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Unemployment and Household Spending in Rural and Urban India

Evidence from Panel Data (2019)

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Abstract

India has recorded high levels of unemployment and low labor force participation rates in recent years even before the onset of the COVID-19 pandemic and the lockdown. How does an episode of unemployment or loss of income affect household consumption expenditure is an important question for designing effective safety nets. We use data on household-specific episodes of job loss and decline in income, from an earlier year (March-April 2019) to estimate the household response to employment shocks. We apply diff-in-diff and quantile regressions to a high-frequency panel data from a nationally representative survey of 1,75,000 households to estimate the impact of a job loss (and change in income) on household consumption expenditure—for urban and rural households, and households across different expenditure levels. We find that loss of employment of an earning member leads to a significant immediate decline in household consumption expenditure. The decline is much larger for urban households and households in the lowest and the highest deciles of monthly per capita consumption expenditure. Durable expenses go down the most. Expenditure on health and education also goes down significantly and there is evidence of adjustments in discretionary expenses too, especially for urban households. For households with only one earning member, borrowing does not increase after the job loss, suggesting credit constraints. Government cash transfers help rural households, as the beneficiaries show a smaller reduction in consumption expenditure after the shock. Our findings highlight the high vulnerability of urban households to economic shocks and can inform the design and targeting of income support and other safety-net programs in India and other developing countries.

Keywords: employment shock, consumption smoothing, permanent income hypothesis, direct cash transfers, credit constraints, consumer spending

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List of Acronyms

CMIE: Centre for Monitoring Indian Economy

CPHS: Consumer Pyramids Household Survey

CWS: Current Weekly Status

DBT: Direct Benefit Transfer

DDD: Difference in Difference in Differences Method

DID: Difference in Differences Method

EMI: Equated Monthly Installment

GoI: Government of India

LPG: Liquefied Petroleum Gas

MGNREGS: Mahatma Gandhi National Rural Employment Guarantee Scheme

MPC: Marginal Propensity to Consume

MPCE: Monthly Per Capita Consumption Expenditure

NSO: National Statistical Office

OLS: Ordinary Least Square

PCA: Principal Component Analysis

PDS: Public Distribution System

PIH: Permanent Income Hypothesis

PLFS : Periodic Labour Force Survey

RBI: Reserve Bank of India

RRR: Relative Risk Ratio

1. Introduction

India experienced high levels of unemployment even before the onset of COVID-19. The Periodic Labour Force Survey (PLFS) by the National Statistical Office (NSO) estimated unemployment to be 6.1% in 2017-18: the highest in 45 years. It declined marginally to 5.8% in 2018-19¹. The unemployment rate, when measured by the current weekly status (CWS), was even higher at 8.9% in 2017-18 and 8.8% in 2018-19. At 8.78% CMIE's (Centre for Monitoring Indian Economy) estimates of unemployment were similar to the CWS numbers reported by PLFS². How do households respond when a working member loses her job or business? How do they cope with the resulting loss of income? How does the effect of a job loss or the responses vary across different types of households--rural and urban; rich and poor? And what expenditure categories are more elastic to a loss of income or employment? These are all important questions—not only to understand and estimate the ill-fare caused by the pandemic but also for designing effective and well-targeted policy responses to mitigate the impact on households and the overall economy.

Researchers have used administrative or transaction-level data to assess changes in consumption during episodes of high unemployment like the COVID-19 pandemic or the great recession in 2008 (Baker et al, 2020; and Chen, Qian, and Wen, 2020 are two examples from the US and China, respectively). Despite the recent increase in digital payments after demonetization, India remains a largely cash-based economy (RBI, undated). Therefore, using transaction-level data may leave out a large share of households' financial transactions.

We use CPHS (Consumer Pyramids Household Survey) data from December 2018 to April 2019 to understand how households in India respond instantly to an episode of job loss or change in the family income. CPHS is a panel survey that collects data from 63,000 rural and 110,000 urban households across India every four months. In each round, households report the job status of all the adult members, household income, and detailed consumption expenditure in each of the previous calendar months since the last round. Thus, we have panel data of monthly consumption and employment status. 4.7% of households reported that at least one member who was working in March 2019 had become unemployed in April 2019. We compare total consumption expenditure and expenses on food, education, health, durable and discretionary items of these households with other households in the sample to causally estimate the immediate impact of job losses on consumption patterns using the difference-in-differences (DID) method. We do this analysis for the whole sample and separately for rural

and urban households. We also measure the heterogeneity in responses to job loss for households at different levels of monthly per capita consumption expenditure (MPCE) levels using quantile DID.

We find that an episode of a job loss leads to an immediate reduction in the household consumption expenditure by 7.2%. The decline is statistically significant and much higher in urban areas (12.3% vs 6.7%). Poor and rich households respond similarly quite like Baker et al (2020) and Kaplan, Violante, and Weidner (2014) find in the US. In urban India, however, households in the top decile of MPCE report larger reductions. This could be because richer urban households have higher discretionary expenditures that can be easily given up or there are a significant number of “wealthy-hand-to-mouth” families in urban India. Expenditure on food shows the smallest change while durable and discretionary expenses go down sharply after a job loss. Families also reduce expenditure on health and education significantly which could potentially lead to long-term consequences even from a temporary shock. Finally, household incomes can change even if there is no change in the employment status of any of the members. We regress the change in consumption expenditure on change in household income showing that the income elasticity of consumption expenditure is positive and statistically significant, and it is 5 times as high for urban households (0.262) compared to their rural counterparts (0.056).

Though we find significant reductions in consumption expenditure after a job loss or income loss, we do not test for the violation of the permanent income hypothesis (PIH) because we do not know if the job losses reported in CPHS were expected or unexpected. Expected and unexpected income shocks have different effects on the consumption response. Jappelli and Pistaferri (2010) argue that while consumption should not respond to expected income changes, it does respond to unanticipated income shocks.

There is a substantial body of recent work documenting the sensitivity of changes in consumption to changes in income that uses administrative or linked financial accounts data before and after a macroeconomic shock, like the 2008 financial crisis, or a policy shock, like tax refunds, stimulus payments, or the temporary shutting down of the Federal government in the US (Souleles, 1999; Johnson, Parker and Souleles, 2006; Hurd and Rohwedder, 2010; Baker and Yannelis, 2013; Kaplan and Violante, 2014; Baker, 2018; Gelman et al. 2018; Baker et al. 2020). Transactions level data are less useful (and not easily available) in a largely cash-based economy like India. We, therefore, use panel data from a high-frequency (monthly)

survey of household consumption expenditure. Although a number of papers have looked at the impact of unemployment on household expenditures and the role of unemployment insurance and other mechanisms to smooth consumption (Dynarski and Gruber 1997; Castilo, Dolado, and Jimeno 2000; Stephens 2001, 2002, 2004; Carbone and Hey 2004; Bentolila and Ichino 2008), most of them use data (or laboratory experiments) from developed countries. This is probably the first paper that explores the effect of unemployment on household spending in rural and urban India and also adduces some evidence on the effect of cash transfers on consumption smoothing.

We make four main contributions. First, we provide evidence of the limited ability of both rich and poor households in India to smooth consumption after an employment or income shock and contribute to the growing literature on the heterogeneous impact of idiosyncratic employment (and income) shocks on the consumption behaviour of households of different income classes and locations. Second, we examine the impact of shocks on different categories of household expenditure separately and not only on the overall spending. The disaggregated analysis allows for a greater understanding of household smoothing behaviour. Third, we test the effectiveness of the ongoing direct cash transfer programs of the Government of India in helping households smooth their consumption and find a small but significant positive impact of these programs. Finally, we adduce evidence on the high vulnerability of India's urban households to employment and income shocks and their limited ability to smooth consumption after a shock. This is important to highlight because India's workfare programs (like MGNREGS) focus only on rural areas. Large safety-net programs like the public distribution system (PDS) have a clear rural bias that is even more pronounced in the recently announced COVID relief package called the *Atma Nirbhar Bharat Yojana* (or the self-dependent India scheme).

The rest of this paper is organized as follows. Section 2 describes the CPHS data and presents relevant summary statistics on employment, consumption expenditure, and demographic characteristics of households in the sample. We discuss the economic strategy in section 3 and section 4 presents our main results and robustness checks. Section 5 concludes the paper.

2. Data and Summary Statistics

We use the Consumer Pyramids Household Survey (CPHS) data collected by the Centre for Monitoring Indian Economy (CMIE) from December 2018 to April 2019³ to analyze the effects

of job loss on household consumption expenditures. The CPHS covers a representative sample of nearly 175,000 households across India⁴. The sample is drawn based on a stratified multi-stage survey design where the primary sampling units are towns and villages from the Census 2011 data. Urban areas are oversampled in CPHS and account for 63.8% of the sampled households compared to the urbanization rate of 31.16% in India in 2011.

Each sampled household is interviewed thrice in a year in three waves where each wave spans four months⁵. In each wave, the CPHS collects month-wise recall data on household income and money spent on 80 different goods and services (including food, health, education, utility bills, recreation, remittances, EMIs, etc.). The CPHS also collects information on the employment status of all adult members in each of the calendar months since it was interviewed the last time.

The demographic module of the CPHS has information on the age, sex, and education levels of all members of the household and the family's caste, religion, and domicile (migrant or born in the current location). We use the monthly recall data to create the high-frequency panel for our analysis in this paper. We analyze data on expenditure on both durable and non-durable items.

We present results based on consumption and employment data from March and April 2019—exactly a year before the lockdown was imposed in 2020. We also use data from earlier months to test for parallel trends between average consumption expenditures of households in which at least one member had lost a job in April 2019 (treatment) and other households that serve as the control group.

4.7% of households in the CPHS reported a decline in the total number of earning members from March to April 2019⁶ while the number of earning members increased in this period for 5.3% of households. This paper focuses mainly on the impact of a job loss on household expenditures. However, we also show how the consumption expenditure changes when the number of earning members in the family increases. Table A2 in the appendix shows regression results where we analyze the impact of changes in employment on consumption expenditure between the two months for -a) households where the earning members decreased between the two months and b) households where the earning members increased between the two months—both compared to the reference group that saw no change in earning members. In rural areas, the average household consumption expenditure increases when the number of employed people in the family goes up and declines when a member becomes unemployed. In

urban areas, however, the coefficient on the increase in the number of employed people in the household is positive, but statistically not significant.

Change in the number of employed people in the family affects expenditure patterns mainly through a change in income (and the expectations of future income). We also directly measure the impact of change in total household income—from wage and business earnings plus other sources—on the total household consumption expenditure, separately for rural and urban households.

When analyzing the impact of a job loss, we exclude the households that reported an increase in earning members across March-April 2019 from the sample such that our control group comprises only of households that see no change in earning members, while our treated group consists of households that see a decline in earning members from March-April 2019.

We recognize that there is nothing special about March and April, and therefore, we also test the impact of job loss on household consumption for other pairs of months (June and July) as a robustness check. Our results are quite similar even when we use data from other months of 2019 as shown in Table A.4 and A.5 in the appendix.

Table 1 below presents the summary statistics on household variables from our data. In March 2019, the average monthly income of rural and urban households were Rs. 17,735 and Rs. 27,009 while the average expenditure on consumption goods were Rs. 11,746 and Rs. 15,187 respectively. Income from wages & business profits accounted for more than 80% of the total household income in both rural and urban areas. Food accounts for the largest share (>40%) of the household expenditure. One in two families reported zero expenditure on education probably because their children are enrolled in government schools or universities. For an average family, discretionary expenditures are significantly larger than the expenditure on health and education.

The average family size is 4.2 in rural areas and 3.9 in urban areas. More than 75% of families have only one working member. Farming (39%) and on- and off-farm wage labor (31.7%) are the most common occupations in rural areas while salaried work (38%) and own enterprise or business (33%) employ the two largest occupations for urban households. Two-thirds of all rural households and 84% of all urban households had some liquid savings in March 2019 with an average of three saving instruments, while almost every second household had some outstanding debts. 56.2% of all households in our sample also reported getting some cash transfer from the government with the average value of transfer being Rs. 474/month.

Table 1: Baseline Summary Statistics of household-level variables

VARIABLES	FULL SAMPLE		URBAN SAMPLE		RURAL SAMPLE	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Total Consumption Expenditure (In Rs.)	12875.92	9830.62	15187.01	8284.09	11745.56	10317.62
Total Household Income (In Rs.)	20780.97	23822.25	27009.53	24160.39	17734.54	23050.12
<i>Proportion of wages, business profits to Total Income</i>	88.6%	24.8%	95.0%	14.1%	85.5%	28.2%
Expenditure on Food (In Rs.)	5647.83	6841.77	6209.39	2216.42	5373.17	8189.77
<i>Proportion of Food to Total Expenditure</i>	47.2%	11.5%	44.4%	11.4%	48.6%	11.3%
Expenditure on Health (In Rs.)	357.93	733.52	445.71	909.12	315.00	625.60
<i>Proportion of Health to Total Expenditure</i>	2.7%	3.0%	2.8%	2.9%	2.7%	3.0%
Expenditure on Education (In Rs.) **	416.16	958.43	539.15	1270.30	356.00	753.40
<i>Proportion of Education to Total Expenditure**</i>	5.30%	4.98%	5.71%	5.64%	5.10%	4.62%
<i>Households that report Education expenditure</i>	52.7%	49.9%	52.2%	50.0%	53.0%	49.9%
Expenditure on Discretionary Items (In Rs.)	3413.17	4204.37	3902.69	4058.38	3173.74	4253.48
<i>Proportion of Discretionary to Total Expenditure</i>	25.3%	9.2%	24.2%	9.5%	25.8%	9.0%
Expenditure on Durable Items (In Rs.)	276.30	1411.12	367.69	1866.89	231.60	1120.01
<i>Proportion of Durables to Total Expenditure**</i>	3.79%	6.25%	4.29%	6.91%	3.54%	5.87%
<i>Households that report Durable expenditure</i>	38.68%	48.70%	39.76%	48.94%	38.16%	48.57%
Earning Members per household	1.08	0.74	1.14	0.69	1.05	0.76
Households with multiple earning members	21.6%	41.1%	21.4%	41.0%	21.7%	41.2%
Households who lost earning member(s) in April 2019	4.7%	21.1%	2.5%	15.6%	5.7%	23.3%
Households who gained earning member(s) in April 2019	5.3%	22.5%	2.4%	15.3%	6.8%	25.2%
Household Size	4.13	1.55	3.97	1.48	4.21	1.59
Occupation of Majority Household Members						
<i>Entrepreneurial Class</i>	19.4%	39.5%	33.0%	47.0%	12.7%	33.3%
<i>Salaried Class</i>	21.5%	41.1%	38.1%	48.6%	13.4%	34.0%
<i>Farmer Class</i>	27.2%	44.5%	3.0%	17.0%	39.0%	48.8%
<i>Daily Wage Labour Class</i>	27.8%	44.8%	19.8%	39.9%	31.7%	46.5%
<i>Business & Salaried Class</i>	1.7%	12.7%	3.1%	17.3%	0.9%	9.7%
<i>Others</i>	2.5%	15.6%	3.0%	17.0%	2.2%	14.8%
Average saving instruments per household	3.50	1.31	3.98	1.38	3.26	1.20
Households with outstanding borrowings	50.1%	50.0%	48.2%	50.0%	51.1%	50.0%
Households that received cash transfers from government	56.2%	49.6%	58.7%	49.2%	55.0%	49.7%
Average cash transfer received by a household (In Rs.) **	473.38	1293.20	382.90	1059.89	520.58	1397.23
Households that report imputed income (self-production)	32.1%	46.7%	9.8%	29.8%	43.0%	49.5%
Households that report remittance income	1.6%	12.5%	0.8%	9.2%	1.9%	13.8%
N	120,146		77,187		42,959	

Note: All values in the table above are for March in 2019.

Discretionary Expenses include clothing, footwear, appliances, restaurants/eating out, and travel expenses.

**For education expenses, durable expenses and cash transfer incomes, we include only those households that report positive values in these categories in March 2019 for our average statistics.

3. Econometric strategy

We use the Difference in Difference (DID) method to measure the immediate effect of a job loss on the family's monthly consumption expenditure. We compare the total household expenditure in March 2019 (pre-treatment) with expenditure in April 2019 (post-treatment) for households that reported a reduction in the number of earning members in April (treated) with other households (control). We compare expenditure right before and after the job loss, to minimize confounding effects from other sources of variation in consumption across the two groups of households.

In our main specification, we estimate the following equation:

$$C_{hvt} = \beta_0 + \beta_1 T + \beta_2 U_{hvt} + \delta_{12} T * U_{hvt} + \beta_3 X_{hv} + \varepsilon_{hvt} \quad (1)$$

Where C_{hvt} is the consumption expenditure or the natural log of it for household h , in town/village v , in month t . We estimate equation 1 with both levels and natural logs of the dependent variable (consumption). Our coefficient of interest is the interaction term between T (the post-period dummy which takes the value of 1 for observations in April 2019 in the main specification) and U_{hvt} , an indicator of whether the total number of earning members of the household went down in the post period. While β_1 measures the average change in consumption expenditure between the two time periods for both the treatment and control groups, β_2 accounts for the permanent difference in consumption between the two groups and can be interpreted as a treatment group specific effect. The coefficient of the interaction term, δ_{12} , gives us our difference in difference estimator or the treatment effect, i.e., the causal effect of unemployment for the treated group, on consumption expenditure between March and April 2019, comparative to the control group. X_{hv} is a vector of household-level controls like the household size, composition (% adult members), the number of earning members in March 2019 (to account for single vs multiple income households), occupation group of the household, and other demographic characteristics like the location of residence (Urban or Rural), the social category the household belongs to (upper caste, intermediate caste, scheduled caste, scheduled tribe, or other backward classes), and if they have any savings or outstanding debts. We also control for ancillary sources of household income which include imputed (self-production) income, remittances, government transfers, dividends, interest earned, and investments in fixed deposits and public provident funds as well as a wealth index created from the household asset and amenities listing using the Principal Component Analysis (PCA).

We test for the identifying assumption of parallel or similar trends in the dependent variables between treatment and control groups both graphically (Figure 1) and using parametric tests with data from earlier months where we regress the consumption expenditure on a linear measure of time trend, a dummy variable for the employment loss, and interaction of the time trend and the employment loss dummy (Table A.7 in the appendix). The dummy variable takes the value of one for households that saw no change in the number of earning members from December 2018 to March 2019 and then experienced a reduction in April 2019. The number of earning members did not change throughout the 4 months from December 2018 to April 2019 for the control group (employment dummy = 0). The interaction term is statistically not significant for the full sample of households and the rural sub-sample, but it is significant for urban households. The graphs of consumption expenditure in figure 1 also show that the average consumption expenditure of urban families that experienced a job loss in March-April 2019 was more unstable in the earlier months. Even for urban households, the decline in the average consumption expenditure immediately after the job loss was much bigger than the amplitude of fluctuations in the months before the shock. Therefore, despite the absence of parallel trends, we are confident that a negative employment shock leads to a significant decline in household consumption expenditure. The magnitude of the decline, however, is less precisely estimated. It may be smaller or larger than what our DID coefficient estimates.

Figure 1: Parallel Trends in Average Monthly Per Capita Consumption (In Rs.) across treated and control households (Dec 2018-April 2019)

Note: The graphs above depict the trends in average monthly consumption expenditure per capita from December 2018 – April 2019 for households that experienced an employment shock in April 2019 (red line) and households that did not (blue line). The green dotted line marks the month of March 2019 when the shock occurred. The y-axis records the average monthly household expenditure in Rs. and the x-axis plots the months where 2019m1 refers to the first month of 2019, i.e. January 2019. Figure (a) represents the full sample, figure (b) represents the urban sub-sample and figure (c) represents the rural sample. (Colour print required)

The sensitivity of different types of expenditure to a job loss

Besides the total monthly consumption expenditure, we also measure the impact of job loss on 5 broad categories of expenditure—food, health, education, durable items, and discretionary expenditures—by estimating equation 1 separately for each category. Discretionary expenses include expenditure on clothing and footwear, recreation, restaurants/eating out, travel, social and religious obligations, beauty and fitness expenses, intoxicants, pets, etc. Durable expenses include expenditure on appliances, furnishings, lighting, utensils, and jewelry.

Quantile DID

The effect of a job loss or a reduction in income may vary across households with different per capita expenditure levels. We use quantile DID to explore heterogeneity across different MPCE deciles. It is important to note that the quantile treatment effects here do not correspond to the distribution of the treatment effect itself, but the heterogeneous effects of the treatment (the employment shock) on households of different MPCE deciles (Callaway and Li 2019).

The income elasticity of consumption expenditure

Job losses are not the only reasons for changes in household incomes. Family incomes may go up or down for other reasons too. The lockdown after COVID-19 will also affect the incomes of more households than the job status. Many employees may keep their jobs but will have to accept pay cuts. Enterprises may also remain operational but earn smaller profits. Therefore, we also estimate the income elasticity of consumption expenditure by running a regression on first differences with the March-April panel data where we regress the change in expenditure from March to April against change in the household income over the same period.

$$\Delta Y_{hvt} = \beta_0 + \beta_1 \Delta I_{hvt} + \varepsilon_{hvt} \quad (2)$$

ΔI measures the percentage change in household income from all wage & business or total income from all sources from March to April 2019 and β_1 is the coefficient of interest in equation 2. We estimate this equation for both urban and rural sub-samples.

Credit and government cash transfers as coping mechanisms

The CPHS collects data on household income from any government transfers from one or more of the direct benefit transfer (DBT) programs (like the Ujjawala subsidies for LPG cylinders, handicap/widow pensions, student scholarships, etc.) run by GoI and state governments. 56% of the households in our sample received some cash transfer from a government agency in March 2019 where the average transfer was Rs. 474. We estimate a triple difference (DDD) model (see Equation 3) to measure the impact of government transfer by comparing the impact of job loss on the change in consumption expenditure from March to April between households that received cash transfers from the government in April and those who did not. The main parameter of interest is θ_{123} , the triple-difference estimate. It measures the average additional impact of the government cash transfer on the consumption expenditure of families where at least one member became unemployed in period two (April 2019).

β_1 measures the trend in the household consumption expenditure, β_2 captures the initial difference in average monthly consumption expenditures of households that experienced job loss and those who did not while β_3 measures the difference in consumption levels of households that received government transfer(s) and those who did not, and β_4 is the coefficient of a vector of household-level controls. δ_{12} , δ_{13} and δ_{23} are the estimates of the double interaction terms.

$$C_{hvt} = \beta_0 + \beta_1 T + \beta_2 U_{hvt} + \beta_3 G_{hvt} + \delta_{12} T * U_{hvt} + \delta_{13} T * G_{hvt} + \delta_{23} U_{hvt} * G_{hvt} + \theta_{123} U_{hvt} * G_{hvt} * T + \beta_4 X_{hv} + \varepsilon_{hvt} \quad (3)$$

CPHS also collects month-wise data on if the household switched from a debt-free to an indebted status or vice-versa. It does not have information on the change in the level of indebtedness. Given this data limitation, we estimate a multinomial logit model to test if the probability of switching to an indebted status (starting a loan) is higher for households that experienced an employment shock compared to the other households after the shock is realized (April 2019). We control for household's demographic and social characteristics, employment profile (one or more earning members), location (rural/urban), and sources of income in this model and report relative risk ratios (RRR) of a switch to an indebted state or a debt-free status with no switch as reference.

4. Results

We begin this section by showing evidence of an immediate and significant decline in household consumption expenditure after the number of earning members goes down. We then discuss the impact of the shock on different categories or types of household expenditures and test for heterogeneity in the impact of shock across households of different expenditure classes. Finally, we show some evidence of the credit constraints most households face and test if government cash transfer programs help smooth consumption.

4.1 Impact of a job loss on total consumption expenditure

Table 2 shows the impact of a job loss on households' consumption expenditure. We report results from both level and log regressions for expenditure. A job loss leads to an average 12.3% immediate reduction (Rs. 2641) in the monthly expenditure of urban households and a 6.65% reduction (Rs. 767.4) in the expenditure of rural households. Thus, the household expenditure in urban areas is significantly more sensitive to an employment shock compared to their rural counterparts. An unpublished paper by Gupta and Kishore (2020) finds a similar result in our ongoing analysis of the impact of India's demonetization in November 2016 on the consumption expenditures of rural and urban families. Consumption expenditure of urban households declined more sharply after the demonetization. Meng (2003) also finds that Chinese urban households are unable to smooth education expenses in the face of income uncertainties. We can think of three possible reasons for the greater sensitivity of urban household expenditure to shocks. First, it is possible that stronger social networks in rural areas, built over generations of living together, often in homogenous communities, offer rural households better social insurance against an idiosyncratic shock (Townsend, 1994). Second, urban households also have higher average discretionary expenses (see Table 1) that are easier to reduce when the income goes down. Third, rural households are largely agrarian households and have higher levels of imputed (self-production) income (see Table 1) that possibly serves as a buffer against shocks.

Table 2: Average Effect of unemployment on monthly household consumption expenditure

	Full Sample		Urban Sample		Rural Sample	
<i>Monthly Household Consumption Expenditure</i>	Linear (In Rs.)	Log (In %)	Linear (In Rs.)	Log (In %)	Linear (In Rs.)	Log (In %)
	(1)	(2)	(3)	(4)	(5)	(6)
DID Coefficient (Month=April * HH type=lost earning member)	-998.9*** (144.8)	-0.0720*** (0.00988)	-2,641*** (588.6)	-0.123*** (0.0228)	-767.4*** (132.5)	-0.0665*** (0.0109)
HH Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	231,356	231,356	151,062	151,062	80,294	80,294
R-squared	0.160	0.389	0.310	0.374	0.093	0.348

Note: Robust standard errors in parentheses are clustered at town/village (primary sampling unit) level

*** p<0.01, ** p<0.05, * p<0.1

Each cell is a coefficient regression from a difference-in-difference estimation that analyses the difference in monthly consumption expenditure between March and April 2019 between households that lose an earning member(s) in April 2019 and households that maintain the same number of earning members from March-April 2019. In each regression, we control for the household size, the number of original earning members, the composition of household according to the age of members, education of members, gender of members, and occupation of members. We also control for household caste category, household religion group, the region of residence, other sources of household income including imputed income, government transfers, dividends, interest earned, fixed deposits/provident fund account, remittances, sale of assets, gambling, etc. Finally, we account for household savings, wealth asset index, and whether the household had any outstanding borrowings at the time of the survey. Columns (1), (3), and (5) denote linear regressions using actual values of monthly total income measured in Rs as the dependent variable. Columns (2), (4), and (6) denote log regressions using the logarithm of monthly total income as the dependent variable and hence can be interpreted in percentage terms, multiplying the coefficients by 100. Columns (1) and (2) denote regression results using the entire sample (both urban and rural regions) while columns (3) and (4) denote regression results using only the urban sample and columns (5) and (6) denotes regressions results using only the rural sample. All observations are weighted using sampling probability weights.

4.2 Impact of employment shocks on different types of expenditures

We estimate the impact of an employment shock on five different categories of household expenditures by estimating Equation 1 separately for each category. Panels A, B, and C of Table 3 show the results for the full sample along with the urban and rural sub-samples. We estimate this equation in levels because many households report zero expenses for categories like education and health. Like Baker and Yannelis (2015), we also find widely varying responses to job loss on different types of expenditures. Food expenses show a small reduction (4.03%) with a higher reduction in urban (5.9%) vs rural (3.9%) households. This may be a result of higher self-production in rural communities. Durable expenses decline the most—by almost one-third from their level before the shock. Discretionary expenses also reduce, more so for urban households (22%) than rural households (9%). In the case of a positive income shock in Singapore, Agarwal and Qian (2014) also found that consumption rose the most in the discretionary category. Expenditure on education (for the 51% households that report non-zero education expenses in March) shows a significant change (23.7%) after the shock with the change being higher for urban households (36%). Health expenditure also goes down by nearly

14-17% after the shock. CPHS does not distinguish between preventive and palliative expenses. Such sharp declines in health and education spending, even if temporary could lead to long-term consequences for families. Expenditure on domestic help also seems to decline for households when unemployed, with a larger cutback among urban families (47% vs 15%). There is also some evidence of adjustments to EMI (Equated Monthly Instalments on bank loans) payments among urban households with a substantial decline post the job loss.

Table 3: Average Effect of unemployment on sub-categories of monthly consumption expenditure in Rs.

Panel A:

FULL SAMPLE	(1) Food Expense	(2) Discretionary Expense	(3) Durable Expense	(4) Education Expense	(5) Health Expense
DID co-efficient	-224.5*** (43.57)	-386.9*** (75.93)	-207.2** (92.11)	-166.5*** (45.54)	-45.94*** (10.52)
<i>Proportion of baseline expense</i>	(4.03%)	(11.6%)	(31.4%)	(23.7%)	(13.9%)
HH Controls	Yes	Yes	Yes	Yes	Yes
Observations	231,356	231,356	97,618	125,260	231,356
R-squared	0.026	0.077	0.037	0.088	0.050

Panel B:

URBAN SAMPLE	(1) Food Expense	(2) Discretionary Expense	(3) Durable Expense	(4) Education Expense	(5) Health Expense	(6) EMI Expense	(7) Domestic Help Expense
DID co-efficient	-391.1*** (123.8)	-983.0*** (231.8)	-348.7 (355.1)	-402.7*** (123.2)	-94.75* (54.91)	-943.8*** (256.4)	-314.3*** (93.85)
<i>Proportion of baseline expense</i>	5.9%	22%	32.5%	36%	16.5%	38%	46.8%
HH Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	151,062	151,062	63,552	82,236	151,062	32,586	27,620
R-squared	0.288	0.107	0.039	0.105	0.050	0.173	0.268

Panel C:

RURAL SAMPLE	(1) Food Expense	(2) Discretionary Expense	(3) Durable Expense	(4) Education Expense	(5) Health Expense	(6) Domestic Help Expense
DID co-efficient	-208.7*** (47.30)	-280.2*** (81.59)	-197.4*** (69.06)	-135.3*** (46.02)	-38.97*** (8.893)	24.83*** (7.896)
<i>Proportion of baseline expense</i>	3.9%	9%	35.9%	22.2%	14%	14.7%
HH Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	80,294	80,294	34,066	43,024	80,294	6,546
R-squared	0.014	0.057	0.039	0.065	0.044	0.082

Note: Robust standard errors in parentheses are clustered at town/village level

*** p<0.01, ** p<0.05, * p<0.1

Each cell is a coefficient regression from a difference-in-difference estimation that analyses the difference in monthly consumption expenditure on food, education, health, discretionary items, and durable items between March and April 2019 between treated (lower earning members in April 2019) and control households. For urban households, EMI expenses (Equated monthly instalments of loans/purchases) and for urban as well as rural households, expenditure on domestic help is also included. Discretionary Expenses include spending on recreation, restaurants, clothing and other accessories, mobile phone, cosmetics and health enhancements, fitness, pocket money, intoxicants, social and religious obligations, pets, painting and renovation, and travel. Durable expenses include expenditure on appliances, jewellery, furniture, light fixtures, and utensils. In each regression, we control for the household size, the number of original earning members, the composition of household according to the age of members, education of members, gender of members, and occupation of members. We also control for household caste category, household religion group, the household region of residence, other sources of household income including imputed income, government transfers, dividends, interest earned, fixed deposits/provident fund account, remittances, sale of assets, gambling, etc. Finally, we account for household savings, wealth asset index, and whether the household had any outstanding borrowings at the time of the survey. All results denote linear regressions using actual values of the consumption expenditure measured in Rs. as the dependent variable. The coefficients are also expressed as a proportion of the baseline expenditure on the sub-categories in March 2019 for the respective household type, to get a sense of the magnitude of reduction in expense. All observations are weighted using sampling probability weights.

4.3 Heterogeneous effects of employment shock on households of different expenditure classes

Table 4 presents results from a quantile DID regression to show the heterogeneous effect of an employment shock on rural and urban households at different levels of per capita consumption. The employment shock affects the consumption expenditure across the entire distribution of MPCE and the effect is the largest for the richest among urban families—the top MPCE decile. In rural areas, we find a different pattern. There the expenditure levels of the poorest and richest families change the most after a shock.

Discretionary expenses account for a higher share of the total consumption expenditure of the richest households. This may be the reason why their expenses show a higher sensitivity to employment shocks. In rural areas, discretionary expenses are relatively low for all but the richest 10% of families which may explain the lower sensitivity to the shock. The poorest households in both rural and urban areas have low savings and they probably face more binding

credit and liquidity constraints resulting in sharper declines in their consumption if someone in the family becomes unemployed.

Figures 2 (a), (b), (c), (d) & (e) capture the heterogeneity in the sensitivity of expenditures on durable items, discretionary items, education, health, and food across MPCE deciles by plotting smoothed values of kernel-weighted local polynomial regression of category-wise expenditure against MPCE decile dummies for both control (no-change) and treatment (lost an earning member) households in March (pre-treatment) and April (post-treatment). Shaded areas around the lines show the confidence intervals of the local estimates. Non-overlapping confidence intervals imply a statistically significant difference between treatment and control households.

For all five categories of expenditure, these local linear regression plots show little to no difference between treatment and control households across almost all MPCE deciles in March 2019, the pre-shock period. The differences, if any, are small and statistically not significant. However, once the employment shock is realized, visually, we notice a significant gap opens up in expenditures on food, health, and education between treatment and control households across all deciles,. However, for durable and discretionary expenses, we see that the gap exists only for households above-median consumption expenditure. This implies that richer households can afford to reduce these expenses when unemployed. Thus, the non-parametric plots show that employment shocks lead to larger declines in expenditure on durable and discretionary items at higher MPCE levels, but there are sizeable reductions in food, health and education expenses for unemployed households across all income classes.

Table 4: Consumption Quantile Effects of unemployment on log monthly household consumption expenditure

DID Coefficients	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
(Month=April * HH type=lost earning member)	OLS coefficient	10 th percentile	20 th percentile	30 th percentile	40 th percentile	50 th percentile	60 th percentile	70 th percentile	80 th percentile	90 th percentile	Sample size
Full Sample	-0.0720*** (0.00988)	-0.102*** (0.0202)	-0.072*** (0.0163)	-0.057*** (0.0122)	-0.055*** (0.0108)	-0.053*** (0.0112)	-0.054*** (0.0105)	-0.055*** (0.0115)	-0.060*** (0.0130)	-0.075*** (0.0156)	231,356
Urban Sample	-0.123*** (0.0228)	-0.131*** (0.0257)	-0.116*** (0.0242)	-0.128*** (0.0269)	-0.146*** (0.0238)	-0.162*** (0.0315)	-0.126*** (0.0315)	-0.122*** (0.0282)	-0.119*** (0.0357)	-0.149*** (0.0316)	151,062
Rural Sample	-0.066*** (0.0114)	-0.098*** (0.0247)	-0.062*** (0.0176)	-0.048*** (0.0139)	-0.046*** (0.0110)	-0.043*** (0.0120)	-0.048*** (0.0113)	-0.050*** (0.0125)	-0.050*** (0.0132)	-0.071*** (0.0185)	80,294
P-value testing H ₀ : Rural=Urban	<u>0.0261</u>										

Note: Robust standard errors in parentheses clustered at PSU level

*** p<0.01, ** p<0.05, * p<0.1

Each cell is a coefficient regression from a difference-in-difference estimation that analyses the difference in monthly consumption expenditure between March and April 2019 comparing households that lose an earning member in April 2019 relative to March 2019 and households that maintain the same number of earning members from March-April 2019. In each regression, we control for the household size, the number of original earning members, the composition of household according to the age of members, education of members, gender of members, and occupation of members. We also control for household caste category, household religion group, the household region of residence, other sources of household income including imputed income, government transfers, dividends, interest earned, fixed deposits/provident fund account, remittances, sale of assets, gambling, etc. Finally, we account for household savings, wealth asset index, and whether the household had any outstanding borrowings at the time of the survey. All regressions denote log regressions using the logarithm of monthly consumption expenditure as the dependent variable and hence can be interpreted in percentage terms, multiplying the coefficients by 100. Each column represents the progressive household consumption decile classes from 1-9 with column (0) representing the average (OLS regression) coefficient. All observations are weighted using sampling probability weights. The first row denotes regressions based on the entire sample, while the second and third rows show regressions for the urban and rural sample, respectively. A t-test of significance between the OLS coefficients for the urban and rural sample implies that we reject the null hypothesis of equality at a 5% level of significance ($p<0.05$), implying that urban households which lose an earning member show a significantly higher decline in monthly consumption expenditure compared to rural households that lose an earning member.

Figure 2: Graphs comparing the monthly expenses on discretionary items, durable items, education, health, and food by decile classes across households with unemployment and those with no change in employment

Note: The figures above graphically depict the average expenditure on discretionary items, durable items, education, health and food across different decile classes. The comparison is made between the two months- baseline (March 2019) and endline (April 2019), distinguishing between households that experienced job loss in April 2019 and those that did not. *(Colour print required)*

4.4 Borrowing to smooth consumption?

Households rely on diverse kinds of credit arrangements and their precautionary savings to smooth consumption when there is an income shock (Besley, 1995; Townsend, 1994; 1995; Sullivan, 2008). The CPHS measures total spending with some precision, but not savings or debt. In every wave, it only asks if the household had any savings or outstanding loans in the last 4 calendar months but does not collect data on the amount saved or borrowed. Nor does it directly ask the respondent if they took new loans. We can only see if the change in the debt status of a household across time. Some households who had not reported any debts in the earlier wave may report it in the next one and vice-versa. Similarly, some households may continue to report outstanding debts (no debts) in both waves. Table 5 reports summary statistics on the status of borrowing for our sample households between the two waves of data collection on debt holdings (January-April 2019 and May-August 2019).

Since we cannot measure changes in the value of savings or debts, we limit our analysis to check if the households that experienced an employment shock had a higher probability of switching from a debt-free status to indebtedness in months after the shock.

Table 5: Summary Statistics on Borrowing Status : (Jan-April 2019 and May-August 2019)

Borrowing Status of Households	FULL SAMPLE	TREATED SAMPLE	CONTROL SAMPLE
% Households with no debts in both periods	41.21%	35.83%	41.48%
% Households reporting outstanding loans Debt in both periods	42.37%	45.67%	42.21%
% Households that initiated new debt in May-Aug 2019	8.79%	10.39%	8.71%
% Households that paid off the debt by May-Aug 2019	7.63%	8.11%	7.60%

We run a multinomial logit regression where the dependent variable takes on a value of 0 for no change in the status of borrowing (base category) before and after the shock, a value of 1 if the household had no debt in January-April 2019 but reported some outstanding debt in May-August 2019, and value of -1 if there was an opposite switch from indebted to a debt-free status over the same period. Table 6 shows the model results as relative risk ratios (RRR) of starting fresh borrowing (category 1) or paying off old debts (category 2) compared to no change in the household debt status (the reference category). Whether anyone in the family lost their job in April 2019, if there were more than one earning member in the household, and an interaction term between the employment shock and the multiple earning members dummies are our main

variables of interest. We also retain the usual controls for demographic characteristics (the household size, caste category, and rural or urban residence), occupation of the household, other sources of income (like imputed incomes, dividends, interest income, etc.), and if the family has any savings, but do not report these coefficients in the table.

Among households that started with only one earning member, those who experience job loss have the relative risk of starting fresh borrowings or switching from debt-free to indebted status (compared to no change in the debt status) of 1.12 (12%). The coefficient, however, is statistically not significant. That is, for single earning households, the loss of employment is not statistically significantly associated with either an increased probability of starting a new loan or a reduced probability of paying off existing loans (0.932). Families with more than one earning member have a significantly higher probability of starting a new loan (38.7%) after one of the family members loses her job, but they are also more likely to pay off old debts (36.3%) after such an episode.

Lenders may find families whose only earning member has lost his or her job less creditworthy, but they are willing to lend to families that have at least one member who is still gainfully employed. Unfortunately, due to low female labor force participation rates (Andres et al. 2017), four out of five (77%) families in India have only one earning member and our limited analysis suggests that these families face a binding credit constraint to consumption smoothing when there is a loss of employment.

We are not sure why these families are more likely to repay their existing loans when one of their earning members becomes unemployed.

Table 6: Average effects of unemployment on the probability of borrowing in subsequent months using a Multinomial Logit Estimation

<i>Base Category= No change in borrowing status</i>	Category 1: Initiated Debt	Category 2: Paid off Debt
	<i>Relative Risk Ratio</i>	
HH= Lost earning member	1.114 (.2227)	.9639 (.1799)
HH has multiple earning members in March 2019	.8039*** (.0408)	.9512 (.0694)
Interaction term:	1.400*	1.303*
Lost earning member * has multiple earning members	(.2514)	(.2070)
HH Controls	Yes	Yes
Observations	115,678	115,678
Pseudo R-squared	0.0145	0.0145

Note: Robust standard errors in parentheses are clustered at town/village level

*** p<0.01, ** p<0.05, * p<0.1

Each cell is an exponentiated coefficient regression from a multinomial logit estimation that analyses the probability of a household initiating debt in May-August 2019. The values represent relative risk ratios such that any value below 1 denotes a relatively lower probability while values exceeding 1 denote higher probabilities. The base category of the dependent variable is 0= no change in borrowing status. Category 1 is if the household started borrowing. Category 2 is if the household paid off existing debt and has no current outstanding borrowings. The independent variables include the type of household which distinguishes between households that lose an earning member in April 2019 compared to March 2019 and households that maintain the same number of earning members from March-April 2019. We include another characteristic variable that takes on a value of 0 if the household has one earning member and a value of 1 if the household has multiple earning members. An interaction between the type and composition variables is also included in the regression. In each regression, we control for the household size, composition of household according to the age of members, education of members, the gender of members, and occupation of members. We also control for household caste category, household religion group, the region of residence, other sources of household income including imputed income, government transfers, dividends, interest earned, fixed deposits/provident fund account, remittances, sale of assets, gambling, etc. Finally, we account for household savings and the wealth asset index.

4.5 Do government transfer programs help?

In 2013, the Government of India started direct benefit transfer (DBT) of subsidies under 13 different schemes. By 2019-20, the DBT system had expanded rapidly to cover more than 700 million beneficiaries who received \$ 50.5 billion in the financial year under 426 different schemes ⁷. 56% of households in the CPHS reported receiving some government transfer in March 2019, the average value of transfer being Rs. 473.00⁸.

Except for MGNREGS, India's other 425 cash transfer schemes are not designed as unemployment benefit programs. Even then we find a small, but statistically significant impact of the cash transfer on the impact of job loss on consumption expenditures, only for rural households. We construct a triple difference (DDD) estimate of the impact of DBT by comparing the double differences for DBT beneficiaries and non-beneficiaries (Table 7). The

triple interaction term (employment shock*DBT Beneficiary*April) is statistically significant but only at the 10% level and appears to be driven by the rural households. There is a 3.6% smaller reduction in consumption expenditure after the job loss for rural households that received a direct benefit transfer from the government which translates into a 3.1% smaller reduction in consumption expenditure from unemployment for beneficiaries across the entire sample. This may be indicative of the fact that these transfers constitute a larger portion of household income in rural families (6.9%) vs urban families (2.5%).

Most of India's DBT programs are not flexible to help families deal with transient poverty. However, as a part of the COVID-19 relief package, the Government of India has transferred \$3.75 billion to 310 million beneficiaries under the *Pradhan Mantri Garib Kalyan Yojana* (Prime Minister Poor's Welfare Scheme)⁹. Our analysis suggests that these cash transfers will help families maintain their consumption levels to some extent, particularly, if they are well-targeted, delivered on time, and without too many hassles for the beneficiaries (Bazzi, Sumarto, and Suryahadi, 2015).

Table 7: Triple Difference Estimation Results for the effects of unemployment on monthly consumption expenditure for DBT beneficiaries

Log (monthly consumption expenditure)	Full Sample (1)	Urban Sample (2)	Rural Sample (3)
Triple Diff Coefficient (April * Unemployed* DBT)	0.0311* (0.0188)	0.00126 (0.0428)	0.0355* (0.0205)
HH Controls	Yes	Yes	Yes
Observations	231,356	151,062	80,294
R-squared	0.405	0.380	0.376

Note: Robust standard errors in parentheses are clustered at town/village level

*** p<0.01, ** p<0.05, * p<0.1

The coefficients in the table above are based on a triple difference estimation that analyses the difference in monthly consumption expenditure between March and April 2019 between treated (lost earning member in April) households vs control households and across DBT beneficiaries and non-beneficiaries. In each regression, we control for the household size, the number of original earning members, the composition of household according to the age of members, education of members, gender of members and occupation of members, household caste category, household religion group, and household region of residence. Finally, we account for household savings, wealth asset index, and whether the household had any outstanding borrowings at the time of the survey. The values are basis log regressions using the logarithm of monthly consumption expenditure as the dependent variable and hence can be interpreted in percentage terms, multiplying the coefficients by 100. All observations are weighted using sampling probability weights.

4.6 Income elasticity of consumption expenditure

87% of rural and 57% of urban workers in India do not have regular salaried jobs (PLFS, 2019). Therefore, household incomes fluctuate from month-to-month even if there are no shocks to

the employment status of the working members. Table 8 presents the result of a fixed-effects regression of the change in consumption expenditure on change in the business & wage income of the household (columns 1 and 2) and total income from all sources (columns 3 and 4). The two panels of Figure 3 show non-parametric versions of the same regressions by plotting the percentage change in households' consumption expenditure between March and April 2019 against percentage change in their incomes.

Table 8 and the scatter plots in Figure 3 (a) and (b) show two interesting patterns. First, compared to rural families, the income elasticity of consumption expenditure is nearly 5 times higher for urban households for both business & wage income and total income. Second, the marginal propensity to consume (MPC) from business & wage incomes is twice as high compared to other sources of income in both rural and urban areas.

Table 8: Fixed Effects Regression of Log of Total Monthly Consumption Expenditure on Log Monthly Income and Log Business/Wage Income

<i>Log Monthly Household Consumption Expenditure</i>	(1) Rural Sample	(2) Urban Sample	(3) Rural Sample	(4) Urban Sample
Log Monthly Income (Business Profits/Wages)	0.0570*** (0.00693)	0.263*** (0.0390)		
Log Monthly Total Income			0.0297*** (0.00263)	0.110*** (0.0275)
FE	Yes	Yes	Yes	Yes
Observations	77,337	152,152	84,741	154,180
R-squared	0.022	0.066	0.027	0.033
Number of HHs	41,218	76,488	42,785	77,171

Note: Robust standard errors in parentheses clustered at the primary sampling unit level

*** p<0.01, ** p<0.05, * p<0.1

The coefficients above are from a Fixed Effects Panel OLS regression of log expenditure on log income differentiating between the log of household income from wages, bonuses, and business profits (Column (1) and (2)) and log of total household income (Column (3) and Column (4)). Columns (1) and (3) report results for the rural sample while Columns (2) and (4) report results for the urban sample. We control for household size and number of earning members. Assuming equal elasticity on both sides, we can induce the reduction in consumption expenditure for a 1% reduction in income from the values above. The sample sizes are different for the business/wage income and total income regressions, but results remain the same even when we run both sets of regressions for the same subset of households.

Figure 3: Scatterplots showing income elasticity of consumption expenditure for rural vs urban households

Note: The figures above depict the income elasticity of income to consumption expenditure based on changes between March 2019 and April 2019. Figure (a) displays the same for total household income, while Figure (b) displays the results for only household income from wages and business profits. The left panel in both figures is for the rural sub-sample, while the right panel is for the urban sub-sample. The Y-axis reports the percentage change in consumption expenditure and the X-axis reports the percentage change in total (business/wage) income. It is evident that in both cases the urban sample shows a higher elasticity of income to consumption expenditure, represented by the positive slope of the red line in the right panels compared to the relatively flat slope in the left panels.

4.7. Robustness Checks

To check if our results are robust to alternate specifications in terms of our time variable, we perform two tests.

First, we restrict our sample to the balanced panel (97,342 households) for which parallel trends are reported from Dec 2018-April 2019 in Figure 1. We run the regression for this sample, using different pre-treatment months (Dec 2018-Feb 2019) besides March 2019, to ensure that our results were not confounded by any March¹⁰ specific consumer behaviour. Table A.3 reports the results of the DID regressions for the full balanced sample as well as the urban sub-sample. We find that the effect of unemployment is significant and higher in magnitude ranging from 11%-14%, with urban households experiencing a fall of 10%-14% for this sample subset.

Second, we substitute the months in our analysis from March-April 2019 to June-July 2019 to check if the effects of unemployment on consumption expenditure are consistent across different seasons. 5% of our sample see a reduction in earning members over this period. Table A.4 reports results for the DID regressions across June-July 2019. The results are consistent with our March-April 2019 estimates, with an average fall in consumption of 8.09% (13.3% for urban and 7.3% for rural) post the unemployment shock. Table A.5 provides similar

estimates for the expense category DID regressions in June-July 2019, while Table A.6 provides the fixed effects income elasticity regression for this period. As before, we find a significant fall in health, education, and discretionary expenditure. The income elasticity of expenditure for urban households is almost 5 times higher than in rural households.

5. Conclusion

This paper uses panel data from a large nationally representative consumption and employment survey of nearly 175,000 households in India to analyse how consumption of non-durable and durable items responded to idiosyncratic employment shocks in 2019. Nearly 5% of households in our sample reported a decline in the number of earning members from March to April 2019. We use difference-in-differences regression, supported by tests for parallel trends in earlier months, to estimate the immediate response of the employment shock on consumption expenditures for both rural and urban households. Families, where the number of working members did not go down in this period, serve as the control group.

A negative employment shock leads to an average 7.2% reduction in consumption expenditure. However, there are significant heterogeneities in the response to the shock between a) rural and urban households; b) households at different expenditure (MPCE) levels; and c) among different categories of household expenditure. Urban household expenditures are more than twice as sensitive to an employment shock as rural household expenses (12.3% vs. 6.7%). Similarly, a one percent change in household income leads to a 5-6 times bigger change in the monthly expenditure of urban households. If there is a job loss, expenditures of the poorest and the richest households (those in the bottom and top MPCE deciles) decline the most. Liquidity or credit constraints may be the reason for the high sensitivity of the poorest to a shock. Equally large responses among the richest may be due to the presence of wealthy hand-to-mouth families in India or because these families have high levels of discretionary expenses that are easy to reduce when required. Expenditure on durable and discretionary goods shows the sharpest decline after the shock, but families also cut back on health and education expenses which may lead to long-term consequences even if the shock is temporary or short-lived.

Access to credit and liquid savings are often essential to smooth consumption after an income shock (Zeldes, 1989). Whether the shock is anticipated, or unanticipated, low and illiquid savings and credit constraints lead to an immediate reduction in household expenditure. Unfortunately, our dataset does not have data on the change in the amount of savings or debt.

However, aggregate data shows that India's household saving rate has declined from 23.6% in 2011-12 to 18.2% in 2018-19¹¹ and illiquid physical assets dominate the household portfolio of investments¹². According to an estimate, 90% of the household assets in India are held in the form of land and buildings (*see endnote 10 for the source of this data*). The CPHS data allows us to check if a family's debt status changed month-to-month. We find that households with more than one earning members are significantly more likely to start a loan after a member becomes unemployed as well as pay off existing debt. Families with only one working member do not show this switch. Nearly 80% of Indian households have only one working member. Binding credit constraints are a major reason why Indian families cannot smooth their consumption after a shock.

We find evidence that direct cash transfer from government to households, although not designed like unemployment benefit programs, helped mitigate the impact of the employment shock on the consumption expenditure to some extent for rural families in particular. These transfers can be more effective if they are paid regularly and targeted to the deserving families. At present more than 53% of households that receive some government transfer fall above the median level of MPCE.

We show that consumption of Indian households, including that of the richest ones, goes down significantly after an employment (or income) shock, but our results are not necessarily evidence of the failure of PIH. Many households in our data may have expected the shock and adjusted their expenditure levels as theory would predict. Even if the shock was unexpected, liquidity constraints can be a major determinant of consumption response to income shocks and there is some evidence of binding liquidity constraints for a majority of families that experienced employment shock in our data. Expenditures will decline also if households do not engage in intertemporal optimization and mechanically follow a simple rule where consumption is a constant fraction of their incomes (Gali, Lopez-Salido, and Valles 2004). An increase in home production after unemployment could be another reason for the decline in consumption expenditure.

Though our dataset does not allow us to test for the violation of the permanent income hypothesis, we make four contributions to the literature on the impact of employment or income shock on households. First, we show that household consumption is sensitive to idiosyncratic shocks and more so in urban areas of India. Second, our large sample and detailed consumption data allow us to show the heterogeneity in response across different MPCE levels and among various categories of household expenditure. Third, we present some evidence of the credit

constraints faced by a majority of Indian households in case of a shock and estimate the contribution of government cash transfers to consumption smoothing after a shock. Finally, we find that the income elasticity of consumption is higher in urban areas, and in both rural and urban areas, the marginal propensity to consume out of regular (wage and business) incomes is significantly higher than other income sources.

Appendix

Table A.1 Balance Test of Summary Statistics across treated and control households

VARIABLES	Control	Treated	Diff
Total HH Expenditure	12971.94	12443.17	-528.8**
Total HH Income	20926.21	28828.98	7,903***
Food Expense	5671.66	5569.72	-101.9
Health Expense	361.77	330.28	-31.48**
Education Expense	426.42	339.41	-87.01***
Durable Expense	284.47	233.69	-50.77
Discretionary Expense	3436.58	3372.11	-64.47
% HHs with Education expense	53.4%	47.5%	-0.0590***
% HHs with durable expense	39.4%	34.8%	-0.0460***
HH size	4.10	4.32	0.223***
Earning Members per household	1.10	1.55	0.455***
Households with multiple earning members	21.4%	42.3%	0.209***
Households that report imputed income (self-production)	30.2%	53.4%	0.232***
Households that report remittance income	1.5%	1.3%	-0.00258
Households that received cash transfers from government	55.7%	62.1%	0.0631***
Region (Urban)	34.7%	17.5%	-0.172***
Average number of saving instruments/Household	3.52	3.46	-0.0682
Households with outstanding borrowings	49.9%	54.2%	0.0436**
Income from other sources (excluding wage/business)	6047.26	2041.15	-4,006***
N	111,915	4,053	

Note: All values in the table are for March 2019

Table A.2: Average Effect of change in employment on monthly household consumption expenditure (March-April '19)

	Full Sample		Urban Sample		Rural Sample	
<i>Monthly Household Consumption Expenditure</i>	(1)	(2)	(3)	(4)	(5)	(6)
	Linear (In Rs.)	Log (In %)	Linear (In Rs.)	Log (In %)	Linear (In Rs.)	Log (In %)
<i>Base Category (Treatment=0) No change in Earning Members</i>						
DID Coefficient where Treatment= 1 (Decrease in Earning members) *April '19	-1,003*** (145.6)	-0.0723*** (0.00992)	-2,653*** (591.2)	-0.123*** (0.0228)	-769.6*** (132.7)	-0.0667*** (0.0109)
DID Coefficient where Treatment= 2 (Increase in Earning members) *April '19	619.9*** (179.2)	0.0644*** (0.0130)	-350.5 (672.9)	9.73e-05 (0.0326)	789.5*** (179.3)	0.0731*** (0.0141)
HH controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	239,700	239,700	154,002	154,002	85,698	85,698
R-squared	0.162	0.387	0.309	0.374	0.094	0.343

Note: Robust standard errors in parentheses are clustered at town/village (primary sampling unit) level

*** p<0.01, ** p<0.05, * p<0.1

Each cell is a coefficient regression from a difference-in-difference estimation that analyses the difference in monthly consumption expenditure between March and April 2019 for a categorical treatment variable that takes on a value of 0 for households that show no change in earning members (base category), a value of 1 for households that lose an earning member(s) in April and a value of 2 for households that gain an earning member(s) from March-April 2019. Both categories of households are compared to the base category of households that see no change in employment. In each regression, we control for the household size, the number of original earning members, the composition of household according to the age of members, education of members, gender of members, and occupation of members. We also control for household caste category, household religion group, the household region of residence, other sources of household income including imputed income, government transfers, dividends, interest earned, fixed deposits/provident fund account, remittances, sale of assets, gambling, etc. Finally, we account for household savings, wealth asset index, and whether the household had any outstanding borrowings at the time of the survey. Columns (1), (3), and (5) denote linear regressions using actual values of monthly total income measured in Rs as the dependent variable. Columns (2), (4), and (6) denote log regressions using the logarithm of monthly total income as the dependent variable and hence can be interpreted in percentage terms, multiplying the coefficients by 100. Columns (1) and (2) denote regression results using the entire sample (both urban and rural regions) while columns (3) and (4) denote regression results using only the urban sample and columns (5) and (6) denotes regressions results using only the rural sample. All observations are weighted using sampling probability weights.

Table A.3: Average Effect of unemployment on log monthly household consumption expenditure (balanced panel Dec'18 - April '19)

	March vs April 2019		Feb vs April 2019		Jan vs April 2019		Dec '18 vs April 2019	
<i>Household Monthly Consumption Expenditure</i>	(1) Full Sample	(2) Urban Sample	(3) Full Sample	(4) Urban Sample	(5) Full Sample	(6) Urban Sample	(7) Full Sample	(8) Urban Sample
DID Coefficient (Month=April *HH type=lost earning member in April)	-0.145*** (0.0174)	-0.149*** (0.0207)	-0.118*** (0.0187)	-0.127*** (0.0216)	-0.144*** (0.0182)	-0.150*** (0.0221)	-0.120*** (0.0183)	-0.105*** (0.0217)
HH controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	194,684	130,806	194,684	130,806	194,684	130,806	194,684	130,806
R-squared	0.418	0.389	0.420	0.392	0.425	0.397	0.434	0.402

Note: Robust standard errors in parentheses are clustered at town/village level

*** p<0.01, ** p<0.05, * p<0.1

Each cell is a coefficient regression from a difference-in-difference estimation that analyses the difference in monthly consumption expenditure between March and April 2019 in Column (1) and (2), February and April 2019 in Column (3) and (4), January and April 2019 in Column (5) and (6) and December 2018 and April 2019 in Column (7) and (8). The comparison is between households that lose an earning member in April 2019 compared to the baseline month and households that maintain the same number of earning members over the entire period. In each regression, we control for the household size, the number of original earning members, the composition of household according to the age of members, education of members, gender of members, and occupation of members. We also control for household caste category, household religion group, the household region of residence, other sources of household income including imputed income, government transfers, dividends, interest earned, fixed deposits/provident fund account, remittances, sale of assets, gambling, etc. Finally, we account for household savings, wealth asset index, and whether the household had any outstanding borrowings at the time of the survey.

All results denote log regressions using the logarithm of monthly consumption expenditure as the dependent variable and hence can be interpreted in percentage terms, multiplying the coefficients by 100. Columns (1), (3), (5) and (7) denote regression results using the entire sample (both urban and rural regions) while columns (2), (4), (6) and (8) denote regression results using only the urban sample. All observations are weighted using sampling probability weights.

Table A.4: Average Effect of unemployment on monthly household consumption expenditure (June-July '19)

	Full Sample		Urban Sample		Rural Sample	
<i>Monthly Household Consumption Expenditure</i>	(1) Linear (In Rs.)	(2) Log (In %)	(3) Linear (In Rs.)	(4) Log (In %)	(5) Linear (In Rs.)	(6) Log (In %)
DID Coefficient (Month=July * HH type=lost earning member)	-1,166*** (147.7)	-0.0809*** (0.0109)	-2,416*** (514.2)	-0.133*** (0.0346)	-939.7*** (128.7)	-0.0729*** (0.0104)
HH controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	232,868	232,868	153,160	153,160	79,708	79,708
R-squared	0.301	0.384	0.316	0.375	0.240	0.334

Note: Robust standard errors in parentheses are clustered at town/village (primary sampling unit) level

*** p<0.01, ** p<0.05, * p<0.1

Each cell is a coefficient regression from a difference-in-difference estimation that analyses the difference in monthly consumption expenditure between June and July 2019 between households that lose an earning member(s) in July 2019 comparative to June 2019 and households that maintain the same number of earning members from June-July 2019. In each regression, we control for the household size, the number of original earning members, the composition of household according to the age of members, education of members, gender of members, and occupation of members. We also control for household caste category, household religion group, the household region of residence, other sources of household income including imputed income, government transfers, dividends, interest earned, fixed deposits/provident fund account, remittances, sale of assets, gambling, etc. Finally, we account for household savings, wealth asset index, and whether the household had any outstanding borrowings at the time of the survey. Columns (1), (3), and (5) denote linear regressions using actual values of monthly total income measured in Rs as the dependent variable. Columns (2), (4), and (6) denote log regressions using the logarithm of monthly total income as the dependent variable and hence can be interpreted in percentage terms, multiplying the coefficients by 100. Columns (1) and (2) denote regression results using the entire sample (both urban and rural regions) while columns (3) and (4) denote regression results using only the urban sample and columns (5) and (6) denotes regressions results using only the rural sample. All observations are weighted using sampling probability weights.

Table A.5: Average Effect of unemployment on sub-categories of monthly consumption expenditure in Rs. (June-July '19)

	(1)	(2)	(3)	(4)	(5)
FULL SAMPLE	Food Expense	Discretionary Expense	Durable Expense	Education Expense	Health Expense
DID Coefficient	-293.3***	-378.9***	-38.68	-78.77	-82.25***
(Month=July*HH type=lost earning member)	(65.87)	(66.23)	(57.83)	(53.60)	(28.77)
(Proportion of Baseline Expenditure)	(5.22%)	(12.22%)	(7.7%)	(9.2%)	(24.5%)
HH Controls	Yes	Yes	Yes	Yes	Yes
Observations	232,868	232,868	98,396	125,356	232,868
R-squared	0.258	0.093	0.035	0.086	0.040

Note: Robust standard errors in parentheses are clustered at town/village level

*** p<0.01, ** p<0.05, * p<0.1

Each cell is a coefficient regression from a difference-in-difference estimation that analyses the difference in monthly consumption expenditure on food, education, health, discretionary items, and durable items, between June and July 2019 between treated (lower-earning members in April 2019) and control households. Discretionary Expenses include spending on recreation, restaurants, clothing and other accessories, mobile phone, cosmetics and health enhancements, fitness, pocket money, intoxicants, social and religious obligations, pets, painting and renovation, and travel. Durable expenses include expenditure on appliances, jewelry, furniture, light fixtures, and utensils. In each regression, we control for the household size, the number of original earning members, the composition of household according to the age of members, education of members, gender of members, and occupation of members. We also control for household caste category, household religion group, the household region of residence, other sources of household income including imputed income, government transfers, dividends, interest earned, fixed deposits/provident fund account, remittances, sale of assets, gambling, etc. Finally, we account for household savings, wealth asset index, and whether the household had any outstanding borrowings at the time of the survey. All results denote linear regressions using actual values of the consumption expenditure measured in Rs. as the dependent variable. The coefficients are also expressed as a proportion of the baseline expenditure on the sub-categories in March 2019 for the respective household type, to get a sense of the magnitude of reduction in expense. All observations are weighted using sampling probability weights

Table A.6: Fixed Effects Regression of Log of Total Monthly Consumption Expenditure on Log Monthly Income (June-July 2019)

	(1)	(2)
<i>Log Monthly Household Consumption Expenditure</i>	Rural Sample	Urban Sample
Log Monthly Total Income	0.0144*** (0.00175)	0.0515*** (0.0111)
FE	Yes	Yes
Observations	79,864	153,332
R-squared	0.018	0.020
Number of HHs	39,932	76,666

Note: Robust standard errors in parentheses clustered at the primary sampling unit level

*** p<0.01, ** p<0.05, * p<0.1

The coefficients above are from a Fixed Effects Panel OLS regression of log expenditure on log income between June-July 2019. Column (1) reports results for the rural sample while Column (2) reports results for the urban sample. We control for household size and number of working members. Assuming equal elasticity on both sides, we can induce the reduction in consumption expenditure for a 1% reduction in income from the values above.

Table A.7: Parametric Parallel Trend Regression of monthly household consumption expenditure (Dec 2018- March 2019)

	Full Sample		Urban Sample		Rural Sample	
<i>Monthly Household Consumption Expenditure</i>	(1) Linear (In Rs.)	(2) Log (In %)	(3) Linear (In Rs.)	(4) Log (In %)	(5) Linear (In Rs.)	(6) Log (In %)
DID Coefficient (Continuous-time variable * HH type=lost earning member in April 2019)	65.67 (44.32)	0.00394 (0.00269)	223.9** (87.10)	0.0116*** (0.00436)	-19.25 (44.21)	-0.000143 (0.00316)
Observations	390,352	390,352	262,248	262,248	128,104	128,104
R-squared	0.013	0.046	0.016	0.045	0.017	0.068

Note: Robust standard errors in parentheses are clustered at town/village level

*** p<0.01, ** p<0.05, * p<0.1

Each cell is a coefficient regression from a difference-in-difference estimation that analyses the month-on-month difference in consumption expenditure between households that lose an earning member in April 2019 comparative to March 2019 while experiencing no change before March 2019 and households that maintain the same number of earning members from Dec 2018- March 2019. The time variable takes on a value of 0 for December 2018, 1 for January 2019, 2 for February 2019, and 3 for March 2019. It is interacted with the treatment variable to get the monthly change in consumption expenditure for the treated group in the pre-unemployment periods compared to the control group. In each regression, we control for the household size. Columns (1), (3), and (5) denote linear regressions with the dependent variable measured in Rs. Columns (2), (4), and (6) denote log regressions using the logarithm of monthly consumption expenditure as the dependent variable and hence can be interpreted in percentage terms, multiplying the coefficients by 100. Columns (1), and (2) denote regression results using the entire sample (both urban and rural regions) while columns (3) and (4) denote regression results using only the urban sample and Column (5) and (6) report rural sub-sample results. All observations are weighted using sampling probability weights.

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Endnotes

¹ The usual status PLFS unemployment rate is based on whether a person worked for a relatively long part of the preceding 365 days from the date of the survey or at least 30 days during the year-long reference period.

² The unemployment rate as per the PLFS current weekly status (CWS) provides the number of persons who worked for at least 1 hour in the 7 days preceding the date of survey, following the guidelines of the International Labour Organisation. This is comparable to the CPHS (CMIE) unemployment rates which are based on whether a person was employed or not, as on the day of survey.

³ CPHS Data collection is ongoing

⁴ The areas not covered by CPHS are Arunachal Pradesh, Nagaland, Manipur, Mizoram, Sikkim, Andaman & Nicobar Islands, Lakshadweep, Dadra & Nagar Haveli, Daman & Diu

⁵ Every month, roughly one-fourth of the sample is interviewed under CPHS

⁶ In our analysis we exclude households that report loss of earning members due to migration, as well as households that report an increase in earning members in April 2019 relative to March 2019, from our sample.

⁷ <https://dbtbharat.gov.in/>

⁸ Hereon after we refer to these households as DBT beneficiaries and those that report no government transfer income, as non-beneficiaries

⁹ <https://www.livemint.com/news/india/covid-19-digital-payments-aids-cash-transfer-under-garib-kalyan-scheme-11586701007067.html>

¹⁰ March is the last month of a financial year in India.

¹¹ <https://www.hindustantimes.com/business-news/what-does-a-gdp-contraction-in-fy-2020-21-entail-for-india/story-88T2zz1A7Ld2FNh1OkaYEJ.html>

¹² <https://www.livemint.com/money/personal-finance/false-alarm-over-household-savings-in-india-11578902664194.html>

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