty was that India saw a sharp spike in poverty around April 2020, but this recovered to pre-pandemic levels in the months that followed. The dynamic decile analysis suggested that there was no change in inequality during the lockdown (because all deciles had a proportionate fall in consumption), while inequality reduced in the following months (because the poorer deciles recovered quicker). Here, the surprising result was that poorer deciles recovered consumption quicker. The static decile analysis suggested that the pre-pandemic rich witnessed higher drops in consumption even during lockdown. Similar to the dynamic decile case, the pre-pandemic poor recovered consumption quicker. It was hypothesized here that drop in the rich-household-dominated discretionary spending is driving the drop in consumption for the richer households.

The regression analysis was carried out to rigorously verify the trends presented in the static decile analysis of Chapter 3. Its other objective was to bifurcate MPCE into essential and non-essential categories to verify whether the drop in discretionary spending was the reason behind the richer population experiencing higher drops in consumption with a slower recovery. The first set of regressions confirmed that the richer households experienced higher drops in consumption expenditure after the first lockdown. Since the month*percentile coefficient was negative and significant in all months, it the richer households also had an incomplete recovery. This was in agreement with the findings of Bussolo et al. (2021) and Gupta et al. (2020b). The other regression exercise, carried out to provide a mechanism for the counter-intuitive finding supported the hypothesis from Chapter 3, and presented an unexplained result.

The negative values on the month coefficients for non-essentials were significant and much larger when compared to their essential month coefficient counterpart. These negative month coefficients also lasted much longer for non-essential goods. This confirmed that discretionary spending witnessed a higher fall in spending, and the fall lasted longer when compared with essential goods. Next, the month*percentile interaction coefficients were negative and significant for the non-essential category for all months. This was expected- the richer percentiles carry out more discretionary spending, so as we increase percentile rank by one unit, discretionary spending will fall further. The surprising result here was the negative and significant month*percentile coefficients on the essential category for several months in many iterations of the model- this remains unexplained. However, since the level of non-essential spending is relatively much higher, which is also carried out by the richer population, it can still be argued that the drop in these drove down the consumption for the rich. The fact that richer households fared worse-off even in the essential category remains unexplained.

This thesis contributes to the existing literature by providing a mechanism that explains the counter-intuitive finding (richer population experienced a higher fall in consumption and had a slower recovery). For future research, it might be worthwhile to examine trends in consumption expenditure, disaggregated by occupations. The prior there is that some kinds of occupations are expected to be less affected by exogenous shocks.

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Appendix A

Regression Results

A.1 Changes in Consumption: Basic Model

A.1.1 With State FE

Dependent Variable:	$\Delta Consumption_{i,t}$	
Model:	Rural	Urban
Variables		
Feb_2020	-0.0905***	-0.0811***
	(0.0065)	(0.0058)
Mar_2020	-0.1589***	-0.1710***
	(0.0068)	(0.0052)
Apr_2020	-0.3718***	-0.4526***
	(0.0065)	(0.0056)
May_2020	-0.3097***	-0.3793***
	(0.0067)	(0.0059)
Jun_2020	-0.1701***	-0.2474***
	(0.0068)	(0.0062)
Jul_2020	-0.1243***	-0.1863***
	(0.0066)	(0.0059)
Aug_2020	-0.0633***	-0.1178***
	(0.0066)	(0.0078)
Sep_2020	-0.0394***	-0.0879***
	(0.0066)	(0.0059)
Oct_2020	0.0224***	-0.0438***
	(0.0066)	(0.0060)
Nov_2020	0.0858***	0.0135**
	(0.0067)	(0.0059)
Dec_2020	0.0217***	-0.0622***
	(0.0066)	(0.0059)
Jan_2021	-0.0062	-0.0406***
	(0.0066)	(0.0060)

Feb_2021	-0.0149**	-0.0261***
	(0.0072)	(0.0060)
Mar_2021	0.0089	-0.0017
	(0.0068)	(0.0062)
Apr_2021	0.0190***	0.0814
	(0.0068)	(0.0854)
May_2021	0.0133*	-0.0493***
	(0.0069)	(0.0059)
Jun_2021	0.0951***	-0.0048
	(0.0084)	(0.0058)
Jul_2021	0.1415***	0.0428***
	(0.0069)	(0.0058)
Aug_2021	0.1733***	0.0790***
	(0.0068)	(0.0061)
Sep_2021	0.2101***	0.0906***
	(0.0071)	(0.0061)
Oct_2021	0.2749***	0.1469***
	(0.0073)	(0.0061)
Jan_2020 × State_Static_Pctile	-0.0021***	-0.0008***
	(0.0003)	(0.0003)
Feb_2020 × State_Static_Pctile	-0.0028***	-0.0018***
	(0.0001)	(0.0003)
Mar_2020 × State_Static_Pctile	-0.0036***	-0.0023***
	(0.0001)	(0.0002)
Apr_2020 × State_Static_Pctile	-0.0029***	-0.0025***
	(8.34×10^{-5})	(9.92×10^{-5})
May_2020 × State_Static_Pctile	-0.0032***	-0.0027***
	(8.73×10^{-5})	(10×10^{-5})
Jun_2020 × State_Static_Pctile	-0.0036***	-0.0034***
	(9.81×10^{-5})	(0.0001)
Jul_2020 × State_Static_Pctile	-0.0036***	-0.0037***
	(8.76×10^{-5})	(0.0001)
Aug_2020 × State_Static_Pctile	-0.0038***	-0.0040***
	(8.3×10^{-5})	(0.0001)
Sep_2020 × State_Static_Pctile	-0.0041***	-0.0042***
	(7.96×10^{-5})	(9.52×10^{-5})
Oct_2020 × State_Static_Pctile	-0.0045***	-0.0045***
	(8.09×10^{-5})	(9.96×10^{-5})
Nov_2020 × State_Static_Pctile	-0.0048***	-0.0044***
	(8.83×10^{-5})	(8.54×10^{-5})
Dec_2020 × State_Static_Pctile	-0.0046***	-0.0043***
	(7.94×10^{-5})	(8.2×10^{-5})
Jan_2021 × State_Static_Pctile	-0.0045***	-0.0042***
	(8.55×10^{-5})	(9.53×10^{-5})
Feb_2021 × State_Static_Pctile	-0.0049***	-0.0043***
	(0.0001)	(9.66×10^{-5})
Mar_2021 × State_Static_Pctile	-0.0050***	-0.0045***
	(9.34×10^{-5})	(0.0001)

Apr_2021 × State_Static_Pctile	-0.0052***	-0.0085**
	(9.67×10^{-5})	(0.0041)
May_2021 × State_Static_Pctile	-0.0052***	-0.0049***
	(0.0001)	(8.52×10^{-5})
Jun_2021 × State_Static_Pctile	-0.0053***	-0.0052***
	(0.0002)	(8.36×10^{-5})
Jul_2021 × State_Static_Pctile	-0.0055***	-0.0053***
	(0.0001)	(8.24×10^{-5})
Aug_2021 × State_Static_Pctile	-0.0058***	-0.0056***
	(0.0001)	(0.0001)
Sep_2021 × State_Static_Pctile	-0.0062***	-0.0057***
	(0.0001)	(0.0001)
Oct_2021 × State_Static_Pctile	-0.0066***	-0.0059***
	(0.0001)	(0.0001)
Fixed-effects		
as.factor(state)	Yes	Yes
Fit statistics		
Observations	792,574	1,672,266
R^2	0.15245	0.00189
Within R^2	0.13760	0.00157

Clustered (hhid) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

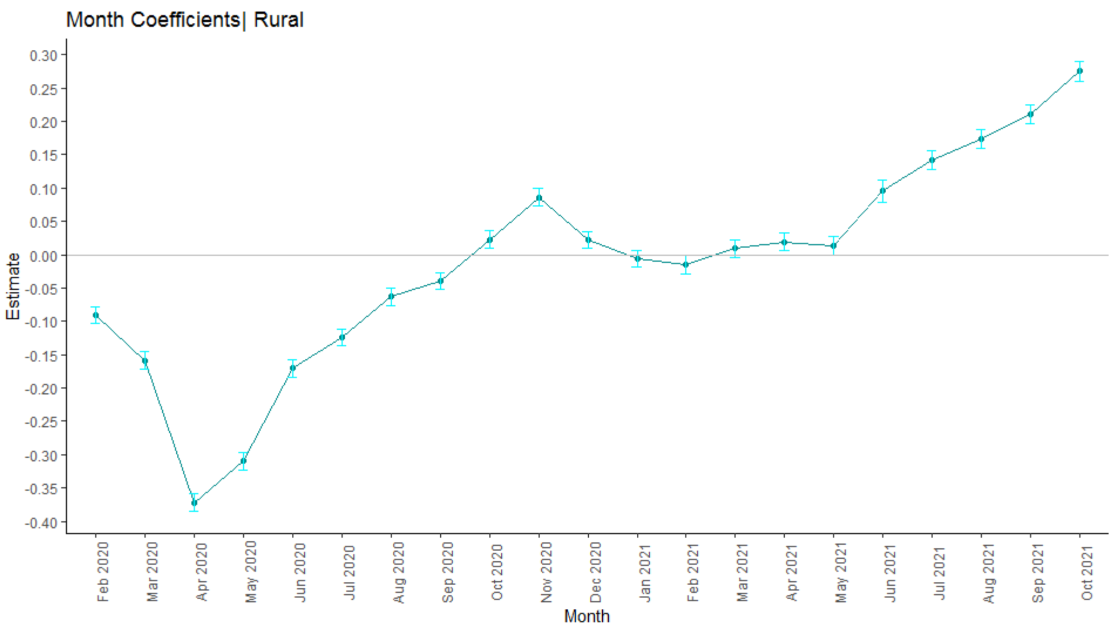

Figure A.1: Rural month coefficients

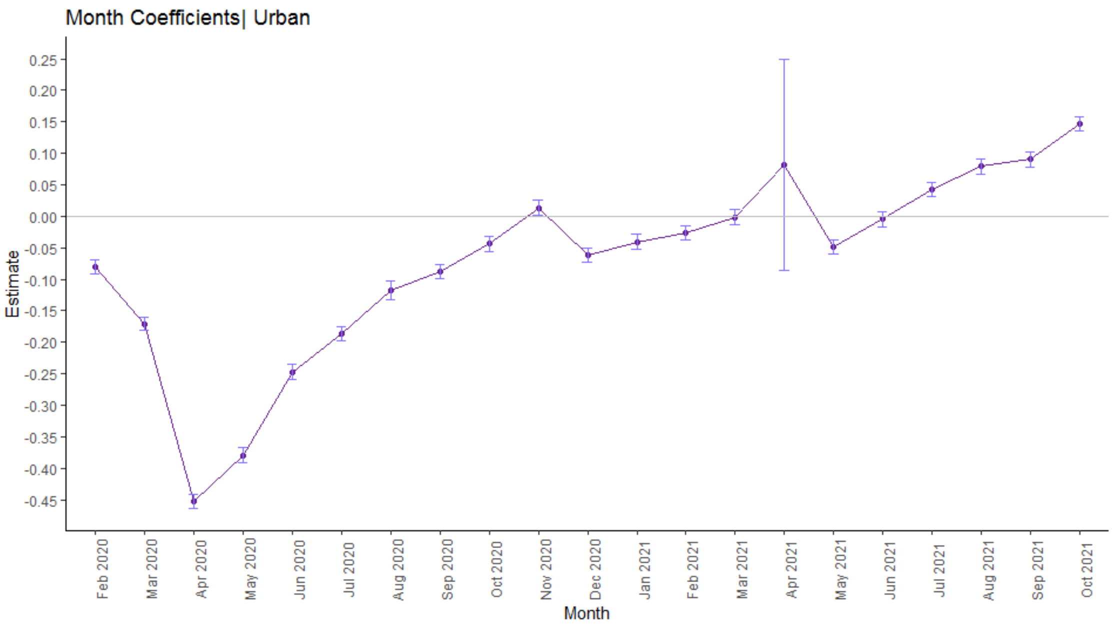

Figure A.2: Urban month coefficients

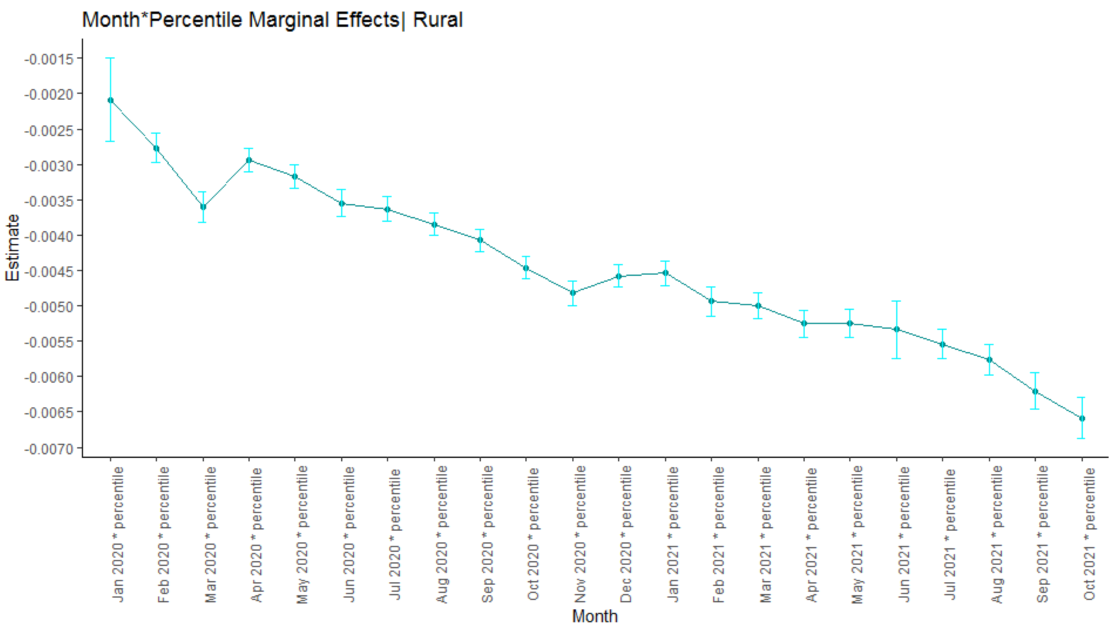

Figure A.3: Progressive impact: interaction coefficient is negative and significant for all months

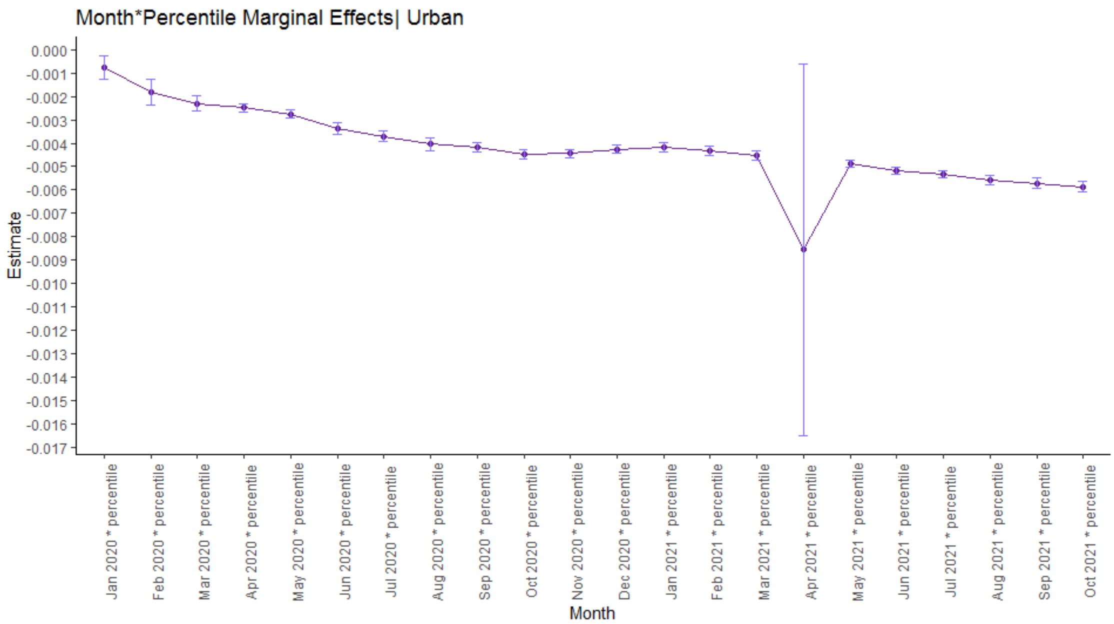

Figure A.4: Progressive impact: interaction coefficient is negative and significant for all months

A.1.2 Without State FE

Removing the State fixed effects have no impact on the results.

Dependent Variable:	$\Delta Consumption_{i,t}$	
Model:	Rural	Urban
Variables		
(Intercept)	0.0419***	0.0668***
	(0.0062)	(0.0063)
Feb_2020	-0.0909***	-0.0830***
	(0.0065)	(0.0056)
Mar_2020	-0.1594***	-0.1738***
	(0.0069)	(0.0060)
Apr_2020	-0.3712***	-0.4560***
	(0.0065)	(0.0063)
May_2020	-0.3095***	-0.3830***
	(0.0067)	(0.0066)
Jun_2020	-0.1698***	-0.2525***
	(0.0068)	(0.0069)
Jul_2020	-0.1238***	-0.1911***
	(0.0066)	(0.0066)
Aug_2020	-0.0630***	-0.1238***
	(0.0066)	(0.0083)
Sep_2020	-0.0391***	-0.0936***
	(0.0066)	(0.0066)
Oct_2020	0.0226***	-0.0502***

	(0.0066)	(0.0067)
Nov_2020	0.0860***	0.0069
	(0.0067)	(0.0066)
Dec_2020	0.0215***	-0.0677***
	(0.0066)	(0.0066)
Jan_2021	-0.0072	-0.0456***
	(0.0066)	(0.0067)
Feb_2021	-0.0171**	-0.0290***
	(0.0072)	(0.0067)
Mar_2021	0.0072	-0.0053
	(0.0068)	(0.0068)
Apr_2021	0.0176***	0.0742
	(0.0068)	(0.0817)
May_2021	0.0130*	-0.0534***
	(0.0069)	(0.0065)
Jun_2021	0.0951***	-0.0118*
	(0.0085)	(0.0065)
Jul_2021	0.1415***	0.0356***
	(0.0069)	(0.0065)
Aug_2021	0.1728***	0.0709***
	(0.0068)	(0.0067)
Sep_2021	0.2092***	0.0822***
	(0.0071)	(0.0068)
Oct_2021	0.2745***	0.1378***
	(0.0073)	(0.0068)
Jan_2020 × Static_Pctile	-0.0018***	-0.0006***
	(0.0003)	(0.0002)
Feb_2020 × Static_Pctile	-0.0025***	-0.0017***
	(0.0001)	(0.0003)
Mar_2020 × Static_Pctile	-0.0034***	-0.0023***
	(0.0001)	(0.0001)
Apr_2020 × Static_Pctile	-0.0034***	-0.0027***
	(8.49×10^{-5})	(8.44×10^{-5})
May_2020 × Static_Pctile	-0.0031***	-0.0028***
	(9.24×10^{-5})	(7.73×10^{-5})
Jun_2020 × Static_Pctile	-0.0035***	-0.0035***
	(9.84×10^{-5})	(9.51×10^{-5})
Jul_2020 × Static_Pctile	-0.0036***	-0.0036***
	(9.23×10^{-5})	(8.59×10^{-5})
Aug_2020 × Static_Pctile	-0.0038***	-0.0040***
	(8.64×10^{-5})	(8.32×10^{-5})
Sep_2020 × Static_Pctile	-0.0043***	-0.0041***
	(8.41×10^{-5})	(7.78×10^{-5})
Oct_2020 × Static_Pctile	-0.0048***	-0.0043***
	(8.19×10^{-5})	(8.17×10^{-5})
Nov_2020 × Static_Pctile	-0.0053***	-0.0044***
	(9.01×10^{-5})	(7.16×10^{-5})
Dec_2020 × Static_Pctile	-0.0046***	-0.0039***

	(8.04×10^{-5})	(6.68×10^{-5})
Jan_2021 × Static_Pctile	-0.0039***	-0.0036***
	(8.69×10^{-5})	(7.99×10^{-5})
Feb_2021 × Static_Pctile	-0.0038***	-0.0036***
	(0.0001)	(8.53×10^{-5})
Mar_2021 × Static_Pctile	-0.0042***	-0.0040***
	(9.88×10^{-5})	(9.07×10^{-5})
Apr_2021 × Static_Pctile	-0.0044***	-0.0069**
	(0.0001)	(0.0030)
May_2021 × Static_Pctile	-0.0051***	-0.0049***
	(0.0001)	(6.94×10^{-5})
Jun_2021 × Static_Pctile	-0.0054***	-0.0050***
	(0.0001)	(7.11×10^{-5})
Jul_2021 × Static_Pctile	-0.0055***	-0.0051***
	(0.0001)	(7.17×10^{-5})
Aug_2021 × Static_Pctile	-0.0055***	-0.0055***
	(0.0001)	(8.38×10^{-5})
Sep_2021 × Static_Pctile	-0.0062***	-0.0056***
	(0.0001)	(9.4×10^{-5})
Oct_2021 × Static_Pctile	-0.0070***	-0.0059***
	(0.0002)	(9.73×10^{-5})
Fit statistics		
Observations	792,574	1,672,266
R^2	0.13317	0.00155
Adjusted R^2	0.13312	0.00152

Clustered (hhid) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

A.2 Changes in Consumption: Robustness Check

A.2.1 Model with state fixed effects for an unbalanced panel.

$\hat{Y}$ was made for each month at the household level using the linear trend of consumption between Jan 2018 till Feb 2020. Static percentile ranks were assigned state-wise and region-wise based on the distribution of average consumption of households between Jan 2018 and Feb 2020. Note: month 74 is Feb 2020.

Dependent Variable:	Percentage change from $\hat{Y}$	
Model:	Rural	Urban
Variables		
Feb_2020	-0.0534***	0.0217
	(0.0092)	(0.0423)
Mar_2020	-0.0373*	-0.0093
	(0.0213)	(0.0607)

Apr_2020	-0.2761***	-0.2305***
	(0.0132)	(0.0485)
May_2020	-0.1989***	-0.1724***
	(0.0169)	(0.0430)
Jun_2020	-0.0109	-0.0548
	(0.0401)	(0.0526)
Jul_2020	-0.1311	0.0904
	(0.1229)	(0.1515)
Aug_2020	0.0237	-1.046
	(0.0576)	(1.769)
Sep_2020	0.1154***	0.1234
	(0.0398)	(0.0789)
Oct_2020	0.2861**	-0.0246
	(0.1138)	(0.2297)
Nov_2020	0.2559***	0.9810
	(0.0716)	(1.015)
Dec_2020	0.3008***	4.138
	(0.1143)	(4.215)
Jan_2021	0.3212***	0.8084
	(0.1238)	(1.009)
Feb_2021	0.1682	-0.3560
	(0.1244)	(0.6432)
Mar_2021	-0.0964	0.1531*
	(0.4081)	(0.0782)
Apr_2021	0.7657*	0.5184*
	(0.4475)	(0.3150)
May_2021	0.4192	0.0268
	(0.3886)	(0.1651)
Jun_2021	-0.1857	0.2343
	(0.3847)	(0.3368)
Jul_2021	0.1063	1.292
	(0.2340)	(0.8922)
Aug_2021	0.3375	-0.1714
	(0.2504)	(0.5982)
Sep_2021	0.9857	-0.2860
	(0.6060)	(1.523)
State_Static_Pctile	-0.0007**	-0.0006
	(0.0003)	(0.0008)
Feb_2020 × State_Static_Pctile	-0.0004*	-0.0022**
	(0.0003)	(0.0009)
Mar_2020 × State_Static_Pctile	-0.0018***	-0.0026**
	(0.0004)	(0.0013)
Apr_2020 × State_Static_Pctile	-0.0012***	-0.0037***
	(0.0004)	(0.0012)
May_2020 × State_Static_Pctile	-0.0012**	-0.0030***
	(0.0006)	(0.0009)
Jun_2020 × State_Static_Pctile	-0.0032**	-0.0029**
	(0.0014)	(0.0013)

Jul_2020 × State_Static_Pctile	0.0032	-0.0042**
	(0.0046)	(0.0017)
Aug_2020 × State_Static_Pctile	-0.0019*	-0.0148
	(0.0011)	(0.0093)
Sep_2020 × State_Static_Pctile	-0.0021**	-0.0032
	(0.0009)	(0.0025)
Oct_2020 × State_Static_Pctile	-0.0037**	-0.0018
	(0.0017)	(0.0062)
Nov_2020 × State_Static_Pctile	-0.0027	-0.0335
	(0.0027)	(0.0365)
Dec_2020 × State_Static_Pctile	-0.0041*	-0.1366
	(0.0022)	(0.1466)
Jan_2021 × State_Static_Pctile	-0.0081**	0.0028
	(0.0035)	(0.0047)
Feb_2021 × State_Static_Pctile	-0.0055**	0.0021
	(0.0026)	(0.0071)
Mar_2021 × State_Static_Pctile	0.0062	-0.0029
	(0.0106)	(0.0022)
Apr_2021 × State_Static_Pctile	-0.0090*	-0.0092*
	(0.0049)	(0.0050)
May_2021 × State_Static_Pctile	-0.0049	0.0022
	(0.0109)	(0.0067)
Jun_2021 × State_Static_Pctile	0.0104	-0.0009
	(0.0086)	(0.0060)
Jul_2021 × State_Static_Pctile	-0.0069	-0.0273
	(0.0063)	(0.0277)
Aug_2021 × State_Static_Pctile	-0.0012	0.0078
	(0.0052)	(0.0161)
Sep_2021 × State_Static_Pctile	-0.0175*	0.0085
	(0.0093)	(0.0222)
Fixed-effects		
as.factor(state_no)	Yes	Yes
Fit statistics		
Observations	756,712	1,588,306
R^2	0.00015	3.17×10^{-5}
Within R^2	0.00011	2.29×10^{-5}

Clustered (hhid) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

A.2.2 Model without state fixed effects for an unbalanced panel

$\hat{Y}$ was made for each month at the household level using the linear trend of consumption between Jan 2018 till Feb 2020. Static percentile ranks were assigned region-wise based on the distribution of average consumption of households between Jan 2018 and Feb 2020.

Dependent Variable:	Percentage change from $\hat{Y}$	
Model:	Rural	Urban
Variables		
(Intercept)	-0.0136**	-0.0418***
	(0.0068)	(0.0101)
Feb_2020	-0.0491***	-0.0241*
	(0.0075)	(0.0132)
Mar_2020	-0.0360*	-0.0638***
	(0.0192)	(0.0179)
Apr_2020	-0.2438***	-0.2443***
	(0.0100)	(0.0311)
May_2020	-0.1976***	-0.1785***
	(0.0194)	(0.0199)
Jun_2020	0.0035	-0.0449
	(0.0477)	(0.0427)
Jul_2020	-0.1201	0.1869
	(0.1098)	(0.2420)
Aug_2020	0.0699**	-3.263
	(0.0298)	(3.836)
Sep_2020	0.1375***	0.2088**
	(0.0397)	(0.0823)
Oct_2020	0.3164***	0.0165
	(0.1104)	(0.1694)
Nov_2020	0.1501	0.1361
	(0.1312)	(0.1294)
Dec_2020	0.2609**	5.585
	(0.1176)	(5.759)
Jan_2021	0.2551*	0.2646
	(0.1438)	(0.5032)
Feb_2021	0.0847	-0.0960
	(0.1172)	(0.4429)
Mar_2021	-0.0540	0.1660**
	(0.2843)	(0.0794)
Apr_2021	0.2085	0.6131**
	(0.1573)	(0.2772)
May_2021	0.4247	0.2902**
	(0.2837)	(0.1343)
Jun_2021	0.0025	0.2711
	(0.4650)	(0.2924)
Jul_2021	0.4014*	0.9888
	(0.2296)	(0.7514)
Aug_2021	0.7869	0.6086**
	(0.5486)	(0.2570)
Sep_2021	1.070*	0.1177
	(0.6269)	(1.152)
static_pctile	-0.0003	0.0008***

	(0.0002)	(0.0003)
Feb_2020 × static_pctile	-0.0006**	-0.0012***
	(0.0002)	(0.0004)
Mar_2020 × static_pctile	-0.0019***	-0.0015***
	(0.0004)	(0.0005)
Apr_2020 × static_pctile	-0.0019***	-0.0033***
	(0.0003)	(0.0009)
May_2020 × static_pctile	-0.0013**	-0.0028***
	(0.0007)	(0.0004)
Jun_2020 × static_pctile	-0.0036**	-0.0031***
	(0.0016)	(0.0012)
Jul_2020 × static_pctile	0.0032	-0.0060*
	(0.0046)	(0.0034)
Aug_2020 × static_pctile	-0.0029**	0.0292
	(0.0013)	(0.0358)
Sep_2020 × static_pctile	-0.0026***	-0.0048**
	(0.0009)	(0.0022)
Oct_2020 × static_pctile	-0.0045***	-0.0026
	(0.0017)	(0.0043)
Nov_2020 × static_pctile	-0.0007	-0.0167
	(0.0039)	(0.0176)
Dec_2020 × static_pctile	-0.0035*	-0.1640
	(0.0020)	(0.1758)
Jan_2021 × static_pctile	-0.0072*	0.0136
	(0.0039)	(0.0108)
Feb_2021 × static_pctile	-0.0041	-0.0032
	(0.0026)	(0.0034)
Mar_2021 × static_pctile	0.0057	-0.0032
	(0.0085)	(0.0022)
Apr_2021 × static_pctile	0.0019	-0.0111***
	(0.0065)	(0.0038)
May_2021 × static_pctile	-0.0052	-0.0031
	(0.0090)	(0.0051)
Jun_2021 × static_pctile	0.0070	-0.0016
	(0.0085)	(0.0057)
Jul_2021 × static_pctile	-0.0133*	-0.0212
	(0.0073)	(0.0252)
Aug_2021 × static_pctile	-0.0105	-0.0078
	(0.0085)	(0.0102)
Sep_2021 × static_pctile	-0.0201**	0.0003
	(0.0101)	(0.0169)
Fit statistics		
Observations	756,712	1,588,306
R^2	0.00012	2.77×10^{-5}
Adjusted R^2	6.15×10^{-5}	1.86×10^{-6}

Clustered (hhid) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Essential and Non-essential Spending

Presented below are two sets of regression results. While the first set has multiple items under the essential heading, the second set only has four food items under the essential heading. These two extreme models give similar results: (1) The drop in essential consumption is small and significant for a few months around the lockdown, while the drop in non-essential consumption is large and significant for more months, and (2) Nothing conclusive can be said about the percentile coefficients- they are strangely negative in many tables presented below.

A.3 With a broader set of items in essentials

The table below lists how the total consumption was split between essential and non-essential heads.

Table A.5: The Binning of Variables

Essentials	**Non-essentials**
cereals and pulses	ghee
(adjusted) edible oils	dry fruits and saffron
dry spices	(adjusted)mithai
(adjusted) vegetables and wet spices	(adjuated) bread
(adjusted) fruits	(adjusted) biscuits
(adjusted) potatoes and onions	(adjusted) namkeens and salty snacks
(adjusted) milk and milk powder	noodles and flakes
(adjusted) meat, eggs and fish	(adjusted) chocolates, cakes and ice-cream
tea/coffee	jam/ketchup/pickles
sugar and other sweeteners	health supplements
	ready-to-eat food
	(adjusted) beverages and water
	juices/jams
	baby food
	other
(monthly) bills and rent	(monthly) clothing and footwear
(adjusted) power and fuel	(monthly) cosmetics and toiletries
(monthly) education	(monthly) appliances
(monthly) health - parlor and spas	(adjusted) restaurants
(monthly) all EMIs	(monthly) recreation
	(adjusted) transport (remainder)
Daily Bus/Train/Ferry Fare	(monthly) misc items
Auto-rickshaw/Taxi Fare	(monthly) communication and info (remainder)
cell phone	(monthly) all types of detergent

A.3.1 Rural, With State FE

Note: Since this model has state fixed effects, the static percentile assignment was done by region and by state. The Y variable is the difference between essential(non-essential) expenditure and 2019's mean essential(non-essential) expenditure, divided by the 2019's mean essential(non-essential) expenditure. Column 1 is for essential while column 2 is for non-essential.

Dependent Variables:	ΔEssentials	ΔNon-Essentials
Model:	(1)	(2)
Variables		
Feb_2020	-0.0399***	-0.1247***
	(0.0038)	(0.0120)
Mar_2020	-0.0575***	-0.2277***
	(0.0026)	(0.0125)
Apr_2020	-0.1369***	-0.5491***
	(0.0032)	(0.0118)
May_2020	-0.0991***	-0.4682***
	(0.0038)	(0.0120)
Jun_2020	-0.0389***	-0.2615***
	(0.0030)	(0.0123)
Jul_2020	0.0011	-0.2127***
	(0.0029)	(0.0120)
Aug_2020	0.0326***	-0.1252***
	(0.0028)	(0.0120)
Sep_2020	0.0648***	-0.1078***
	(0.0027)	(0.0120)
Oct_2020	0.0988***	-0.0221*
	(0.0027)	(0.0119)
Nov_2020	0.1361***	0.0605***
	(0.0028)	(0.0120)
Dec_2020	0.1036***	-0.0289**
	(0.0027)	(0.0119)
Jan_2021	0.0750***	-0.0568***
	(0.0028)	(0.0120)
Feb_2021	0.0779***	-0.0732***
	(0.0030)	(0.0129)
Mar_2021	0.1103***	-0.0561***
	(0.0032)	(0.0121)
Apr_2021	0.1336***	-0.0567***
	(0.0034)	(0.0121)
May_2021	0.1427***	-0.0723***
	(0.0033)	(0.0122)
Jun_2021	0.1911***	0.0336**
	(0.0033)	(0.0148)
Jul_2021	0.2298***	0.0892***
	(0.0036)	(0.0121)

Aug_2021	0.2552***	0.1248***
	(0.0036)	(0.0121)
Sep_2021	0.2927***	0.1660***
	(0.0044)	(0.0122)
Oct_2021	0.3539***	0.2363***
	(0.0052)	(0.0123)
Jan_2020 × State_Static_Pctile	-0.0010***	-0.0027***
	(7.39×10^{-5})	(0.0006)
Feb_2020 × State_Static_Pctile	-0.0019***	-0.0033***
	(9.24×10^{-5})	(0.0001)
Mar_2020 × State_Static_Pctile	-0.0024***	-0.0042***
	(0.0001)	(0.0002)
Apr_2020 × State_Static_Pctile	-0.0026***	-0.0025***
	(0.0001)	(9.17×10^{-5})
May_2020 × State_Static_Pctile	-0.0024***	-0.0031***
	(0.0001)	(0.0001)
Jun_2020 × State_Static_Pctile	-0.0024***	-0.0041***
	(8.98×10^{-5})	(0.0001)
Jul_2020 × State_Static_Pctile	-0.0026***	-0.0040***
	(8.43×10^{-5})	(0.0001)
Aug_2020 × State_Static_Pctile	-0.0027***	-0.0045***
	(8.09×10^{-5})	(0.0001)
Sep_2020 × State_Static_Pctile	-0.0030***	-0.0045***
	(7.7×10^{-5})	(0.0001)
Oct_2020 × State_Static_Pctile	-0.0034***	-0.0051***
	(7.88×10^{-5})	(0.0001)
Nov_2020 × State_Static_Pctile	-0.0036***	-0.0056***
	(8.13×10^{-5})	(0.0001)
Dec_2020 × State_Static_Pctile	-0.0037***	-0.0049***
	(7.76×10^{-5})	(0.0001)
Jan_2021 × State_Static_Pctile	-0.0035***	-0.0050***
	(8.22×10^{-5})	(0.0001)
Feb_2021 × State_Static_Pctile	-0.0036***	-0.0056***
	(8.77×10^{-5})	(0.0002)
Mar_2021 × State_Static_Pctile	-0.0039***	-0.0055***
	(9.56×10^{-5})	(0.0001)
Apr_2021 × State_Static_Pctile	-0.0038***	-0.0061***
	(0.0001)	(0.0001)
May_2021 × State_Static_Pctile	-0.0041***	-0.0058***
	(0.0001)	(0.0001)
Jun_2021 × State_Static_Pctile	-0.0042***	-0.0059***
	(0.0001)	(0.0003)
Jul_2021 × State_Static_Pctile	-0.0041***	-0.0063***
	(0.0001)	(0.0001)
Aug_2021 × State_Static_Pctile	-0.0043***	-0.0065***
	(0.0001)	(0.0001)
Sep_2021 × State_Static_Pctile	-0.0048***	-0.0070***
	(0.0002)	(0.0001)

Oct_2021 × State_Static_Pctile	-0.0050***	-0.0075***
	(0.0002)	(0.0002)
Fixed-effects		
as.factor(state)	Yes	Yes
Fit statistics		
Observations	792,232	792,574
R^2	0.14571	0.09916
Within R^2	0.12187	0.08901

Clustered (hhid) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

A.3.2 Urban, With State FE

The same regression as above, run on the urban subset.

Dependent Variables:	ΔEssentials	ΔNon-Essentials
Model:	(1)	(2)
Variables		
Feb_2020	-0.0195***	-0.1177***
	(0.0017)	(0.0112)
Mar_2020	-0.0325***	-0.2585***
	(0.0027)	(0.0073)
Apr_2020	-0.1763***	-0.6324***
	(0.0033)	(0.0076)
May_2020	-0.1250***	-0.5429***
	(0.0035)	(0.0081)
Jun_2020	-0.0644***	-0.3586***
	(0.0034)	(0.0088)
Jul_2020	-0.0137***	-0.2927***
	(0.0035)	(0.0082)
Aug_2020	0.0355***	-0.2090***
	(0.0031)	(0.0113)
Sep_2020	0.0662***	-0.1791***
	(0.0030)	(0.0083)
Oct_2020	0.0927***	-0.1212***
	(0.0034)	(0.0083)
Nov_2020	0.1038***	-0.0323***
	(0.0030)	(0.0082)
Dec_2020	0.0825***	-0.1477***
	(0.0031)	(0.0081)
Jan_2021	0.0852***	-0.1144***
	(0.0032)	(0.0083)
Feb_2021	0.1179***	-0.1118***
	(0.0031)	(0.0082)
Mar_2021	0.1315***	-0.0778***
	(0.0031)	(0.0089)
Apr_2021	0.1414***	0.0394
	(0.0030)	(0.1320)
May_2021	0.1406***	-0.1654***
	(0.0029)	(0.0081)
Jun_2021	0.1473***	-0.0946***
	(0.0028)	(0.0081)
Jul_2021	0.1880***	-0.0427***
	(0.0028)	(0.0081)
Aug_2021	0.2205***	-0.0007
	(0.0032)	(0.0083)
Sep_2021	0.2426***	0.0059
	(0.0035)	(0.0085)

Oct_2021	0.2811***	0.0774***
	(0.0036)	(0.0084)
Jan_2020 × State_Static_Pctile	-0.0007***	-0.0007**
	(7.82×10^{-5})	(0.0003)
Feb_2020 × State_Static_Pctile	-0.0010***	-0.0022***
	(8.98×10^{-5})	(0.0005)
Mar_2020 × State_Static_Pctile	-0.0010***	-0.0026***
	(0.0001)	(0.0002)
Apr_2020 × State_Static_Pctile	-0.0017***	-0.0020***
	(0.0001)	(0.0001)
May_2020 × State_Static_Pctile	-0.0018***	-0.0023***
	(9.87×10^{-5})	(0.0001)
Jun_2020 × State_Static_Pctile	-0.0023***	-0.0033***
	(9.65×10^{-5})	(0.0002)
Jul_2020 × State_Static_Pctile	-0.0024***	-0.0038***
	(9.82×10^{-5})	(0.0001)
Aug_2020 × State_Static_Pctile	-0.0028***	-0.0042***
	(8.41×10^{-5})	(0.0002)
Sep_2020 × State_Static_Pctile	-0.0030***	-0.0043***
	(8.03×10^{-5})	(0.0001)
Oct_2020 × State_Static_Pctile	-0.0031***	-0.0048***
	(9.02×10^{-5})	(0.0002)
Nov_2020 × State_Static_Pctile	-0.0032***	-0.0048***
	(8.16×10^{-5})	(0.0001)
Dec_2020 × State_Static_Pctile	-0.0031***	-0.0043***
	(8.32×10^{-5})	(0.0001)
Jan_2021 × State_Static_Pctile	-0.0030***	-0.0044***
	(9.09×10^{-5})	(0.0001)
Feb_2021 × State_Static_Pctile	-0.0031***	-0.0045***
	(9.44×10^{-5})	(0.0001)
Mar_2021 × State_Static_Pctile	-0.0032***	-0.0049***
	(8.99×10^{-5})	(0.0001)
Apr_2021 × State_Static_Pctile	-0.0033***	-0.0110*
	(8.58×10^{-5})	(0.0063)
May_2021 × State_Static_Pctile	-0.0035***	-0.0050***
	(7.74×10^{-5})	(0.0001)
Jun_2021 × State_Static_Pctile	-0.0036***	-0.0056***
	(7.27×10^{-5})	(0.0001)
Jul_2021 × State_Static_Pctile	-0.0038***	-0.0056***
	(7.22×10^{-5})	(0.0001)
Aug_2021 × State_Static_Pctile	-0.0037***	-0.0061***
	(8.38×10^{-5})	(0.0001)
Sep_2021 × State_Static_Pctile	-0.0036***	-0.0064***
	(0.0001)	(0.0001)
Oct_2021 × State_Static_Pctile	-0.0035***	-0.0067***
	(0.0001)	(0.0002)
Fixed-effects		

as.factor(state)	Yes	Yes
Fit statistics		
Observations	1,671,903	1,672,266
R^2	0.14134	0.00112
Within R^2	0.11547	0.00089

Clustered (hhid) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

A.3.3 Rural, Without State FE

For the models that follow, the percentile assignment was done only by region.

Dependent Variables:	ΔEssentials	ΔNon-Essentials
Model:	(1)	(2)
Variables		
(Intercept)	0.0740***	0.0307***
	(0.0020)	(0.0116)
Feb_2020	-0.0405***	-0.1250***
	(0.0038)	(0.0119)
Mar_2020	-0.0585***	-0.2280***
	(0.0026)	(0.0125)
Apr_2020	-0.1372***	-0.5481***
	(0.0032)	(0.0117)
May_2020	-0.0994***	-0.4679***
	(0.0038)	(0.0120)
Jun_2020	-0.0392***	-0.2609***
	(0.0031)	(0.0123)
Jul_2020	0.0009	-0.2117***
	(0.0029)	(0.0120)
Aug_2020	0.0324***	-0.1248***
	(0.0029)	(0.0120)
Sep_2020	0.0645***	-0.1071***
	(0.0027)	(0.0120)
Oct_2020	0.0988***	-0.0218*
	(0.0027)	(0.0119)
Nov_2020	0.1364***	0.0606***
	(0.0028)	(0.0120)
Dec_2020	0.1031***	-0.0289**
	(0.0027)	(0.0119)
Jan_2021	0.0739***	-0.0577***
	(0.0029)	(0.0120)
Feb_2021	0.0756***	-0.0753***
	(0.0030)	(0.0129)
Mar_2021	0.1083***	-0.0577***
	(0.0033)	(0.0121)

Apr_2021	0.1325***	-0.0584***
	(0.0034)	(0.0121)
May_2021	0.1420***	-0.0722***
	(0.0033)	(0.0122)
Jun_2021	0.1907***	0.0338**
	(0.0033)	(0.0149)
Jul_2021	0.2295***	0.0892***
	(0.0036)	(0.0121)
Aug_2021	0.2546***	0.1243***
	(0.0037)	(0.0121)
Sep_2021	0.2918***	0.1651***
	(0.0044)	(0.0121)
Oct_2021	0.3533***	0.2359***
	(0.0052)	(0.0123)
Jan_2020 × Static_Pctile	-0.0010***	-0.0021***
	(7.41×10^{-5})	(0.0006)
Feb_2020 × Static_Pctile	-0.0016***	-0.0028***
	(0.0001)	(0.0002)
Mar_2020 × Static_Pctile	-0.0021***	-0.0039***
	(0.0001)	(0.0002)
Apr_2020 × Static_Pctile	-0.0026***	-0.0028***
	(0.0001)	(8.94×10^{-5})
May_2020 × Static_Pctile	-0.0023***	-0.0028***
	(0.0001)	(0.0001)
Jun_2020 × Static_Pctile	-0.0022***	-0.0038***
	(9.15×10^{-5})	(0.0001)
Jul_2020 × Static_Pctile	-0.0024***	-0.0040***
	(8.87×10^{-5})	(0.0001)
Aug_2020 × Static_Pctile	-0.0026***	-0.0042***
	(8.33×10^{-5})	(0.0001)
Sep_2020 × Static_Pctile	-0.0031***	-0.0048***
	(7.92×10^{-5})	(0.0001)
Oct_2020 × Static_Pctile	-0.0038***	-0.0053***
	(8.16×10^{-5})	(0.0001)
Nov_2020 × Static_Pctile	-0.0043***	-0.0057***
	(8.35×10^{-5})	(0.0001)
Dec_2020 × Static_Pctile	-0.0037***	-0.0048***
	(7.8×10^{-5})	(0.0001)
Jan_2021 × Static_Pctile	-0.0030***	-0.0041***
	(8.23×10^{-5})	(0.0001)
Feb_2021 × Static_Pctile	-0.0024***	-0.0043***
	(8.73×10^{-5})	(0.0002)
Mar_2021 × Static_Pctile	-0.0030***	-0.0046***
	(9.98×10^{-5})	(0.0001)
Apr_2021 × Static_Pctile	-0.0034***	-0.0047***
	(0.0001)	(0.0001)
May_2021 × Static_Pctile	-0.0037***	-0.0055***
	(0.0001)	(0.0002)

Jun_2021 × Static_Pctile	-0.0042***	-0.0058***
	(0.0001)	(0.0002)
Jul_2021 × Static_Pctile	-0.0041***	-0.0060***
	(0.0001)	(0.0001)
Aug_2021 × Static_Pctile	-0.0042***	-0.0060***
	(0.0001)	(0.0001)
Sep_2021 × Static_Pctile	-0.0048***	-0.0070***
	(0.0002)	(0.0002)
Oct_2021 × Static_Pctile	-0.0053***	-0.0078***
	(0.0002)	(0.0002)
Fit statistics		
Observations	792,232	792,574
R^2	0.11613	0.08454
Adjusted R^2	0.11608	0.08449

Clustered (hhid) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

A.3.4 Urban, Without State FE

Dependent Variables:	ΔEssentials	ΔNon-Essentials
Model:	(1)	(2)
Variables		
(Intercept)	0.0747***	0.0740***
	(0.0021)	(0.0273)
Feb_2020	-0.0205***	-0.1200***
	(0.0018)	(0.0386)
Mar_2020	-0.0339***	-0.2616***
	(0.0028)	(0.0386)
Apr_2020	-0.1782***	-0.6350***
	(0.0033)	(0.0386)
May_2020	-0.1271***	-0.5457***
	(0.0035)	(0.0386)
Jun_2020	-0.0676***	-0.3637***
	(0.0034)	(0.0386)
Jul_2020	-0.0166***	-0.2978***
	(0.0034)	(0.0385)
Aug_2020	0.0321***	-0.2157***
	(0.0031)	(0.0385)
Sep_2020	0.0626***	-0.1854***
	(0.0030)	(0.0385)
Oct_2020	0.0889***	-0.1287***
	(0.0034)	(0.0385)
Nov_2020	0.0996***	-0.0402
	(0.0030)	(0.0385)

Dec_2020	0.0787***	-0.1536***
	(0.0031)	(0.0385)
Jan_2021	0.0819***	-0.1198***
	(0.0032)	(0.0384)
Feb_2021	0.1160***	-0.1146***
	(0.0032)	(0.0387)
Mar_2021	0.1293***	-0.0816**
	(0.0031)	(0.0386)
Apr_2021	0.1388***	0.0304
	(0.0030)	(0.0386)
May_2021	0.1374***	-0.1693***
	(0.0029)	(0.0387)
Jun_2021	0.1422***	-0.1024***
	(0.0028)	(0.0385)
Jul_2021	0.1822***	-0.0503
	(0.0028)	(0.0385)
Aug_2021	0.2143***	-0.0095
	(0.0031)	(0.0385)
Sep_2021	0.2364***	-0.0032
	(0.0034)	(0.0385)
Oct_2021	0.2751***	0.0670*
	(0.0035)	(0.0384)
Jan_2020 × Static_Pctile	-0.0008***	-0.0003
	(7.07×10^{-5})	(0.0009)
Feb_2020 × Static_Pctile	-0.0012***	-0.0018*
	(8.62×10^{-5})	(0.0009)
Mar_2020 × Static_Pctile	-0.0014***	-0.0024**
	(0.0001)	(0.0009)
Apr_2020 × Static_Pctile	-0.0019***	-0.0020**
	(9.95×10^{-5})	(0.0009)
May_2020 × Static_Pctile	-0.0019***	-0.0021**
	(9.3×10^{-5})	(0.0009)
Jun_2020 × Static_Pctile	-0.0024***	-0.0034***
	(9×10^{-5})	(0.0009)
Jul_2020 × Static_Pctile	-0.0025***	-0.0035***
	(8.64×10^{-5})	(0.0009)
Aug_2020 × Static_Pctile	-0.0028***	-0.0041***
	(7.47×10^{-5})	(0.0009)
Sep_2020 × Static_Pctile	-0.0030***	-0.0041***
	(7.27×10^{-5})	(0.0009)
Oct_2020 × Static_Pctile	-0.0030***	-0.0046***
	(7.85×10^{-5})	(0.0009)
Nov_2020 × Static_Pctile	-0.0031***	-0.0048***
	(7.26×10^{-5})	(0.0009)
Dec_2020 × Static_Pctile	-0.0029***	-0.0038***
	(7.39×10^{-5})	(0.0009)
Jan_2021 × Static_Pctile	-0.0026***	-0.0035***
	(8.16×10^{-5})	(0.0009)

Feb_2021 × Static_Pctile	-0.0027***	-0.0036***
	(8.6×10^{-5})	(0.0009)
Mar_2021 × Static_Pctile	-0.0029***	-0.0042***
	(8.33×10^{-5})	(0.0009)
Apr_2021 × Static_Pctile	-0.0031***	-0.0085***
	(8.01×10^{-5})	(0.0009)
May_2021 × Static_Pctile	-0.0037***	-0.0049***
	(7.34×10^{-5})	(0.0009)
Jun_2021 × Static_Pctile	-0.0036***	-0.0052***
	(6.98×10^{-5})	(0.0009)
Jul_2021 × Static_Pctile	-0.0040***	-0.0051***
	(7.09×10^{-5})	(0.0009)
Aug_2021 × Static_Pctile	-0.0040***	-0.0057***
	(8.08×10^{-5})	(0.0009)
Sep_2021 × Static_Pctile	-0.0040***	-0.0058***
	(9.78×10^{-5})	(0.0009)
Oct_2021 × Static_Pctile	-0.0039***	-0.0065***
	(0.0001)	(0.0009)
Fit statistics		
Observations	1,671,903	1,672,266
R^2	0.11660	0.00084
Adjusted R^2	0.11658	0.00082

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

A.4 Minimum food variables as essentials

The baseline here is Jan 2019-Dec 2019.
Essentials consist of only four food items: cereals and pulses, edible oils, potatoes and onions, & milk and milk products.

A.4.1 Rural, with State FE

Dependent Variables:	ΔEssentials2	ΔNon-Essentials2
Model:	(1)	(2)
Variables		
Feb_2020	-0.0228***	-0.1095***
	(0.0073)	(0.0088)
Mar_2020	-0.0246***	-0.1975***
	(0.0033)	(0.0093)
Apr_2020	-0.0718***	-0.4692***
	(0.0039)	(0.0088)
May_2020	-0.0675***	-0.3872***

	(0.0049)	(0.0090)
Jun_2020	-0.0484***	-0.2033***
	(0.0034)	(0.0091)
Jul_2020	-0.0216***	-0.1512***
	(0.0033)	(0.0090)
Aug_2020	0.0033	-0.0770***
	(0.0032)	(0.0089)
Sep_2020	0.0349***	-0.0557***
	(0.0030)	(0.0089)
Oct_2020	0.0719***	0.0133
	(0.0031)	(0.0089)
Nov_2020	0.1122***	0.0841***
	(0.0032)	(0.0090)
Dec_2020	0.0782***	0.0101
	(0.0030)	(0.0089)
Jan_2021	0.0479***	-0.0164*
	(0.0032)	(0.0089)
Feb_2021	0.0503***	-0.0274***
	(0.0033)	(0.0097)
Mar_2021	0.0874***	-0.0085
	(0.0037)	(0.0090)
Apr_2021	0.1262***	-0.0087
	(0.0040)	(0.0091)
May_2021	0.1284***	-0.0164*
	(0.0036)	(0.0092)
Jun_2021	0.1646***	0.0809***
	(0.0036)	(0.0113)
Jul_2021	0.2017***	0.1305***
	(0.0038)	(0.0091)
Aug_2021	0.2295***	0.1639***
	(0.0039)	(0.0091)
Sep_2021	0.2629***	0.2037***
	(0.0043)	(0.0093)
Oct_2021	0.3252***	0.2695***
	(0.0049)	(0.0095)
Jan_2020 × State_Static_Pctile	-0.0011***	-0.0023***
	(8.53×10^{-5})	(0.0004)
Feb_2020 × State_Static_Pctile	-0.0018***	-0.0029***
	(0.0001)	(0.0001)
Mar_2020 × State_Static_Pctile	-0.0026***	-0.0037***
	(0.0001)	(0.0001)
Apr_2020 × State_Static_Pctile	-0.0027***	-0.0027***
	(0.0001)	(8.47×10^{-5})
May_2020 × State_Static_Pctile	-0.0023***	-0.0032***
	(0.0001)	(9.75×10^{-5})
Jun_2020 × State_Static_Pctile	-0.0021***	-0.0039***
	(9.78×10^{-5})	(0.0001)
Jul_2020 × State_Static_Pctile	-0.0023***	-0.0039***

	(9.23×10^{-5})	(9.98×10^{-5})
Aug_2020 × State_Static_Pctile	-0.0024***	-0.0042***
	(8.77×10^{-5})	(9.44×10^{-5})
Sep_2020 × State_Static_Pctile	-0.0029***	-0.0043***
	(8.21×10^{-5})	(9.09×10^{-5})
Oct_2020 × State_Static_Pctile	-0.0033***	-0.0048***
	(8.51×10^{-5})	(9.12×10^{-5})
Nov_2020 × State_Static_Pctile	-0.0034***	-0.0052***
	(8.84×10^{-5})	(0.0001)
Dec_2020 × State_Static_Pctile	-0.0035***	-0.0048***
	(8.1×10^{-5})	(9.08×10^{-5})
Jan_2021 × State_Static_Pctile	-0.0032***	-0.0049***
	(8.74×10^{-5})	(9.73×10^{-5})
Feb_2021 × State_Static_Pctile	-0.0033***	-0.0054***
	(9.18×10^{-5})	(0.0001)
Mar_2021 × State_Static_Pctile	-0.0035***	-0.0054***
	(0.0001)	(0.0001)
Apr_2021 × State_Static_Pctile	-0.0034***	-0.0057***
	(0.0001)	(0.0001)
May_2021 × State_Static_Pctile	-0.0037***	-0.0056***
	(0.0001)	(0.0001)
Jun_2021 × State_Static_Pctile	-0.0037***	-0.0057***
	(0.0001)	(0.0003)
Jul_2021 × State_Static_Pctile	-0.0037***	-0.0060***
	(0.0001)	(0.0001)
Aug_2021 × State_Static_Pctile	-0.0039***	-0.0062***
	(0.0001)	(0.0001)
Sep_2021 × State_Static_Pctile	-0.0041***	-0.0068***
	(0.0001)	(0.0001)
Oct_2021 × State_Static_Pctile	-0.0044***	-0.0072***
	(0.0002)	(0.0002)
Fixed-effects		
as.factor(state)	Yes	Yes
Fit statistics		
Observations	792,574	792,574
R^2	0.09991	0.12794
Within R^2	0.07179	0.11677

Clustered (hhid) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Graphs: The Coefficients by month

Month coefficients

These coefficients tell us the magnitude of impact on essential/non-essential spending for each month.

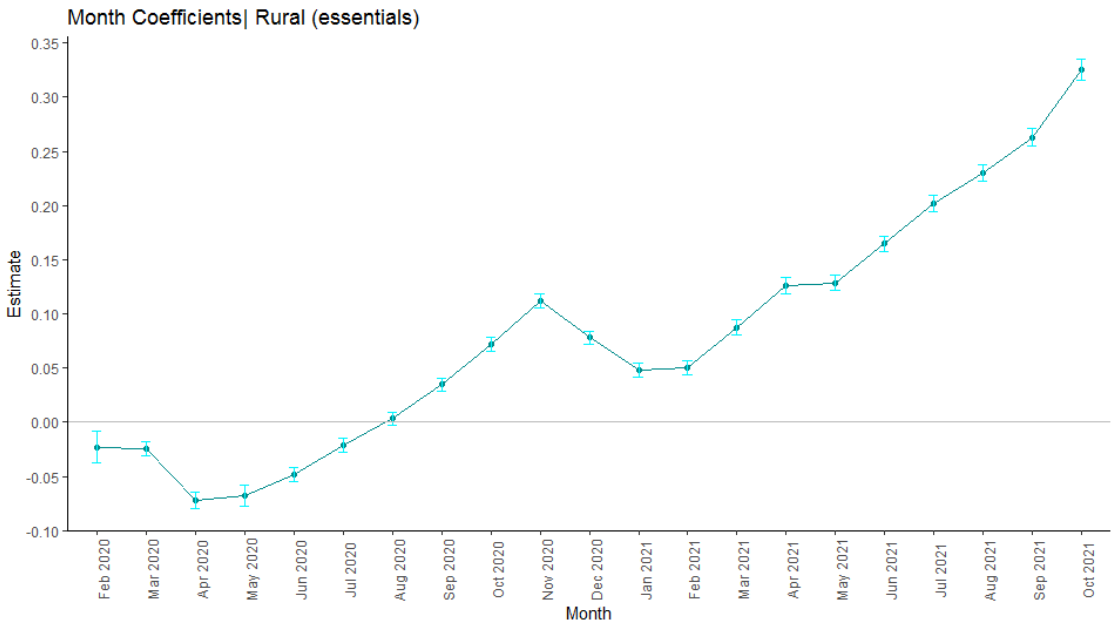

Figure A.5: Expected: turns negative for very few months.

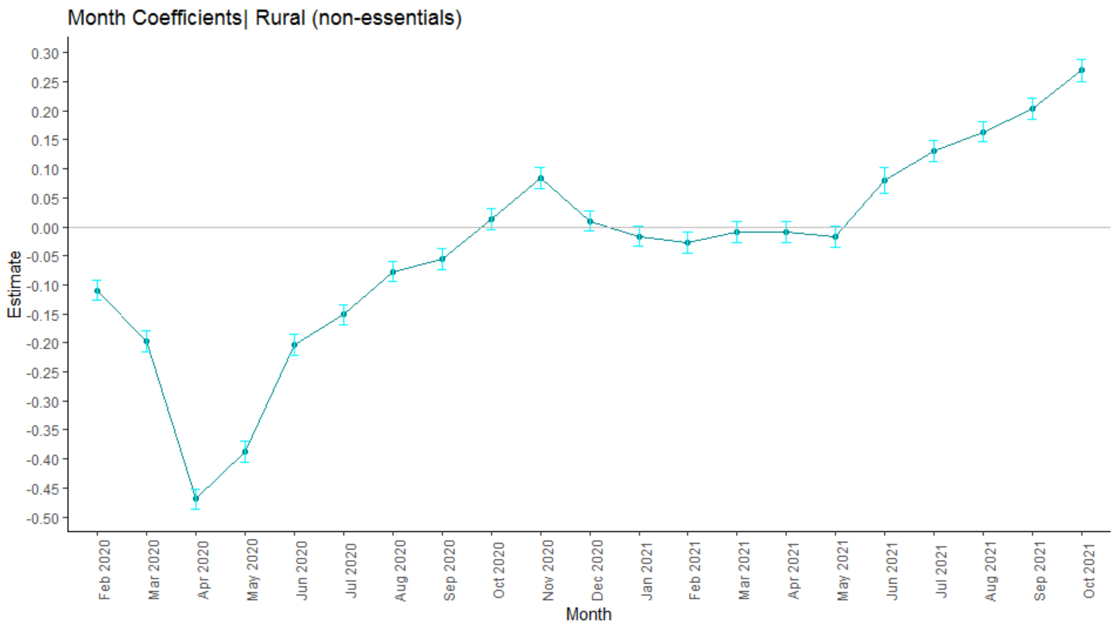

Figure A.6: Much steeper fall when compared to essentials. Drop lasts for many more months.

The Month*Percentile interaction (marginal effects)

The coefficients presented below show the marginal effect of a change in percentile. This tells us whether the impact was progressive/ regressive in a given month. Negative coefficients imply that as we step up a percentile rank, consumption will fall further (progressive).

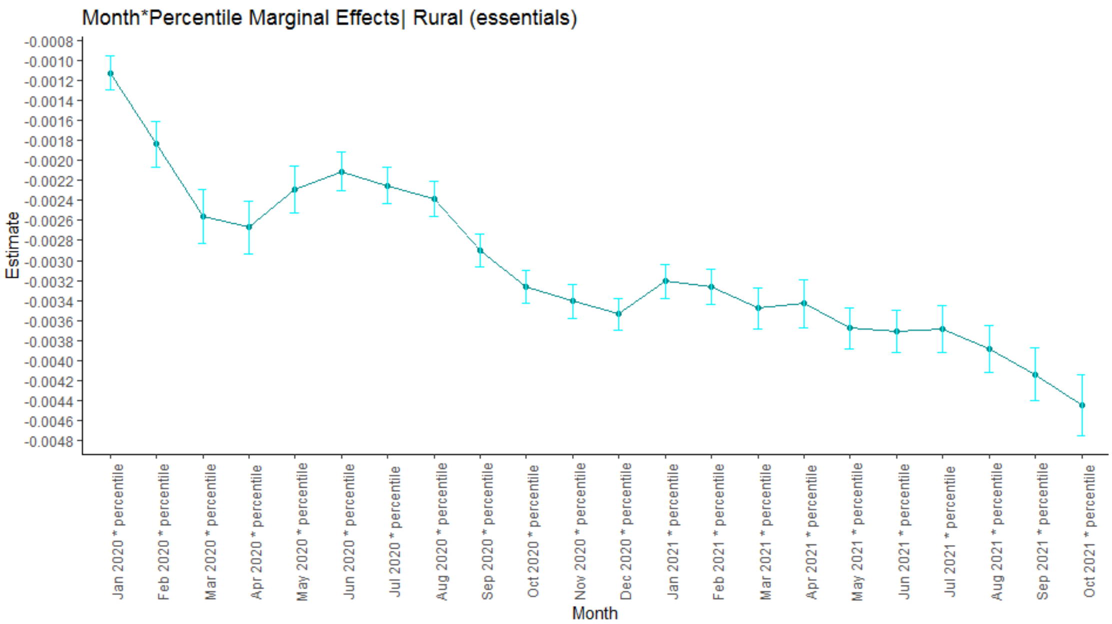

Figure A.7: Surprising Result: Remains negative and significant for most months.

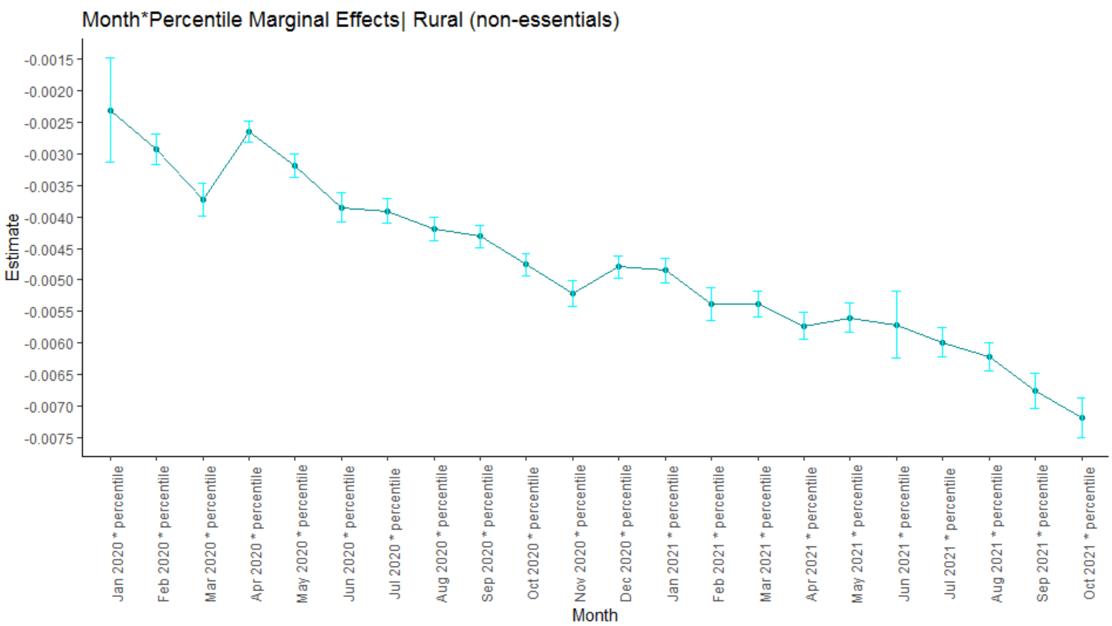

Figure A.8: Expected: remains negative and significant for most part

A.4.2 Urban, with State FE

Dependent Variables:	ΔEssentials2	ΔNon-Essentials2
Model:	(1)	(2)
Variables		
Feb_2020	-0.0115***	-0.0972***

	(0.0020)	(0.0080)
Mar_2020	-0.0027	-0.2125***
	(0.0042)	(0.0060)
Apr_2020	-0.1181***	-0.5409***
	(0.0047)	(0.0064)
May_2020	-0.0909***	-0.4549***
	(0.0047)	(0.0067)
Jun_2020	-0.0680***	-0.2907***
	(0.0046)	(0.0072)
Jul_2020	-0.0243***	-0.2253***
	(0.0046)	(0.0068)
Aug_2020	0.0172***	-0.1480***
	(0.0044)	(0.0090)
Sep_2020	0.0446***	-0.1171***
	(0.0044)	(0.0068)
Oct_2020	0.0683***	-0.0679***
	(0.0044)	(0.0069)
Nov_2020	0.0797***	0.0032
	(0.0042)	(0.0068)
Dec_2020	0.0602***	-0.0895***
	(0.0042)	(0.0068)
Jan_2021	0.0639***	-0.0636***
	(0.0043)	(0.0069)
Feb_2021	0.0990***	-0.0542***
	(0.0044)	(0.0069)
Mar_2021	0.1084***	-0.0250***
	(0.0043)	(0.0072)
Apr_2021	0.1222***	0.0767
	(0.0042)	(0.1090)
May_2021	0.1363***	-0.0935***
	(0.0042)	(0.0068)
Jun_2021	0.1356***	-0.0349***
	(0.0042)	(0.0067)
Jul_2021	0.1811***	0.0126*
	(0.0041)	(0.0067)
Aug_2021	0.2136***	0.0521***
	(0.0045)	(0.0070)
Sep_2021	0.2356***	0.0607***
	(0.0046)	(0.0071)
Oct_2021	0.2701***	0.1240***
	(0.0047)	(0.0071)
Jan_2020 × State_Static_Pctile	-0.0009***	-0.0007**
	(0.0002)	(0.0003)
Feb_2020 × State_Static_Pctile	-0.0012***	-0.0019***
	(0.0002)	(0.0004)
Mar_2020 × State_Static_Pctile	-0.0010***	-0.0024***
	(0.0001)	(0.0002)
Apr_2020 × State_Static_Pctile	-0.0019***	-0.0022***

	(0.0001)	(0.0001)
May_2020 × State_Static_Pctile	-0.0020***	-0.0025***
	(0.0001)	(0.0001)
Jun_2020 × State_Static_Pctile	-0.0022***	-0.0034***
	(9.47×10^{-5})	(0.0002)
Jul_2020 × State_Static_Pctile	-0.0023***	-0.0038***
	(9.85×10^{-5})	(0.0001)
Aug_2020 × State_Static_Pctile	-0.0026***	-0.0042***
	(8.81×10^{-5})	(0.0002)
Sep_2020 × State_Static_Pctile	-0.0028***	-0.0043***
	(8.67×10^{-5})	(0.0001)
Oct_2020 × State_Static_Pctile	-0.0027***	-0.0047***
	(9.16×10^{-5})	(0.0001)
Nov_2020 × State_Static_Pctile	-0.0030***	-0.0047***
	(7.6×10^{-5})	(0.0001)
Dec_2020 × State_Static_Pctile	-0.0029***	-0.0044***
	(8.01×10^{-5})	(9.52×10^{-5})
Jan_2021 × State_Static_Pctile	-0.0028***	-0.0043***
	(8.7×10^{-5})	(0.0001)
Feb_2021 × State_Static_Pctile	-0.0029***	-0.0045***
	(9.48×10^{-5})	(0.0001)
Mar_2021 × State_Static_Pctile	-0.0028***	-0.0048***
	(8.5×10^{-5})	(0.0001)
Apr_2021 × State_Static_Pctile	-0.0028***	-0.0099*
	(8.02×10^{-5})	(0.0052)
May_2021 × State_Static_Pctile	-0.0030***	-0.0051***
	(7.65×10^{-5})	(9.9×10^{-5})
Jun_2021 × State_Static_Pctile	-0.0032***	-0.0055***
	(7.25×10^{-5})	(9.85×10^{-5})
Jul_2021 × State_Static_Pctile	-0.0034***	-0.0056***
	(7.26×10^{-5})	(9.55×10^{-5})
Aug_2021 × State_Static_Pctile	-0.0031***	-0.0059***
	(8.29×10^{-5})	(0.0001)
Sep_2021 × State_Static_Pctile	-0.0030***	-0.0061***
	(9.57×10^{-5})	(0.0001)
Oct_2021 × State_Static_Pctile	-0.0029***	-0.0063***
	(9.75×10^{-5})	(0.0001)
Fixed-effects		
as.factor(state)	Yes	Yes
Fit statistics		
Observations	1,672,266	1,672,266
R^2	0.12731	0.00140
Within R^2	0.09241	0.00115

Clustered (hhid) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

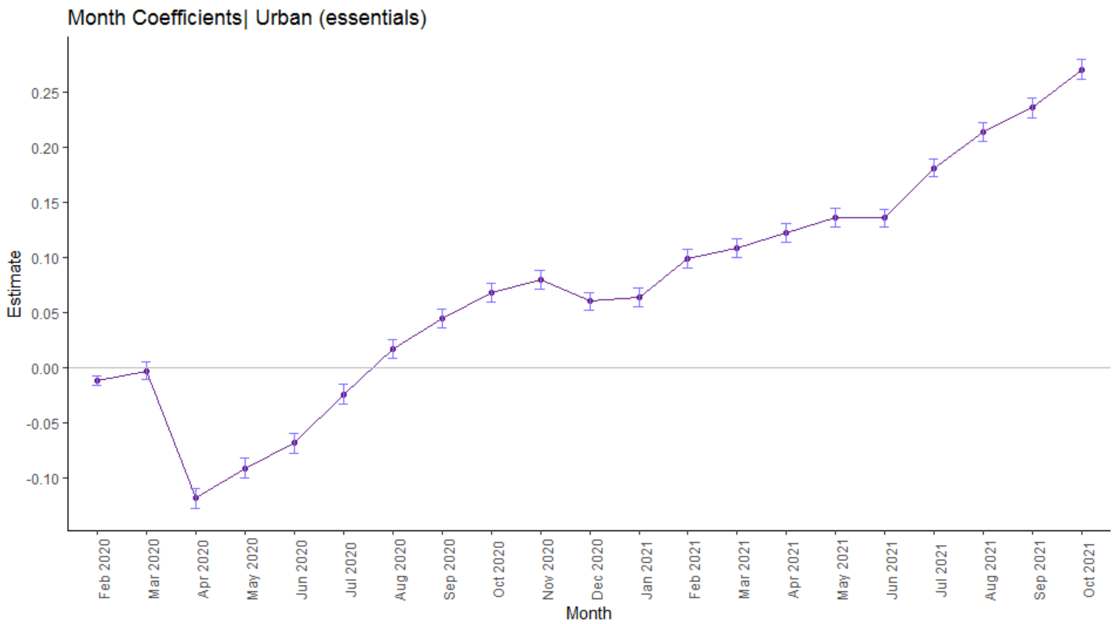

Figure A.9

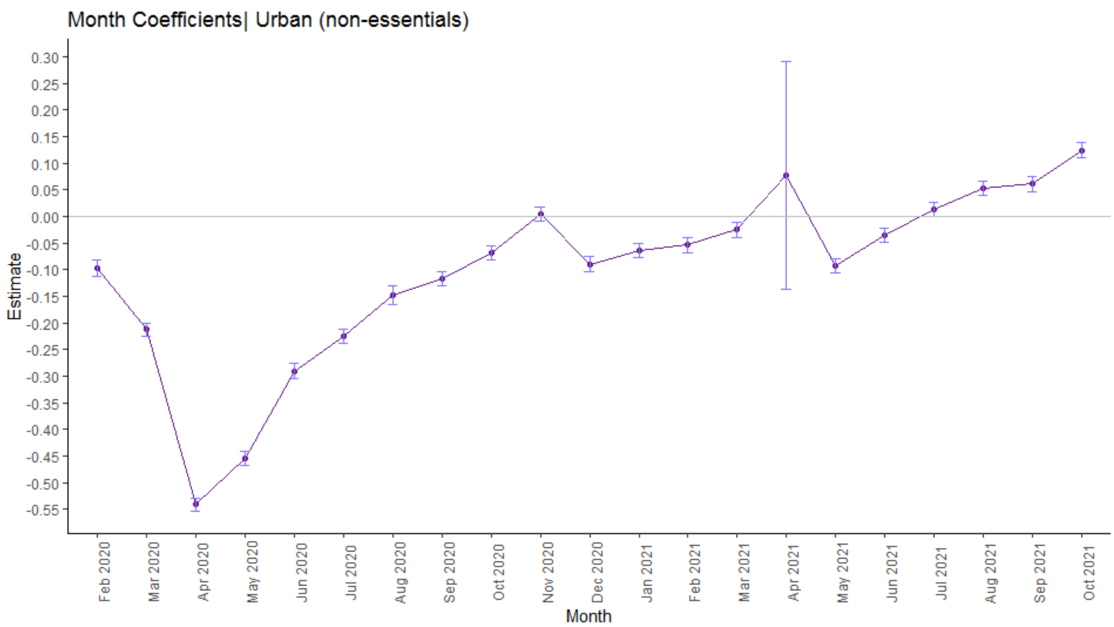

Figure A.10: Non-essential urban consumption remains negative for several months

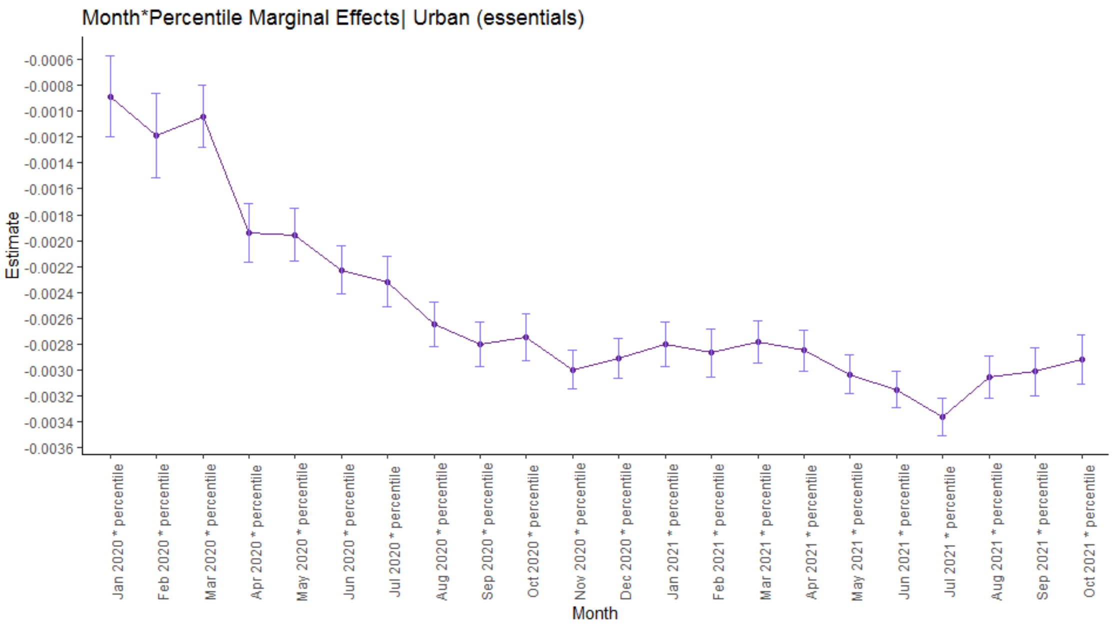

Figure A.11: Strange result strikes again: the interaction term is small but negative and significant for most months.

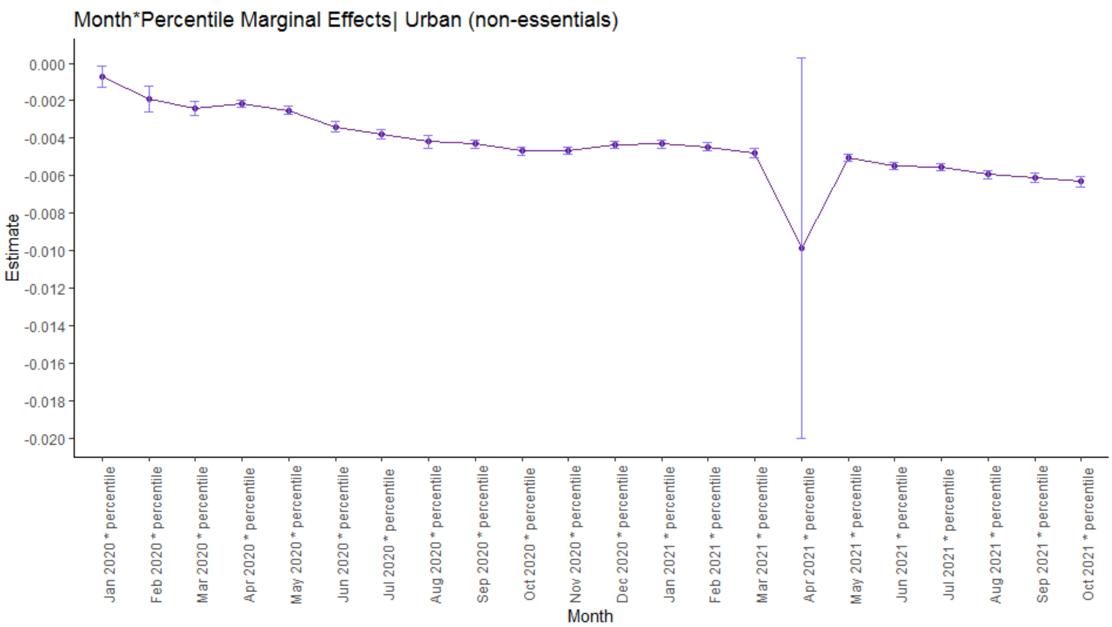

Figure A.12

A.4.3 Rural Without State FE

Dependent Variables:	ΔEssentials2	ΔNon-Essentials2
Model:	(1)	(2)
Variables		

(Intercept)	0.0901***	0.0316***
	(0.0023)	(0.0086)
Feb_2020	-0.0231***	-0.1099***
	(0.0071)	(0.0088)
Mar_2020	-0.0248***	-0.1982***
	(0.0033)	(0.0093)
Apr_2020	-0.0713***	-0.4688***
	(0.0039)	(0.0087)
May_2020	-0.0672***	-0.3873***
	(0.0050)	(0.0090)
Jun_2020	-0.0485***	-0.2030***
	(0.0035)	(0.0091)
Jul_2020	-0.0219***	-0.1504***
	(0.0033)	(0.0090)
Aug_2020	0.0031	-0.0766***
	(0.0032)	(0.0089)
Sep_2020	0.0346***	-0.0551***
	(0.0031)	(0.0089)
Oct_2020	0.0721***	0.0135
	(0.0031)	(0.0089)
Nov_2020	0.1127***	0.0842***
	(0.0032)	(0.0090)
Dec_2020	0.0779***	0.0099
	(0.0030)	(0.0089)
Jan_2021	0.0469***	-0.0173*
	(0.0032)	(0.0089)
Feb_2021	0.0482***	-0.0295***
	(0.0033)	(0.0097)
Mar_2021	0.0858***	-0.0102
	(0.0038)	(0.0091)
Apr_2021	0.1256***	-0.0104
	(0.0041)	(0.0091)
May_2021	0.1277***	-0.0165*
	(0.0036)	(0.0092)
Jun_2021	0.1642***	0.0810***
	(0.0036)	(0.0114)
Jul_2021	0.2014***	0.1305***
	(0.0038)	(0.0091)
Aug_2021	0.2290***	0.1633***
	(0.0039)	(0.0091)
Sep_2021	0.2622***	0.2027***
	(0.0043)	(0.0093)
Oct_2021	0.3248***	0.2689***
	(0.0049)	(0.0095)
Jan_2020 × Static_Pctile	-0.0011***	-0.0019***
	(8.62×10^{-5})	(0.0004)
Feb_2020 × Static_Pctile	-0.0018***	-0.0025***
	(0.0002)	(0.0001)

Mar_2020 × Static_Pctile	-0.0027***	-0.0033***
	(0.0001)	(0.0001)
Apr_2020 × Static_Pctile	-0.0033***	-0.0027***
	(0.0001)	(8.34×10^{-5})
May_2020 × Static_Pctile	-0.0026***	-0.0028***
	(0.0002)	(0.0001)
Jun_2020 × Static_Pctile	-0.0020***	-0.0036***
	(0.0001)	(0.0001)
Jul_2020 × Static_Pctile	-0.0020***	-0.0039***
	(9.7×10^{-5})	(0.0001)
Aug_2020 × Static_Pctile	-0.0023***	-0.0041***
	(9×10^{-5})	(9.83×10^{-5})
Sep_2020 × Static_Pctile	-0.0029***	-0.0046***
	(8.52×10^{-5})	(9.64×10^{-5})
Oct_2020 × Static_Pctile	-0.0038***	-0.0050***
	(8.99×10^{-5})	(9.24×10^{-5})
Nov_2020 × Static_Pctile	-0.0043***	-0.0055***
	(9.34×10^{-5})	(0.0001)
Dec_2020 × Static_Pctile	-0.0037***	-0.0047***
	(8.34×10^{-5})	(9.2×10^{-5})
Jan_2021 × Static_Pctile	-0.0028***	-0.0041***
	(8.82×10^{-5})	(9.87×10^{-5})
Feb_2021 × Static_Pctile	-0.0021***	-0.0042***
	(9.09×10^{-5})	(0.0002)
Mar_2021 × Static_Pctile	-0.0028***	-0.0045***
	(0.0001)	(0.0001)
Apr_2021 × Static_Pctile	-0.0033***	-0.0046***
	(0.0001)	(0.0001)
May_2021 × Static_Pctile	-0.0032***	-0.0054***
	(0.0001)	(0.0001)
Jun_2021 × Static_Pctile	-0.0037***	-0.0058***
	(0.0001)	(0.0001)
Jul_2021 × Static_Pctile	-0.0037***	-0.0058***
	(0.0001)	(0.0001)
Aug_2021 × Static_Pctile	-0.0037***	-0.0059***
	(0.0001)	(0.0001)
Sep_2021 × Static_Pctile	-0.0042***	-0.0068***
	(0.0001)	(0.0002)
Oct_2021 × Static_Pctile	-0.0049***	-0.0074***
	(0.0002)	(0.0002)
Fit statistics		
Observations	792,574	792,574
R^2	0.07034	0.11181
Adjusted R^2	0.07029	0.11176

Clustered (hhid) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

A.4.4 Urban without state FE

Dependent Variables:	ΔEssentials2	ΔNon-Essentials2
Model:	(1)	(2)
Variables		
(Intercept)	0.0795***	0.0664***
	(0.0042)	(0.0071)
Feb_2020	-0.0124***	-0.0991***
	(0.0021)	(0.0077)
Mar_2020	-0.0039	-0.2153***
	(0.0046)	(0.0068)
Apr_2020	-0.1196***	-0.5437***
	(0.0051)	(0.0071)
May_2020	-0.0924***	-0.4581***
	(0.0051)	(0.0074)
Jun_2020	-0.0699***	-0.2960***
	(0.0050)	(0.0079)
Jul_2020	-0.0260***	-0.2304***
	(0.0050)	(0.0075)
Aug_2020	0.0150***	-0.1545***
	(0.0048)	(0.0096)
Sep_2020	0.0423***	-0.1233***
	(0.0047)	(0.0075)
Oct_2020	0.0659***	-0.0749***
	(0.0048)	(0.0076)
Nov_2020	0.0766***	-0.0042
	(0.0046)	(0.0075)
Dec_2020	0.0576***	-0.0954***
	(0.0046)	(0.0075)
Jan_2021	0.0619***	-0.0689***
	(0.0047)	(0.0076)
Feb_2021	0.0983***	-0.0571***
	(0.0048)	(0.0076)
Mar_2021	0.1074***	-0.0288***
	(0.0047)	(0.0078)
Apr_2021	0.1212***	0.0684
	(0.0046)	(0.1042)
May_2021	0.1343***	-0.0975***
	(0.0046)	(0.0075)
Jun_2021	0.1321***	-0.0423***
	(0.0046)	(0.0074)
Jul_2021	0.1771***	0.0051
	(0.0045)	(0.0074)
Aug_2021	0.2095***	0.0435***
	(0.0048)	(0.0077)
Sep_2021	0.2315***	0.0519***

	(0.0050)	(0.0077)
Oct_2021	0.2661***	0.1142***
	(0.0050)	(0.0077)
Jan_2020 × Static_Pctile	-0.0012***	-0.0005*
	(0.0002)	(0.0003)
Feb_2020 × Static_Pctile	-0.0016***	-0.0016***
	(0.0002)	(0.0004)
Mar_2020 × Static_Pctile	-0.0016***	-0.0022***
	(0.0001)	(0.0001)
Apr_2020 × Static_Pctile	-0.0022***	-0.0023***
	(0.0001)	(8.83×10^{-5})
May_2020 × Static_Pctile	-0.0021***	-0.0024***
	(9.89×10^{-5})	(8.21×10^{-5})
Jun_2020 × Static_Pctile	-0.0024***	-0.0035***
	(8.95×10^{-5})	(0.0001)
Jul_2020 × Static_Pctile	-0.0024***	-0.0036***
	(8.84×10^{-5})	(9.46×10^{-5})
Aug_2020 × Static_Pctile	-0.0026***	-0.0041***
	(7.72×10^{-5})	(9.24×10^{-5})
Sep_2020 × Static_Pctile	-0.0028***	-0.0042***
	(7.61×10^{-5})	(8.55×10^{-5})
Oct_2020 × Static_Pctile	-0.0027***	-0.0045***
	(8.09×10^{-5})	(9.17×10^{-5})
Nov_2020 × Static_Pctile	-0.0029***	-0.0046***
	(6.85×10^{-5})	(8.19×10^{-5})
Dec_2020 × Static_Pctile	-0.0027***	-0.0039***
	(7.15×10^{-5})	(7.46×10^{-5})
Jan_2021 × Static_Pctile	-0.0024***	-0.0036***
	(7.79×10^{-5})	(8.91×10^{-5})
Feb_2021 × Static_Pctile	-0.0024***	-0.0037***
	(8.44×10^{-5})	(9.46×10^{-5})
Mar_2021 × Static_Pctile	-0.0025***	-0.0042***
	(7.96×10^{-5})	(0.0001)
Apr_2021 × Static_Pctile	-0.0025***	-0.0078**
	(7.57×10^{-5})	(0.0038)
May_2021 × Static_Pctile	-0.0030***	-0.0050***
	(7.35×10^{-5})	(7.73×10^{-5})
Jun_2021 × Static_Pctile	-0.0030***	-0.0052***
	(6.97×10^{-5})	(8.09×10^{-5})
Jul_2021 × Static_Pctile	-0.0033***	-0.0053***
	(7.12×10^{-5})	(8×10^{-5})
Aug_2021 × Static_Pctile	-0.0031***	-0.0058***
	(7.85×10^{-5})	(9.39×10^{-5})
Sep_2021 × Static_Pctile	-0.0032***	-0.0058***
	(9.09×10^{-5})	(0.0001)
Oct_2021 × Static_Pctile	-0.0031***	-0.0063***
	(9.3×10^{-5})	(0.0001)

Fit statistics		
Observations	1,672,266	1,672,266
R^2	0.09038	0.00112
Adjusted R^2	0.09036	0.00109

Clustered (hhid) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

* * *