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Abstract

Existing evidence shows that the Covid-19 pandemic led to larger employment losses for working women in India. We examine the heterogeneity that underlies these trends by studying the impact of income shocks due to Covid-19 induced national lockdown (April-May 2020) on female employment. Using individual-level panel data and a difference-in-differences strategy that exploits the imposition of the national lockdown and accounts for seasonal employment trends, we find that women in households facing a hundred percent reduction in male income during the lockdown were 1.57 pp (27%) more likely to take up work after the restrictions eased (June-August 2020). We find these results to be predominant in poorer and less educated households. However, these positive employment trends are largely transitory as the effect on female employment reduces to 13% in these households during September-December 2020. These findings underscore the use of women's labor as insurance during low-income periods by poorer households.

Keywords: Employment, Covid-19, income shocks, gender, India
JEL Codes: J22, J23, J16

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1 Introduction

The Covid-19 pandemic and the ensuing lockdowns have inflicted unprecedented human and socioeconomic losses worldwide. India enforced one of the strictest national lockdowns across the world, starting March 24, 2020, up to May 2020, leading to a contraction of its GDP by 24% year-on-year during April-June 2020, with unemployment levels reaching historic highs of 23.5% in April 2020 and 21.7% in May 2020.[1] Notably, the lockdown was imposed with only 500 Covid-19 cases in India (Balajee et al., 2020) and throughout 2020, the health impact of the pandemic was little on the Indian economy. The impacts of the lockdown due to the pandemic, as with any crisis, were not gender-neutral.[2]

Existing studies estimate the gendered impacts of employment as a result of the Covid-19 pandemic-induced lockdown in India (Desai et al., 2021; Deshpande, 2020; Alon et al., 2020; Ham, 2021). While there is increasing evidence of larger losses borne by working women, the overall female employment effects and the heterogeneous effects underlying these trends remain under-explored. For instance, in the context of Covid-19, greater state capacity to generate public works employment has been shown to increase Female Labor Force Participation (FLFP) (Afridi et al., 2021b). In another study, Afridi et al. (2021a) find no impacts on job losses for women but only for men post the national lockdown among the urban poor. This paper looks at one such determinant of FLFP – the income effect. We examine whether negative income shocks faced by male members in a household, due to the national lockdown, led to an increase in labor market participation by women in these households to support their families.

Previous studies examining the cyclicity of women's work find that women's labor supply is pro-cyclical in the context of the developed economies (Killingsworth and Heckman, 1986; Joshi et al., 1985; Darby et al., 2001). However, this relationship reverses for the developing economies, where higher income in households is associated with a decline in female labor

[1] Bloomberg Quint and Scroll.in. The national lockdown was imposed only during March 24, 2020-May 2020. Thereafter, only local lockdowns were imposed based on Covid-19 cases in a state or district.

[2] UN Women.

supply (Bhalotra and Umana-Aponte, 2010; Sabarwal et al., 2011; Skoufias and Parker, 2006; Attanasio et al., 2005). Conversely, this would imply that a negative male income shock, like the Covid-19 lockdown, can increase female labor force participation in developing countries like India.

To the best of our knowledge, no study thus far has examined the heterogeneous impacts of income shocks due to the Covid-19 pandemic on women's employment. The underlying theoretical framework leading to counter-cyclicality of women's work has been laid out in Lundberg (1985), Ashenfelter (1980), Heckman and MaCurdy (1980), Ehrenberg and Smith (2003) and Borjas (2005) and is discussed in detail in Section 2.2. The framework assumes a married woman to be a secondary worker who temporarily increases her labor supply in the face of a negative economic shock due to loss in family income (income effect) and reduced opportunity cost for women to work with greater time devoted to house-work by husbands (substitution effect). This increase in the labor supply of married women when their husbands become unemployed is often referred to as the Added Worker Effect (AWE). The AWE primarily arises from the income effect since the substitution effect is generally small (Bhalotra and Umana-Aponte, 2010). From a lifecycle point of view, this implies that the effect only matters if the decline in the husband's income is a significant proportion of his lifelong income. Therefore, the AWE effect is likely to be large in families that face high liquidity constraints or fixed consumption commitments (Lundberg, 1985; Mincer, 1962).

We use the individual-level panel data, collected by the Center for Monitoring of Indian Economy (CMIE), through the Consumer Pyramid Household Surveys (CPHS), to analyze the heterogeneous impacts of male income losses during the lockdown (April 2020-May 2020) on female labor force participation as the restrictions eased during the un-lockdown phase (June-August 2020). Henceforth, for brevity, we refer to the un-lockdown time period as 'unlock' in the paper. The paper employs a difference-in-differences strategy, comparing the employment rates for women post the imposition of the lockdown across different phases of restrictions (lockdown vs unlock) to the employment rates before the lockdown (January-

March 2020), in households that faced a higher negative male income shock versus those that faced a lower male income shock. We estimate these changes over and above the same changes in 2019 to absorb any seasonality in employment. Additionally, we control for individual-level unobserved heterogeneity and yearly trends in labor market outcomes in all the specifications.

We find that, relative to the months before the lockdown, the probability of overall employment of women goes up by 1.57 pp (27%) during the unlock months (June-August 2020) if the household faces a hundred percent decline in male income during the lockdown period. For rural women, this is driven by an increase in casual labor employment for women by 1 pp (24%). For urban women, on the other hand, there is an increase across all categories of work, including self-employed (0.45 pp or 34%), casual labor (0.3 pp or 38.4%), salaried permanent work (0.29 pp or 26%) and salaried temporary work (0.57 pp or 38.6%). These findings are robust to attrition of households in the CMIE data during the pandemic months as the household survey shifted to a phone-based survey, district-specific trends, inclusion of an income shock dummy instead of a continuous variable, and non-linear effects. The increase in female employment is larger for low-income households and among less educated and married women. However, the increase in female employment in these households reduces to half during September-December 2020. These findings show that the insurance provided by female labor in households that are asset constrained is the primary mechanism behind our findings. We also test for pre-trends in female employment in 2019 for the households that faced a larger negative male income shock during the lockdown and find no differential trends, thus, finding support for our identifying assumption.

Our paper has implications for the response of female labor supply to the Covid-19 pandemic. These findings speak to the presence of heterogeneity in female employment response across households after the restrictions were eased, based on the male income shocks suffered during the lockdown. We also find that this differential increase was largely transitory in nature to meet the income needs of the households. Therefore, a sustained increase in women's engagement in the Indian labor market needs to attend to other constraints that hold back women from participating in the labor market. Apart from this, our paper also lends to the existing literature on understanding the causal relationship between economic shocks and FLFP in the developing economies.

2 Background and Literature

2.1 National Lockdown in India

The Indian government imposed one of the most stringent nationwide shutdowns to control the spread of Covid-19 that started with a "Janta Curfew" for one day on March 22, 2020, followed by a 21-day national lockdown from March 24, 2020. The lockdown was one of the strictest economic shutdowns across the world (Balajee et al., 2020) and was enforced when there were only 500 confirmed cases of Covid-19 recorded in the country. The re-opening of the economy (or the "unlock" phase) began in a phased manner on June 8, 2020 (unlock 1.0), permitting marketplaces, including shopping malls, religious places, hotels, and restaurants, to open up. In July 2020 (unlock 2.0), small shops were allowed to open up, and most other restrictions were lifted, and in August 2020 (unlock 3.0) night curfews and any remaining restrictions on economic activities and mobility were lifted.

The strict lockdown had severe repercussions for the Indian economy. The GDP contracted by about 24% year-on-year in the first quarter of 2020-2021. Bertrand et al. (2021) and Bertrand et al. (2020) discuss how some of the key indicators like employment, income, and consumption changed over time and across different categories of employment – self-employed, casual labor, fixed wage work – due to the lockdown in India. Thereafter, only local lockdowns were imposed depending on the severity of Covid-19 incidence. Notably, in 2020 the income shock due to the lockdown was more significant than the health shock due to the Covid-19 pandemic. The major wave of Covid-19 infections occurred in the country only from March 2021-May 2021, when many states imposed lockdowns. However, fewer restrictions on manufacturing, retail, and transport, meant that the 2021 shutdown measures were less stringent. In this paper, we look at the employment patterns in 2020 due to the negative income shock since the health shock of 2021 could have led to differential employment outcomes by gender due to other factors.

2.2 Literature Review

The theoretical framework behind an increase in female labor supply during idiosyncratic negative spousal income shocks has been extensively discussed in the literature (Lundberg, 1985; Ashenfelter, 1980; Heckman and MaCurdy, 1980; Ehrenberg and Smith, 2003; Borjas, 2005). This framework assumes a married woman to be a secondary worker who temporarily increases her labor supply when the husband faces a negative economic shock. This increase compensates for the loss in family income caused by the shock. This phenomenon is commonly referred to as the Added Worker Effect (AWE) in the literature.

The female labor supply can generally change in response to household income shocks due to both the substitution effect and the income effect. Since the substitution effect is generally small, the AWE is primarily driven by the income effect (Bhalotra and Umana-Aponte, 2010). From a lifecycle perspective, this implies that female labor supply goes up if the decline in the husband's income is a significant proportion of his lifelong income (Mincer, 1962; Lundberg, 1985). In other words, female labor could be treated as an insurance by households facing idiosyncratic income shocks (Attanasio et al., 2005; Sabarwal et al., 2011). In the absence of complete credit and insurance markets or any other physical and financial assets, poor households, when faced with negative income shocks, may resort to the only asset they have, i.e., labor.

In developed countries, unemployment insurance and other provisions can crowd out the need for women's labor as insurance.[3] However, the relationship reverses in the context of

[3]Empirical studies from developed countries show that female labor supply is pro-cyclical in aggregate (Joshi et al. (1985) for the UK, Killingsworth and Heckman (1986) for the US, and Darby et al. (2001) for other OECD countries).

developing countries where more women tend to take up work when spousal income reduces, often concentrated in low-income households facing liquidity constraints.[4] This tendency of women to act as secondary workers may also be magnified due to low skills and education levels among women and social norms that discourage women from working at usual times, particularly in the context of India.

In the context of the Covid-19 pandemic, research indicates gendered differences in employment losses with larger losses for women due to the pandemic-induced lockdowns (see Alon et al. (2020) for the USA, Ham (2021) for South Korea and Deshpande (2020) and Desai et al. (2021) for India). Alon et al. (2020) argues that women are likely to face a relatively larger brunt of job losses because the industries facing closures, like restaurants, retail spaces, and domestic care, employ more women than men. Technically advanced jobs that allow telecommuting tend to hire fewer women. Seck et al. (2021) also finds that in the context of Asia and the Pacific, the demand for unpaid domestic and care work has increased substantially, and the burden of that has disproportionately fallen on women. Findings in Kabeer et al. (2021) reinforce both channels in a cross-country context.

Deshpande (2020) examines the impact on employment by gender of the Covid-19 induced lockdown in India using the CMIE-CPHS data and finds that conditional on being employed before the lockdown, women are 20 pp less likely to be employed than men after the lockdown is lifted. Desai et al. (2021) also analyzes the same question but using data collected by the National Council of Applied Economic Research (NCAER) for the state of Delhi. In contrast, they find that job losses for men were greater than for women. The authors attribute this difference in result to the lack of accurate capturing of agricultural and other home-based employment in the CMIE-CPHS surveys. They find that self-employment in agriculture and home-based enterprises was relatively well-protected during the lockdown and that these sectors employ more women than men. This resulted in relatively lower employment losses

[4] See Bhalotra and Umana-Aponte (2010) for evidence on a number of developing economies including India, Skoufias and Parker (2006) for Latin America, Frankenberg et al. (2003) for Indonesia and Pessino et al. (1997) for Argentina and Lim (2000) for the Philippines.

during the lockdown for women in Delhi in their sample.

Another potential reason why Deshpande (2020) finds a significant decline in women's labor force compared to men is that the sample includes only women employed before the lockdown. Hence, it does not capture the possibility that women who were not working prior to the lockdown might have been pushed into the labor force after the lockdown restrictions were lifted. According to the AWE hypothesis, we can expect non-working women to enter the workforce after the lockdown to support their families. In order to allow for this possibility, we include all women in our analyses in the working age group, irrespective of their working status before the pandemic. Additionally, we complement the Deshpande (2020) and Desai et al. (2021) studies, which aim to understand the trend in FLFP by analyzing the underlying heterogeneous effects of male income losses on determining this trend.

3 Data

We use the Consumer Pyramids Household Surveys (CPHS) panel data by the Centre for Monitoring Indian Economy (CMIE). The CPHS survey follows a multi-stage stratified sampling where the Primary Sampling Units (PSUs) are the villages and towns of the 2011 Census and Ultimate Sampling Units (USUs) are the households from these PSUs.[5] The survey is conducted across all the major Indian states[6] and each household is surveyed once in each of the three waves every year since 2014: January to April (Wave-1), May to August (Wave-2), and September to December (Wave-3). It collects information on the demographics of households and individuals, employment status of individuals including industry, and

[5]The broad strata are the homogeneous regions which are a collection of neighboring districts within a state that have similar agro-climatic conditions. Each homogeneous region (HR) is then divided into rural and urban sub-strata. The urban region of an HR are further stratified into four strata based on town size. Thus, each HR has five sub-strata. From each sub-strata PSUs are selected randomly. Additionally, CPHS provides household-level sampling weights. We do not use weights in our analyses since there was attrition in the sampled households due to the pandemic. Our results, however, remain robust to conducting a weighted analysis. The results are available on request. For more details on the sampling strategy and the sampling weights, refer to CMIE's documentation here.

[6]The excluded states are mostly inaccessible or difficult to access regions. These include the four border states in the Northeast- Arunachal Pradesh, Nagaland, Manipur and Mizoram and some islands. Despite these exclusions, the survey represents almost 98.5% of the total population in India.

occupation codes once in every wave. The income of individual members is recorded for each of the four preceding months from the date of the interview in a wave. Therefore, we have access to individual-level monthly income data and wave level employment and occupation data.

We use data from January-August 2019 and January-August 2020 in our main analyses. During the lockdown month i.e., April 2020, the surveys were moved from door-to-door in-person surveys to phone based surveys. As a result, the sample size reduced by almost 40%. In our analyses, we therefore restrict the sample to households for which we have data during the period of lockdown, before the lockdown, and after the unlock. To elaborate, we keep households which were surveyed for all the three waves in 2020 as well as in 2019. We further keep only those households for which income data is available for the months of April and May in 2019 and 2020, the months we use to create the income shock measure, as discussed later. Lastly, we use data on the working-age population i.e., individuals aged 15-59. Our analysis is, therefore, based on a balanced panel of 179,404 unique individuals from 50,661 households. The sample includes 83,091 women and 96,313 men. Later, we check the robustness of our results to household attrition.

Our main outcome of interest is the employment status of an individual. We also analyze employment by the nature of work undertaken. The types of employment are divided into the following five categories – *Self-employed*, *Casual labor*, *Salaried Temporary*, and *Salaried Permanent*. *Self-employed* is defined as work not done under any employer and *Casual labor* is defined as work done for daily wages. An individual is classified as a *Salaried temporary* and *Salaried permanent* worker if the nature of the job involves fixed monthly wages. Here, salaried permanent jobs have relatively greater job security and a written contract with social security benefits.

3.1 Income Shock Measure

To construct the measure of income shock for a household, we use data on the monthly incomes received by each member of a given household recorded in the CPHS. We use data across four months to construct the measure- April-May 2019 and April-May 2020. We choose these months because April and May in 2020 saw the most significant income contraction due to the lockdown in India. Next, we only keep the male members to calculate the income shock so that the shock measure remains exogenous to female employment status. We add the incomes of all male members in a household and average them for April-May 2019 and April-May 2020. We take an average of incomes instead of using total male incomes to account for differences in the number of male members across households over time. There are often multi-generational households in India, hence, it is important to account for household size while calculating the income shock measure. Finally, we calculate the percentage change in average male income for a given household between April-May 2019 and April-May 2020. This value is used as the income shock measure $shock_h$.

$$shock_h = \frac{(Avg\ Inc\ in\ April - May\ 2019)_h - (Avg\ Inc\ in\ April - May\ 2020)_h}{(Avg\ Inc\ in\ April - May\ 2019)_h} \tag{1}$$

Here, a higher value of $shock_h$ implies a greater decline in income during April-May 2020 due to the lockdown as compared to April-May 2019. The range of the shock measure lies between $-\infty$ to 100%, however, to restrict our analysis within a reasonable range we restrict the negative value of the shock up to -1000 by dropping the households where the shock is less than -1000. There are such 1,426 unique individuals in households with an extreme value of income shock. The final range of the income shock thus lies between -1000 to 100, with a positive value showing a larger negative male income shock for a household during the lockdown. Figure 1 plots the distribution of the income shock measure $shock_h$. We find that there is a peak at 100% which represents households where the male members who were working in April-May 2019 are jobless during April-May 2020. The peak then keeps decreasing as we move to the left representing households where the male members faced a lower income decline in 2020.

3.2 Descriptive Statistics

Table 1 shows the summary statistics of the various employment outcomes considered in our analyses. The variable *Employed* takes a value of one if the individual is employed in any type of work in the labor market and zero otherwise. The types of work included in the analyses are – *Self-employed*, *Casual labor*, *Salaried Temporary* and *Salaried Permanent*. *Self-employed* takes a value of one if an individual is employed in their own business or enterprise and zero otherwise. *Casual labor* takes a value of one if an individual is employed in daily wage work and zero otherwise. *Salaried temporary* takes a value of one if an individual is employed in monthly wage work without any written contract and zero otherwise. *Salaried permanent* takes a value of one if an individual is employed in monthly wage work with a written contract and social security benefits and zero otherwise.

The mean employment rate for women in the sample is 5.7%, while for men it is 67.7%.[7] Among women, 1.7% are self-employed, 1.8% are engaged in casual labor while 1% and 1.2% are engaged in salaried permanent and salaried temporary work, respectively. Among men, 29.5% are self-employed, 16.8% are engaged in casual labor work and 11.6% and 8.9% are engaged in salaried permanent and salaried temporary work respectively. Panels B and C report the employment statistics for rural and urban areas respectively. Clearly, the employment rates on average are higher in rural areas. The type of employment in rural areas is largely self-employed and casual labor whereas in urban areas it is mostly salaried in nature.

[7]The survey does not collect data on days and hours worked in 2019 and hence we cannot use the intensive margin of work as an outcome variable in our analyses. Also, in general, employment rates obtained using the CPHS data have been shown to approximate employment rates for women in the daily status of nationally representative data like national Sample Surveys (Afridi et al., 2021b). Recently, CPHS was criticized for its systematic sampling strategy that over-samples well-to-do households. However, given that we are interested in heterogeneity across households and not aggregate trends, we believe this is not a major cause of concern in our analyses.

As a first step, we examine employment changes for both men and women during the treated months of April-May 2020 (lockdown) and June-August 2020 (unlock) compared to the control months of January-March 2020. Throughout the analyses, we control for seasonality in employment trends using data from 2019 (the detailed estimation strategy and results are discussed in Appendix A). We find that employment declined for both men and women during the lockdown months. During the unlock months, while both male and female employment recovered, male employment did not reach the pre-lockdown levels (Columns 1 and 2 of Appendix Table A1). On the other hand, female employment bounced back to the levels before the lockdown. We observe this for both rural and urban areas.

4 Empirical Strategy

We use a difference-in-differences strategy to identify the causal impact of the male income shock on female employment - overall and by type. We exploit the variation in employment changes during pre (year 2019) and post (year 2020) for the control months of January-March (before the lockdown) compared with the treated months of April-May (lockdown) and June-August (unlock). We further interact this with the level of income shock constructed in Section 3.1 to examine the differential impact on female employment of the male income shock faced by the household. We estimate the following specification:

$$\begin{aligned} Emp_{ihdmt} = \beta_0 + \beta_1 lock_m \times shock_h \times post_t + \beta_2 unlock_m \times shock_h \times post_t \\ + shock_h \times lock_m + shock_h \times unlock_m + lock_m \times post_t \\ + unlock_m \times post_t + shock_h \times post_t + post_t + X_{ih} + M_m + \epsilon_{ihdmt} \quad (2) \end{aligned}$$

The dependent variable Emp_{ihdmt} is a dummy variable that takes a value of one for individual i in a given household h in district d, in month m, and time t, if the individual is employed and zero otherwise. We define the different employment categories as follows: (i) Employed: =1 if an individual is employed in any economic activity and zero otherwise, (ii) Self-employed: =1 if an individual is self-employed and zero otherwise, (iii) Casual-labor: =1 if an individual is engaged in casual labor and zero otherwise, (iv) Salaried Temporary: =1 if an individual is engaged in temporary salaried job and zero otherwise (v) Salaried Permanent: = 1 if an individual is engaged in permanent salaried job and 0 otherwise.

Here, $unlock_m$ is a dummy variable that takes value one for the unlock months i.e., from June-August and $lock_m$ is an indicator for the lockdown months of April-May. $Post_t$ is an indicator for the year 2020 and takes the value zero for the year 2019. $Shock_h$ is the household-level measure of male income shock defined in Section 3.1. We control for year-fixed effects ($post_t$) to control for results being driven by overall changes in employment over time. We also include month fixed effects M_m to control for seasonality and individual fixed effects X_{ih} to control for individual-level unobserved time-invariant heterogeneity. The standard errors are clustered at the household-month level.

Our main coefficient of interest is β_2, which captures the impact of the male income shock (during the lockdown) on female employment during the unlock months of June-August 2020 as compared to the months of January-March 2020, over and above the change in outcome during 2019 between the same months. Meanwhile, the coefficient β_1 captures the impact of the male income shock on female employment during the lockdown months of April-May 2020 as compared to January-March 2020, after accounting for any seasonality in 2019. We do not expect β_1 to be significant since no adjustment would practically be possible in female employment during the lockdown period. However, if female labor is used as insurance in the labor market then β_2 would be positive. The identification assumption in our analyses is that in the absence of the lockdown, the households where male incomes fell more would not have observed a differential change in the employment of their female members. We conduct a placebo check to examine if these households experience any differential change in female employment in 2019 and find a null result, as discussed later.

5 Results

5.1 Baseline Results

Table 2 reports the results for the main specification (equation 2) for all India while Table 3 panels A and B report these for rural and urban areas, respectively. Column (1) reports the results for overall employment and columns (2), (3), (4) and (5) report it by the type of employment - self-employed, casual labor, salaried permanent and salaried temporary respectively. We find that the probability of overall female employment, relative to the pre-lockdown months, goes up by 1.57 pp (27%) during the unlock months (June-August) if the household faced a hundred percent decline in male income during the lockdown. We find that the increase is significant and positive across all types of work (Columns (2) to (5)). In particular, the increase in casual labor work is the largest at 0.53 pp for all India. However, we find that this employment response during the unlock months is not significantly different across the four categories of work (Appendix Table B1).

Table 3 shows that the increase in female employment for rural areas is 1.54 pp (19%) and for urban areas is 1.61 pp (34%) during the unlock months if the household faced a hundred percent decline in male income during the lockdown. In rural areas, the increase in the probability of working for women is statistically significant only for casual labor work (1 pp or 24%). While self-employed work, salaried permanent and salaried temporary work show a positive coefficient in rural areas, however, the point estimates are not statistically significant. On the other hand, in urban areas, female employment increases across all the categories of work during the unlock period in households that faced a hundred percent decline in male income: self-employed (0.45 pp or 34%), casual labor (0.3 pp or 38%), salaried permanent work (0.29 pp or 26%) and salaried temporary work (0.57 pp or 39%). In urban areas, the change in female employment in response to negative income shocks is not significantly different across employment categories (Appendix Table B1). However, in rural areas, the increase in casual labor for women is significantly more when compared to self-employed (difference of 0.8pp), salaried permanent (difference of 0.98 pp) and salaried temporary (difference of 0.78pp) work. This shows that women in households facing negative male income shocks are more likely to take up work in less secure non-contractual jobs in the rural areas.

We further examine the type of casual work women participate in when faced with a negative male income shock. To do this, we disaggregate casual work across casual agriculture work which includes laborers who work on agricultural farms for payment in kind and/or in cash and casual non-agriculture work which includes daily wage laborers in non-agriculture sectors. The results are reported in Table 4. Columns (1) and (2) report results for all India, columns (3) and (4) for rural areas and columns (5) and (6) for urban areas. We find that the female employment increase in casual labor due to the male income shock is entirely in casual agriculture work. The point estimate for overall employment for casual agriculture work is 0.44 pp (34.8%) while that for casual non-agriculture though positive and large, is not statistically significant. Thus, in both urban and rural areas, female casual employment increases significantly only in the casual agriculture work category.

Notably, during the lockdown ($lock_m$) months of April-May 2020, we do not find a change in female employment in response to the male income shock ($Lock{*}Shock{*}Post$), overall and across most categories of work, in Table 2 and Table 3. This shows that employment was not easily available during these months due to the stringent mobility restrictions placed in the country for both men and women. Hence, women could only engage in the labor market once the restrictions were lifted i.e., during the unlock months. The only exception is salaried temporary work which increased in rural areas by 0.5 pp for women in negatively male income-hit households, however, as we discuss later this is not robust to alternative specifications of the income shock.

We compare these results with those obtained for the male sample. The results are reported in Appendix Table B2 for the main specification (equation 2) at all India level and in Appendix Table B3 panels A and B for rural and urban areas, respectively. Note that these results are endogenous to the income shock since male incomes in a household are used to create the income shock. The results indicate that male employment in households facing negative income shock decreased by 7.9 pp during the lockdown months ($Lock * Shock * Post$). This lends credence to the insurance mechanism channel behind women working to compensate for the employment loss of men when the lockdown was imposed. During the unlock months, this decline in male employment was much smaller though ($Unlock * Shock * Post$) by 2.8 pp showing that many men who had lost employment during the lockdown came back to work when the restrictions were lifted. In fact, we find a positive effect for self-employed and casual labor work for men which implies that men who had lost more secure fixed-wage monthly jobs were also increasingly taking up self-employed and casual labor employment to sustain their families. Therefore, women might work after the restrictions were removed to compensate for the loss of work for male household members during the lockdown and to some extent during the unlock months as well.[8]

These results concur with the earlier empirical literature for the developing countries which shows that an economic shock (lower income shock) in a household leads to a higher probability of female employment (Bhalotra and Umana-Aponte, 2010; Skoufias and Parker, 2006). These results, in conjunction with those by Deshpande (2020), Afridi et al. (2021b) and Desai et al. (2021) imply that while the probability of female employment might have declined for the women working before the pandemic, there is heterogeneity in the overall impact on female employment. The households facing the most severe male income shocks witness an increase in female employment.

We also extend the above specification to look at persistence in these effects beyond August 2020 and find that the increase in female employment reduces by half (to 0.8 pp) post-August 2020 for women residing in households that suffered a hundred percent decrease in male income during the lockdown. These results show that the increase in women's

[8]It is possible that in households where men could not find employment even when the restrictions were lifted, women entered in sectors which were less affected. For example, home food delivery was common self-employment activity by women during the unlock months. See Huffington post.

engagement in the labor market in households that suffered an income shock was largely a temporary phenomenon. Once the male incomes return to the pre-pandemic levels, at least half of the women again withdraw from the workforce. These results are discussed in Appendix Table A.2 where Panel A reports the results for all India while Panels B and C report the results for rural and urban areas, respectively.

5.2 Heterogeneity

We examine the heterogeneity in response of female employment to the negative household male income shock during the lockdown by household and female demographic characteristics. Given the theoretical foundation provided in Lundberg (1985), Mincer (1962) and Bhalotra and Umana-Aponte (2010), we expect that the results are primarily driven by poor and uneducated women, arising out of consumption and liquidity constraints faced by these households. We also expect these results to be pre-dominant for married women because in the theoretical framework a married woman compensates for the loss of spousal income. The differential effects by age and the presence of children are not clear. It is possible that younger women and women having children are constrained by domestic work and childcare responsibilities, respectively. On the other hand, it is also possible that women with children have more mouths to feed and hence are more likely to join the workforce, after the restrictions are lifted, to compensate for male income losses.

5.2.1 Household Income

Table 5 reports the heterogeneous results by initial levels of household income in 2019. To do this, we examine differential female employment responses across below-median and above-median income households in 2019, when struck by a negative male income shock during the lockdown. The heterogeneous results concur with the literature showing that the income effect is dominant in poorer households. Overall, the probability of employment for women residing in below-median income households increases by 1.6 pp during the unlock months, while for those in above-median income households it increases by 1.04 pp. Additionally, women in lower-income households witness a larger increase in casual labor and salaried temporary work. For casual labor while women in both below and above-median income households witness an increase, the increase is much higher for below-median households (0.58 pp) than above-median households (0.35 pp).

On the other hand, for self-employment, the all India increase in female employment when the households faces a negative male income shock comes predominantly from families that had higher initial incomes. This result might reflect the need for basic liquidity to be able to support one's business. Households with higher income prior to the lockdown are more likely to have money for investment but poorer households would be less likely to fund self-employment based activities. In rural areas, we find that self-employment was not significant for women even with the above-median family income. The increase comes only from urban areas which provides more avenues for women to start a business of their own. In urban areas, both below-median income (0.42 pp) and above-median income (0.42 pp) households show an increase in self-employment for women during the unlock when the male members saw a reduced income due to the lockdown. Notably, average and median household incomes are higher in urban areas than rural areas.

Lastly, only women from below-median income households witness an increase in salaried permanent and salaried temporary jobs, during the unlock, when faced with a negative male income shock in the household. This increase is only limited to the urban areas where salaried permanent and salaried temporary work is easily available with point estimates for increase as 0.49 pp and 0.72 pp, respectively.

5.2.2 Female characteristics

We undertake heterogeneous analysis across a range of female demographic characteristics – (i) marital status, (ii) education level, (iii) age and (iv) children. Table 6 shows the heterogeneous results by the marital status of the women for all areas (Panel A), rural areas

(Panel B) and urban areas (Panel C). We estimate equation 2 for currently married and unmarried women separately and report the results in successive columns for each type of employment. We find that the increase in female employment during the unlock period due to a negative male income shock occurs only for married women. Overall, the probability of employment for married women due to a hundred percent decline in the incomes of male members in the household increases by 1.59 pp during the unlock, while for unmarried women there is no significant change. Across both rural (1.51 pp) and urban areas (1.66 pp), the point estimate is positive and significant only for married women. This result concurs with the theoretical framework that explains the counter-cyclicity of women's work where a married woman temporarily increases her labor supply in order to compensate for the loss of her husband's employment (Lundberg, 1985; Mincer, 1962; Bhalotra and Umana-Aponte, 2010). Unfortunately, the CPHS data does not allow one to match wife-husband pairs, else this hypothesis could have been directly tested in such a setting.

Appendix Table B4 shows the heterogeneous results by female education for all areas (Panel A), rural areas (Panel B) and urban areas (Panel C). We estimate equation 2 for women who are less than secondary school educated (below class 10) and those that have at least secondary education (pass class 10) and report the results in successive columns for each type of employment. We find larger and a more significant employment increase during the unlock months for women with less than secondary education. For rural areas, in particular, less educated women witness a significant increase in the probability of working in the unlock period by 2.11 pp due to a hundred percent decline in male income shock during the lockdown. Both casual labor (1.53 pp) and work for temporary fixed wages (0.35 pp) increase for less educated women in rural areas. In urban areas, female employment increases in overall work for both education categories of women, however, the magnitude of the increase is higher for women having education below class 10 (1.83 pp) as compared to those having at least secondary education (1.29 pp). For self-employed work, we only find a significant increase in employment for women having class 10 education and above (0.56

pp) again pointing at possible asset constraints for starting one's own business which may be less for higher income or more educated households. For casual labor (0.55 pp), salaried permanent (0.29 pp) and salaried work (0.78 pp) the probability of work largely increases for women having less than secondary education.

We further conduct the heterogeneity result by age (15-25 vs 35-59) and presence of children in the household (no child less than 6 years vs house with a child less than 6 years). In the CPHS data, we cannot match a child to the mother, however, we do know if there is an individual less than 6 years of age in a household or not. We construct the child-care indicator using this as a proxy (similar to Deshpande (2020)). The results are reported in Appendix Tables B5 and B6 for differential effects by age and child presence, respectively. While both younger and older women increase employment during the unlock period in response to a negative male income shock during the lockdown, the effects are larger for older women. The effects of the presence of children vary across rural and urban areas. In rural areas, women in households with no children witness an increase in their employment while in urban areas both women witness a similar increase in employment, in response to a negative male income shock. This shows that both demands on female time due to childcare responsibilities and income effects (need to feed more people) may be at play in households with children.

6 Robustness

We conduct a placebo test to show that the above results are indeed due to differential responsiveness of female employment to male income shocks, rather than a general trend in female employment in households that faced a negative income shock during the lockdown. We also check the robustness of our main findings to alternate specifications below.

6.1 Pre-trends in Outcomes

We undertake a falsification exercise using the data from Jan–Aug 2018 and Jan–Aug 2019 and defining $post_t = 1$ if the year was 2019. We do not expect to see any systematic employment trends across households facing a differential male income decline during the lockdown of 2020, for the period in 2019, since this period is before any pandemic-induced lockdowns were implemented. Table 7 reports the results of this falsification exercise. Indeed, we do not find a significant difference between the probability of female employment either during April-May 2019 or June-August 2019 in comparison to Jan-Mar 2019, by the income shock faced by the household in 2020, either at an overall level (Column 1) or across employment types (Columns 2-5). These results show that the parallel employment trends assumption before the shock holds for the difference-in-differences analysis in our case.

6.2 Attrition

We examine whether our results are robust to household attrition during the lockdown months. To do so, we carry out inverse probability weighted estimation to estimate the probability of a 2019 surveyed household being present in the data sample for Q1 of 2020 (Afridi et al., 2021b). This estimation is done using a logit model with predictors including pre-pandemic location (rural/urban) of the household, constructed asset index and other household characteristics.[9] The observed household characteristics used in the estimation include age group, occupation group, education group, gender group, size group, and the total income of all members in the last 12 months. The results reported in Appendix Table B7 show that our main findings are robust to correction for attrition in the sample. We continue to find a relative increase in employment of women after the lockdown restrictions are lifted in households that face a negative male income shock during the lockdown.

[9]The asset index is created using Principal Component Analysis (PCA) for multiple binary indicators depicting ownership of various assets including mobile, health insurance, LIC, bank account, PF account, Kisan credit card, credit card and Demat account.

6.3 District Seasonality

We also check the robustness of our results to seasonality in female employment at a geographically disaggregated level by controlling for district-specific seasonality in outcome variables. We estimate equation 2 with additional controls for interaction between D_d and M_m. The results reported in Appendix Table B8 show that our main findings continue to hold. The significance does not change for any of the coefficients when compared to the main results.

6.4 Negative Shock Dummy

Next, we examine whether the results remain robust to using a dummy variable for the income shock measure instead of the continuous variable used in our main specification. We create an indicator variable that takes a value of one for any household that lost male income on the basis of the income shock measure constructed earlier and zero otherwise. We then estimate the baseline regression equation 2 using this dummy variable as a measure of a negative income shock. The results reported in Appendix Table B9 again show that the probability of female employment increases by 2.52 pp during the unlock period in a household that faced a negative male income shock versus a household that did not face negative male income shock during the lockdown. The significance of the point estimates do not change for the most part except that they become slightly less significant for self-employed work.

6.5 Non-Linear Effects

We also check for non-linear effects of the income shock in the main specification. To do this, we create the following dummy variables, $Shock\ 0 - 50$ which takes a value of one if the negative income shock is between 0% to 50%, and $Shock\ 50 - 100$ which takes a value of one if the negative income shock is between 50% to 100%. We then estimate the baseline specification after interacting with both these shock dummies with $post_t$, $lock_m$, and $unlock_m$ dummies as defined earlier. Appendix Table B10 reports the results for this specification. As expected, households that suffered a higher negative male income shock in the range of 50-100%, are the ones that witness an increase in female employment after the restrictions are lifted.

7 Discussion and Conclusion

The relationship between women's work and recessions has been well documented in the literature, with relative changes in employment determined by either change in differential demand by gender or an increase in the supply of female labor during negative income shocks. In this paper, we examine the heterogeneous impacts of male income shocks, in the context of the Covid-19 induced national lockdown, on female employment in India. Our findings suggest that women who faced a higher negative male income shock in their households during the lockdown (April-May 2020), increase their employment when the restrictions in the economy are lifted (June-August 2020), as compared to women who faced no such income shock. This result adds further evidence to the counter-cyclical nature of the female labor supply in the developing economies. The differences in rural and urban areas reveal that rural women primarily depend on casual labor, especially agricultural labor, but women in urban areas are able to access employment in fixed-wage work and self-employment after the restrictions are lifted, to compensate for the decline in male income during the lockdown.

We also find that the obtained effects vary by the pre-pandemic characteristics of the households, with a larger increase in female employment in poorer households and among the less educated women. Thus, women who face a higher risk of consumption inadequacy take up employment due to a negative male income shock. We also find that the above increase in female employment is primarily for married women. These findings provide evidence for women's labor acting as an insurance mechanism for sustenance of households when hit by a negative male income shock. However, the differential increase in employment for women in households facing a negative male income shock is halved beyond August 2020 up to December 2020. These results show that the increase in female employment, in response to a negative male income shock, is mostly transitory in nature.

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Table 1: Summary Statistics: Employment

Variable	Obs		Mean		S.D.	
	Female (1)	Male (2)	Female (3)	Male (4)	Female (5)	Male (6)
Panel A: Total						
Employed	258489	306461	5.7%	67.7%	0.23	0.47
Self Employed	258489	306461	1.7%	29.5%	0.13	0.46
Casual labor	258489	306461	1.8%	16.8%	0.13	0.37
Salaried Permanent	258489	306461	1.0%	11.6%	0.1	0.32
Salaried Temporary	258489	306461	1.2%	8.9%	0.11	0.28
Panel B: Rural						
Employed	77462	92773	8.2%	69.3%	0.27	0.46
Self Employed	77462	92773	2.7%	34.5%	0.16	0.48
Casual labor	77462	92773	4.1%	21.5%	0.2	0.41
Salaried Permanent	77462	92773	0.6%	6.0%	0.08	0.24
Salaried Temporary	77462	92773	0.7%	5.6%	0.08	0.23
Panel C: Urban						
Employed	181027	213688	4.7%	67.1%	0.21	0.47
Self Employed	181027	213688	1.3%	27.3%	0.11	0.45
Casual labor	181027	213688	0.8%	14.7%	0.09	0.35
Salaried Permanent	181027	213688	1.1%	14.0%	0.1	0.35
Salaried Temporary	181027	213688	1.4%	10.3%	0.12	0.3

Note: The table uses employment data from Consumer Pyramid Household Survey (CPHS) for the relevant time period of the sample (January to August 2019 & January to August 2020). The details for data construction of the sample is discussed in section 3.

Table 2: Impact of income shock on female employment: All India

Variable	**Employed**	**Self-Employed**	**Casual labor**	**Salaried Permanent**	**Salaried Temporary**
	(1)	(2)	(3)	(4)	(5)
Unlock*Shock*Post	0.0157***	0.00359**	0.00527***	0.00213*	0.00454***
	(0.00250)	(0.00146)	(0.00137)	(0.00119)	(0.00140)
Lock*Shock*Post	0.00292	0.00000487	-0.00191	0.000755	0.00394**
	(0.00353)	(0.00239)	(0.00181)	(0.00159)	(0.00188)
Unlock*Post	-0.00741***	0.000656	0.000792	-0.00483***	-0.00403***
	(0.00218)	(0.00131)	(0.00125)	(0.00104)	(0.00120)
Lock*Post	-0.0140***	0.000148	-0.00769***	-0.00263*	-0.00384**
	(0.00308)	(0.00199)	(0.00171)	(0.00144)	(0.00166)
Shock*Unlock	-0.00404***	-0.00108	-0.00156*	-0.000274	-0.000965
	(0.00138)	(0.000821)	(0.000841)	(0.000630)	(0.000787)
Shock*Lock	-0.00283	-0.000842	-0.000777	0.000173	-0.00132
	(0.00177)	(0.00120)	(0.000966)	(0.000798)	(0.00103)
Shock*Post	-0.00108	0.000234	-0.000125	-0.000524	-0.000656
	(0.00172)	(0.00104)	(0.00105)	(0.000868)	(0.00103)
Observations	249558	249558	249558	249558	249558
R-squared	0.644	0.568	0.587	0.663	0.569
Mean Y	0.0576	0.0174	0.0180	0.00966	0.0123

Note: The table uses employment data from Consumer Pyramid Household Survey (CPHS) for the relevant time period of the sample (January to August 2019 & January to August 2020). The details for data construction of the sample is discussed in section 3. Here, *unlock* is the indicator for unlock months including June-August, while *lock* is the indicator for lockdown months April-May. ($\star p < 0.10, \star\star p < 0.05, \star\star\star p < 0.01$)

Table 3: Impact of income shock on female employment: By sector

Variable	**Employed**	**Self-Employed**	**Casual labor**	**Salaried Permanent**	**Salaried Temporary**
	(1)	(2)	(3)	(4)	(5)
			Panel A: Rural		
Unlock*Shock*Post	0.0154***	0.00210	0.0102***	0.000411	0.00243
	(0.00440)	(0.00262)	(0.00352)	(0.00106)	(0.00170)
Lock*Shock*Post	0.00238	0.00194	-0.00624	0.000972	0.00565*
	(0.00625)	(0.00414)	(0.00443)	(0.00150)	(0.00303)
Unlock*Post	-0.0118***	-0.000580	-0.00531*	-0.00256**	-0.00322**
	(0.00406)	(0.00264)	(0.00321)	(0.00111)	(0.00158)
Lock*Post	-0.0346***	-0.00284	-0.0220***	-0.00339**	-0.00589**
	(0.00574)	(0.00392)	(0.00435)	(0.00171)	(0.00247)
Shock*Unlock	-0.00574**	-0.000558	-0.00499**	0.000161	-0.000163
	(0.00264)	(0.00159)	(0.00222)	(0.000682)	(0.000919)
Shock*Lock	-0.00599*	-0.000782	-0.00292	0.0000206	-0.00227
	(0.00344)	(0.00244)	(0.00247)	(0.00102)	(0.00156)
Shock*Post	-0.00505	-0.000245	-0.00382	0.000345	-0.00120
	(0.00313)	(0.00192)	(0.00262)	(0.000841)	(0.00146)
Observations	74860	74860	74860	74860	74860
R-squared	0.687	0.615	0.626	0.705	0.617
Mean Y	0.0827	0.0273	0.0418	0.00621	0.00709
			Panel B: Urban		
Unlock*Shock*Post	0.0161***	0.00448**	0.00300**	0.00293*	0.00565***
	(0.00302)	(0.00176)	(0.00119)	(0.00167)	(0.00187)
Lock*Shock*Post	0.00236	-0.000564	-0.000746	0.000411	0.00309
	(0.00430)	(0.00294)	(0.00160)	(0.00230)	(0.00236)
Unlock*Post	-0.00582**	0.000944	0.00357***	-0.00586***	-0.00454***
	(0.00258)	(0.00150)	(0.00112)	(0.00143)	(0.00158)
Lock*Post	-0.00515	0.00135	-0.00172	-0.00210	-0.00286
	(0.00366)	(0.00229)	(0.00149)	(0.00200)	(0.00214)
Shock*Unlock	-0.00353**	-0.00151	0.00000319	-0.000455	-0.00142
	(0.00162)	(0.000953)	(0.000732)	(0.000860)	(0.00106)
Shock*Lock	-0.00148	-0.00107	0.000391	0.000193	-0.000911
	(0.00205)	(0.00132)	(0.000874)	(0.00108)	(0.00132)
Shock*Post	0.000508	0.000393	0.00141	-0.000886	-0.000452
	(0.00207)	(0.00124)	(0.00103)	(0.00117)	(0.00133)
Observations	174698	174698	174698	174698	174698
R-squared	0.610	0.525	0.487	0.653	0.558
Mean Y	0.0469	0.0131	0.00781	0.0111	0.0146

Note: The table uses employment data from Consumer Pyramid Household Survey (CPHS) for the relevant time period of the sample (January to August 2019 & January to August 2020). The details for data construction of the sample is discussed in section 3. Here, *unlock* is the indicator for unlock months including June-August, while *lock* is the indicator for lockdown months April-May. ($\star p < 0.10, \star\star p < 0.05, \star\star\star p < 0.01$)

Table 4: Impact of income shock on female employment: By type of casual work

Variable	Casual Agri (1)	Casual Non-agri (2)	Casual Agri (3)	Casual Non-agri (4)	Casual Agri (5)	Casual Non-agri (6)
	Total		***Rural***		***Urban***	
Unlock*Shock*Post	0.00435***	0.000377	0.0102***	-0.000501	0.00147***	0.000960
	(0.00105)	(0.000838)	(0.00324)	(0.00131)	(0.000482)	(0.00103)
Lock*Shock*Post	-0.00128	-0.000793	-0.00613	-0.000627	-0.0000757	-0.000664
	(0.00146)	(0.00106)	(0.00430)	(0.00126)	(0.000538)	(0.00146)
Unlock*Post	-0.000967	0.00135*	-0.00753**	0.00207*	0.00216***	0.000890
	(0.000975)	(0.000773)	(0.00301)	(0.00118)	(0.000495)	(0.000971)
Lock*Post	-0.00588***	-0.00211**	-0.0193***	-0.00245*	-0.000107	-0.00215
	(0.00140)	(0.00100)	(0.00421)	(0.00135)	(0.000606)	(0.00134)
Shock*Unlock	-0.00172***	0.000373	-0.00432**	-0.000465	-0.000395	0.000619
	(0.000667)	(0.000493)	(0.00214)	(0.000667)	(0.000255)	(0.000638)
Shock*Lock	-0.00101	0.000402	-0.00199	-0.000662	-0.000263	0.000782
	(0.000762)	(0.000594)	(0.00239)	(0.000827)	(0.000309)	(0.000781)
Shock*Post	-0.00103	0.00117*	-0.00277	-0.000557	-0.000283	0.00186**
	(0.000786)	(0.000670)	(0.00252)	(0.000747)	(0.000408)	(0.000893)
Observations	249558	249558	74860	74860	174698	174698
R-squared	0.612	0.493	0.627	0.482	0.429	0.497
Mean Y	0.0125	0.00492	0.0372	0.00399	0.00192	0.00531

Note: The table uses employment data from Consumer Pyramid Household Survey (CPHS) for the relevant time period of the sample (January to August 2019 & January to August 2020). The details for data construction of the sample is discussed in section 3. Here, *unlock* is the indicator for unlock months including June-August, while *lock* is the indicator for lockdown months April-May. We divide casual labor work in two categories: (a) casual agri work is defined as work done by a person, who doesn't own a land, on fields for a payment in cash and/or kind. (b) casual non-agri work is defined as employment for daily wages from non-agricultural sources. This includes industrial workers, construction site workers, brick-layer, painter etc. ($\star p < 0.10, \star\star p < 0.05, \star\star\star p < 0.01$)

Table 5: Heterogeneity: Household income

Variable	Employed		Self Employed		Casual labor		Salaried Permanent		Salaried Temporary	
	(1) Below Median	(2) Above Median	(3) Below Median	(4) Above Median	(5) Below Median	(6) Above Median	(7) Below Median	(8) Above Median	(9) Below Median	(10) Above Median
Panel A: Total										
Unlock*Shock*Post	0.0160***	0.0104**	0.00259	0.00579**	0.00524***	0.00353**	0.00294**	0.000186	0.00510***	0.00101
	(0.00287)	(0.00414)	(0.00173)	(0.00233)	(0.00163)	(0.00143)	(0.00115)	(0.00282)	(0.00166)	(0.00191)
Lock*Shock*Post	0.000546	-0.00301	0.000769	-0.00525*	-0.00358**	-0.00264	-0.0000503	0.00444	0.00340**	0.000153
	(0.00319)	(0.00474)	(0.00222)	(0.00286)	(0.00159)	(0.00193)	(0.00137)	(0.00284)	(0.00162)	(0.00224)
Observations	125127	124431	125127	124431	125127	124431	130553	119005	130553	119005
R-squared	0.645	0.641	0.557	0.582	0.603	0.538	0.642	0.672	0.577	0.551
Mean Y	0.0680	0.0472	0.0200	0.0148	0.0265	0.00948	0.00567	0.0140	0.0155	0.00886
Panel B: Rural										
Unlock*Shock*Post	0.0101**	0.0215**	0.0000166	0.0127	0.00859**	0.00234	-0.000460	0.00527	0.00166	0.00109
	(0.00467)	(0.0107)	(0.00274)	(0.00822)	(0.00369)	(0.00604)	(0.000975)	(0.00385)	(0.00176)	(0.00400)
Lock*Shock*Post	-0.00205	-0.0133	0.00281	-0.00673	-0.00960***	-0.0127	0.000394	0.00507	0.00424*	0.00112
	(0.00506)	(0.0118)	(0.00335)	(0.00947)	(0.00352)	(0.00811)	(0.000996)	(0.00378)	(0.00240)	(0.00452)
Observations	47615	27245	47615	27245	47615	27245	49120	25740	49120	25740
R-squared	0.675	0.708	0.569	0.674	0.642	0.581	0.696	0.715	0.619	0.613
Mean Y	0.0844	0.0798	0.0241	0.0331	0.0478	0.0313	0.00487	0.00878	0.00755	0.00622
Panel C: Urban										
Unlock*Shock*Post	0.0194***	0.00757*	0.00419*	0.00423*	0.00308**	0.00350***	0.00485***	-0.00101	0.00724***	0.000983
	(0.00362)	(0.00448)	(0.00223)	(0.00229)	(0.00146)	(0.00114)	(0.00171)	(0.00327)	(0.00238)	(0.00217)
Lock*Shock*Post	0.000728	0.000580	-0.000243	-0.00433	-0.00101	-0.0000166	-0.000889	0.00445	0.00294	0.0000170
	(0.00413)	(0.00517)	(0.00297)	(0.00270)	(0.00146)	(0.00120)	(0.00215)	(0.00342)	(0.00213)	(0.00259)
Observations	77512	97186	77512	97186	77512	97186	81433	93265	81433	93265
R-squared	0.617	0.600	0.547	0.491	0.510	0.408	0.616	0.665	0.567	0.540
Mean Y	0.0580	0.0380	0.0175	0.00967	0.0134	0.00337	0.00615	0.0155	0.0203	0.00959

Note: The table uses employment data from Consumer Pyramid Household Survey (CPHS) for the relevant time period of the sample (January to August 2019 & January to August 2020). The details for data construction of the sample is discussed in section 3. Here, *unlock* is the indicator for unlock months including June-August, while *lock* is the indicator for lockdown months April-May. While, *belowmedian* includes the sample of women whose households had below median income in 2019, *abovemedian* includes sample of women who had above median income in 2019. ($\star p < 0.10, \star\star p < 0.05, \star\star\star p < 0.01$)

Table 6: Heterogeneity: Women's marital status

					Panel A: Total					
Variable	**Employed**		**Self Employed**		**Casual labor**		**Salaried Permanent**		**Salaried Temporary**	
	(1) Married	(2) Not Married	(3) Married	(4) Not Married	(5) Married	(6) Not Married	(7) Married	(8) Not Married	(9) Married	(10) Not Married
Unlock*Shock*Post	0.0159***	0.00367	0.00350**	-0.000747	0.00655***	-0.000248	0.00194	0.00152	0.00389**	0.00273
	(0.00280)	(0.00371)	(0.00167)	(0.00205)	(0.00158)	(0.000868)	(0.00127)	(0.00226)	(0.00151)	(0.00235)
Lock*Shock*Post	0.00115	-0.000310	-0.000522	-0.000690	-0.00174	-0.00273	0.000682	0.000163	0.00270*	0.00260
	(0.00319)	(0.00384)	(0.00233)	(0.00156)	(0.00152)	(0.00196)	(0.00141)	(0.00265)	(0.00152)	(0.00275)
Observations	179393	56977	179393	56977	179393	56977	179393	56977	179393	56977
R-squared	0.637	0.655	0.570	0.571	0.594	0.511	0.663	0.660	0.556	0.574
Mean Y	0.0596	0.0273	0.0185	0.00688	0.0212	0.00263	0.00924	0.00716	0.0105	0.00988
					Panel B: Rural					
Unlock*Shock*Post	0.0151***	0.000828	0.000924	0.000248	0.0124***	-0.00181	0.00105	-0.00126	0.000490	0.00300
	(0.00541)	(0.00456)	(0.00331)	(0.00244)	(0.00438)	(0.00180)	(0.00113)	(0.00193)	(0.00170)	(0.00323)
Lock*Shock*Post	-0.00221	-0.00146	0.00131	0.000796	-0.00920**	-0.00658	0.00175	-0.00147	0.00384	0.00593
	(0.00572)	(0.00643)	(0.00416)	(0.00199)	(0.00408)	(0.00451)	(0.00127)	(0.00137)	(0.00270)	(0.00392)
Observations	54545	16870	54545	16870	54545	16870	54545	16870	54545	16870
R-squared	0.680	0.690	0.612	0.660	0.627	0.500	0.677	0.696	0.627	0.579
Mean Y	0.0938	0.0248	0.0310	0.00794	0.0508	0.00456	0.00561	0.00533	0.00636	0.00605
					Panel C: Urban					
Unlock*Shock*Post	0.0166***	0.00526	0.00483**	-0.00126	0.00396***	0.000667	0.00231	0.00315	0.00554***	0.00241
	(0.00324)	(0.00513)	(0.00192)	(0.00287)	(0.00120)	(0.000926)	(0.00176)	(0.00335)	(0.00203)	(0.00315)
Lock*Shock*Post	0.00167	0.000410	-0.00127	-0.00137	0.000853	-0.000226	-0.0000461	0.000785	0.00212	0.000643
	(0.00387)	(0.00469)	(0.00282)	(0.00218)	(0.00117)	(0.00111)	(0.00202)	(0.00437)	(0.00180)	(0.00379)
Observations	124848	40107	124848	40107	124848	40107	124848	40107	124848	40107
R-squared	0.595	0.642	0.524	0.525	0.485	0.521	0.660	0.650	0.539	0.572
Mean Y	0.0446	0.0283	0.0131	0.00643	0.00831	0.00182	0.0108	0.00793	0.0124	0.0115

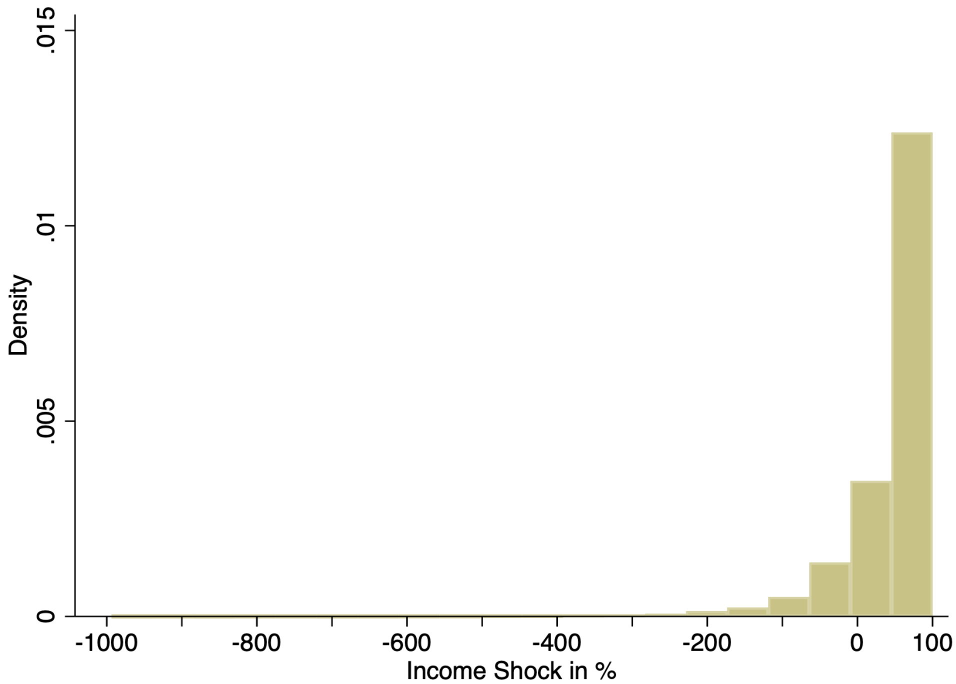
Note: The table uses employment data from Consumer Pyramid Household Survey (CPHS) for the relevant time period of the sample (January to August 2019 & January to August 2020). The details for data construction of the sample is discussed in section 3. Here, *unlock* is the indicator for unlock months including June-August, while *lock* is the indicator for lockdown months April-May. While, $Married$ includes the sample of women who are currently married, $NotMarried$ includes sample of women are unmarried, divorced or widowed. ($\star p < 0.10, \star\star\, p < 0.05, \star\star\star p < 0.01$)

Table 7: Robustness: Placebo

Variable	Employed	Self-Employed	Casual labor	Salaried Permanent	Salaried Temporary
	(1)	(2)	(3)	(4)	(5)
Panel A: Total					
Unlock*Shock*Post	-0.00361	0.000209	-0.00161	-0.00146	-0.000640
	(0.00224)	(0.00134)	(0.00131)	(0.00115)	(0.00120)
Lock*Shock*Post	-0.00239	0.000501	-0.000437	-0.00168*	-0.000794
	(0.00193)	(0.00120)	(0.00114)	(0.000941)	(0.00110)
Observations	252580	252580	252580	252580	252580
R-squared	0.717	0.587	0.675	0.714	0.601
Mean Y	0.0636	0.0162	0.0218	0.0120	0.0134
Panel B: Rural					
Unlock*Shock*Post	-0.00403	0.00106	-0.00520*	-0.000789	0.00110
	(0.00392)	(0.00260)	(0.00298)	(0.00121)	(0.00159)
Lock*Shock*Post	-0.00147	0.00178	-0.000512	-0.000676	-0.00223
	(0.00360)	(0.00247)	(0.00269)	(0.00132)	(0.00173)
Observations	75724	75724	75724	75724	75724
R-squared	0.762	0.607	0.727	0.745	0.641
Mean Y	0.0866	0.0219	0.0495	0.00761	0.00751
Panel C: Urban					
Unlock*Shock*Post	-0.00337	-0.000182	0.000150	-0.00168	-0.00159
	(0.00276)	(0.00158)	(0.00137)	(0.00158)	(0.00159)
Lock*Shock*Post	-0.00210	0.000378	-0.0000613	-0.00211*	-0.000284
	(0.00234)	(0.00139)	(0.00118)	(0.00125)	(0.00142)
Observations	176856	176856	176856	176856	176856
R-squared	0.687	0.576	0.562	0.707	0.592
Mean Y	0.0538	0.0138	0.0100	0.0139	0.0159

Note: The table uses employment data from Consumer Pyramid Household Survey (CPHS) for the relevant time period of the sample (January to August 2018 & January to August 2019). The details for data construction of the sample is discussed in section 3. Here, $post_t$ =1 if the year is 2019 unlike rest of the results to conduct a falsification exercise (6.1). Here, *unlock* is the indicator for unlock months including June-August, while *lock* is the indicator for lockdown months April-May. To control for district-varying time trends, we have included district-month fixed effects to calculate these results.
($\star p < 0.10, \star\star p < 0.05, \star\star\star p < 0.01$)

Figure 1: Income Shock Measure Distribution



Note: The figure uses income data compiled from monthly data from Consumer Pyramid Household Surveys 2019 and 2020. Section 3.1 discusses the details on how the measure was created. A positive value here implies a decline in income in 2020 as compared to 2019. The distribution here has been restricted from -1000% to 100%.

Online Appendix

A Additional Analyses

A.1 Employment trends due to lockdown

A.1.1 Empirical Strategy

In order to understand the trends in employment pre and post Covid-19 lockdown, we employ a difference-in-differences strategy. We exploit the variation in pre (2019) v/s post (2020) and the control months of January- March compared with the treated months of April-May (lockdown) and June-August (unlock). The following is the estimating equation:

$$\begin{aligned} Emp_{ihdmt} = \beta_0 + \beta_1 lock_m \times post_t + \beta_2 unlock_m \times post_t + post_t + lock_m + unlock_m \\ + X_i + M_m + \epsilon_{ihdmt} \quad \text{(A1)} \end{aligned}$$

The dependent variable Emp_{ihdmt} is a dummy variable that takes value one for every employed individual i in a given household h in district d in month m and time t. The definitions for each of the employment categories analyzed can be found in 3.2. Here, $unlock_m$ is a dummy variable that takes value one for the unlock months, i.e. from June to August, $lock_m$ is the indicator for the lockdown months i.e. April to May and $post_t$ is an indicator for the year 2020, as it takes value 0 for the year 2019. Our main coefficients of interest are β_1 and β_2.

The coefficient β_2 on the double interaction captures the impact on employment during the unlock months (June to August) as compared to the months of January to March, over and above the effect in 2019 between the same months. Meanwhile, the coefficient β_1 captures the impact of the lockdown (April to May) on employment as compared with January to March post lockdown, again accounting for any seasonality in 2019.

We control for year fixed effects $post_t$ to control for results being driven by changes over time. We also add month fixed effects M_m to control for seasonality and individual fixed effects X_i to control for individual-level unobserved time-invariant heterogeneity. The standard errors are clustered at the household-month level.

A.1.2 Results

Table A1 presents employment trend results for both men and women across different categories of work. Panel A of the table has the results for all India, Panel B has it for the rural population and Panel C has it for the urban population. Column (1) shows the results for overall employment and columns (2), (3) and (4) show it by the type of employment - self-employed, casual labor and salaried, respectively.

We find that the probability of overall employment for women declined by 1.26 pp (22%) and for men, it declined by 21.1 pp (30%) during the lockdown months (April- May), relative to pre-lockdown months (January to March). However, during the unlock (June to August), male employment significantly fell overall by 3.98 pp (6%) as compared to January to March, while female employment is positive but insignificant. These numbers agree with much of the literature that finds a significant decline in both male and female employment due to Covid-19 with an even sharper decline in male employment Deshpande (2020).

Salaried work, in particular, saw a significant decline in the probability of employment for both men and women, even during the unlock period. To compensate for the lost fixed-wage work, the men and women increasingly started to take up self-employment work from July to August. We find that the probability of employment increased by 0.25 pp (14%) for women and 3.77 (12.6%) for men as compared to January to March. These numbers suggest some recovery in employment through self-employment work. In fact, for women, even casual labor work recovered during the months of July to August relative to lockdown with a point estimate of 0.35 pp (19.4 %) while men employment continued to be lower than the pre-lockdown levels during the unlock months with a point estimate of 2.5 pp (15.9 %).

The same point estimates in rural areas overall for women are 3.29 pp during lockdown (April to May) and 0.4 pp during unlock (June to August) and for men are 19.5 pp during lockdown (April to May) and 4.77 pp during lockdown (June to August). Interestingly, in rural areas, we do not find a significant increase in female employment across any categories of work including self-employment and casual labor. For men, however, there was 4.57 pp (13 %) increase in self-employed work relative to January to March. On the other hand, for urban areas, the overall point estimates for women are statistically insignificant during both lockdown and unlock and for men, they are -21.8 pp during lockdown (April to May) and -3.7 pp during lockdown (June to August). In urban areas, the probability of employment for women significantly increased for both self-employment (0.33 pp) and casual labor (0.5 pp). For men, the increase in the probability of employment came only from self-employment work (3.41 pp).

Table A1: Double Difference: Impact of Covid on employment by gender

Variable	**Employed**		**Self-Employed**		**Casual labor**		**Salaried Permanent**		**Salaried Temporary**	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Total										
Unlock*Post	0.000724	-0.0398***	0.00252**	0.0377***	0.00353***	-0.0251***	-0.00372***	-0.0359***	-0.00167*	-0.0146***
	(0.00182)	(0.00226)	(0.00113)	(0.00329)	(0.00114)	(0.00293)	(0.000731)	(0.00201)	(0.000976)	(0.00238)
Lock*Post	-0.0126***	-0.211***	0.000137	-0.0312***	-0.00860***	-0.114***	-0.00224**	-0.0314***	-0.00193	-0.0316***
	(0.00258)	(0.00432)	(0.00158)	(0.00461)	(0.00157)	(0.00400)	(0.00110)	(0.00291)	(0.00139)	(0.00330)
Post	-0.00565***	0.00467***	0.000224	0.0193***	-0.00469***	-0.0100***	-0.000450	-0.00406***	-0.000781	-0.00633***
	(0.00131)	(0.00162)	(0.000844)	(0.00231)	(0.000846)	(0.00210)	(0.000536)	(0.00133)	(0.000763)	(0.00175)
Observations	249558	297709	249558	297709	249558	297709	249558	297709	249558	297709
R-squared	0.644	0.813	0.568	0.670	0.587	0.649	0.663	0.727	0.569	0.580
Mean Y	0.0576	0.685	0.0174	0.298	0.0180	0.170	0.00966	0.118	0.0123	0.0897
Panel B: Rural										
Unlock*Post	-0.00395	-0.0466***	0.000478	0.0457***	-0.0000728	-0.0411***	-0.00236**	-0.0271***	-0.00197	-0.0174***
	(0.00357)	(0.00410)	(0.00237)	(0.00592)	(0.00291)	(0.00568)	(0.000995)	(0.00275)	(0.00127)	(0.00346)
Lock*Post	-0.0329***	-0.195***	-0.00203	-0.00379	-0.0240***	-0.127***	-0.00305*	-0.0310***	-0.00345*	-0.0259***
	(0.00522)	(0.00777)	(0.00346)	(0.00855)	(0.00423)	(0.00805)	(0.00159)	(0.00415)	(0.00199)	(0.00481)
Post	-0.00101	0.0147***	0.00728***	0.0249***	-0.00864***	-0.0200***	-0.000658	0.00115	0.000669	-0.00353
	(0.00247)	(0.00293)	(0.00173)	(0.00420)	(0.00211)	(0.00405)	(0.000767)	(0.00182)	(0.00102)	(0.00253)
Observations	74860	90097	74860	90097	74860	90097	74860	90097	74860	90097
R-squared	0.687	0.811	0.615	0.700	0.626	0.654	0.705	0.717	0.617	0.577
Mean Y	0.0827	0.701	0.0273	0.349	0.0418	0.218	0.00621	0.0605	0.00709	0.0562
Panel C: Urban										
Unlock*Post	0.00267	-0.0370***	0.00331***	0.0341***	0.00515***	-0.0180***	-0.00431***	-0.0398***	-0.00157	-0.0133***
	(0.00209)	(0.00270)	(0.00126)	(0.00395)	(0.00105)	(0.00340)	(0.000953)	(0.00263)	(0.00128)	(0.00306)
Lock*Post	-0.00400	-0.218***	0.00104	-0.0425***	-0.00213	-0.109***	-0.00188	-0.0315***	-0.00129	-0.0340***
	(0.00293)	(0.00518)	(0.00172)	(0.00546)	(0.00135)	(0.00456)	(0.00141)	(0.00375)	(0.00179)	(0.00423)
Post	-0.00758***	0.000406	-0.00276***	0.0168***	-0.00300***	-0.00565**	-0.000362	-0.00633***	-0.00139	-0.00755***
	(0.00155)	(0.00194)	(0.000954)	(0.00277)	(0.000815)	(0.00245)	(0.000689)	(0.00173)	(0.000993)	(0.00225)
Observations	174698	207612	174698	207612	174698	207612	174698	207612	174698	207612
R-squared	0.610	0.814	0.525	0.653	0.487	0.642	0.653	0.724	0.558	0.578
Mean Y	0.0469	0.679	0.0131	0.277	0.00781	0.149	0.0111	0.143	0.0146	0.104

Note: The table uses employment data from Consumer Pyramid Household Survey (CPHS) for the relevant time period of the sample (January to August 2019 & January to August 2020). The details for data construction of the sample is discussed in section 3. Here, *unlock* is the indicator for unlock months including June-August, while *lock* is the indicator for lockdown months April-May. ($\star p < 0.10, \star\star p < 0.05, \star\star\star p < 0.01$)

A.2 Impact of income shock on employment post unlock

We extend our main results for the months post-August after complete unlock had taken place. In order to identify the causal impact of income shocks on employment, we interact $unlock2_m$ with all the interactions in the equation 2. Here, $unlock2_m$ is 1 for the months of September to December and 0 otherwise. The coefficient on $unlock2_m \times shock_h \times post_t$ captures the impact of income shock on the employment of women from Sept to December 2020 as compared to January to March 2020, relative to 2019. Table A2 presents the results of this specification.

We find that the coefficient on overall employment for all India (Panel A, Column 1) from Sept to Dec 2020, is 0.8 pp. This means that households facing a 100% income shock increased their employment by 0.8pp relative to households that did not face income shock, in Sept to Dec 2020 compared with Jan to March 2020. However, this magnitude of 0.8 pp is less than 1.6 pp which is the point estimate for the months of June to August, which implies a reduction in the probability of employment for women who faced greater income shock.

Table A2: Impact of income shock on employment post unlock

			Panel A: Total		
Variable	**Employed**	**Self-Employed**	**Casual labor**	**Salaried Permanent**	**Salaried Temporary**
	(1)	(2)	(3)	(4)	(5)
Unlock2*Shock*Post	0.00817***	0.00150	0.00264**	0.00157	0.00240*
	(0.00223)	(0.00138)	(0.00125)	(0.00109)	(0.00123)
Unlock*Shock*Post	0.0160***	0.00368***	0.00548***	0.00220**	0.00447***
	(0.00233)	(0.00137)	(0.00127)	(0.00111)	(0.00130)
Lock*Shock*Post	0.00262	-0.000323	-0.00200	0.000899	0.00390**
	(0.00323)	(0.00217)	(0.00165)	(0.00146)	(0.00174)
Observations	380255	380255	380255	380255	380255
R-squared	0.604	0.520	0.540	0.620	0.510
Mean Y	0.0559	0.0171	0.0176	0.00932	0.0116
			Panel B: Rural		
Unlock2*Shock*Post	0.00950**	-0.000638	0.00872***	-0.000799	0.00197
	(0.00389)	(0.00234)	(0.00322)	(0.00103)	(0.00163)
Unlock*Shock*Post	0.0159***	0.00231	0.0104***	0.000375	0.00251
	(0.00414)	(0.00250)	(0.00327)	(0.000976)	(0.00159)
Lock*Shock*Post	0.00222	0.00182	-0.00641	0.00108	0.00564**
	(0.00572)	(0.00377)	(0.00407)	(0.00136)	(0.00275)
Observations	112944	112944	112944	112944	112944
R-squared	0.661	0.579	0.585	0.676	0.570
Mean Y	0.0812	0.0268	0.0414	0.00601	0.00673
			Panel C: Urban		
Unlock2*Shock*Post	0.00796***	0.00261	-0.0000193	0.00272*	0.00266*
	(0.00273)	(0.00170)	(0.00113)	(0.00151)	(0.00162)
Unlock*Shock*Post	0.0163***	0.00452***	0.00318***	0.00306**	0.00551***
	(0.00282)	(0.00163)	(0.00111)	(0.00155)	(0.00174)
Lock*Shock*Post	0.00189	-0.00102	-0.000878	0.000572	0.00305
	(0.00395)	(0.00266)	(0.00146)	(0.00211)	(0.00219)
Observations	267311	267311	267311	267311	267311
R-squared	0.559	0.468	0.419	0.607	0.496
Mean Y	0.0452	0.0130	0.00760	0.0107	0.0137

Note: The table uses employment data from Consumer Pyramid Household Survey (CPHS) for the relevant time period of the sample (January to December 2019 & January to December 2020). The details for data construction of the sample is discussed in section 3. Here, *unlock* is the indicator for unlock months including June-August, while *lock* is the indicator for lockdown months April-May. We also have $unlock_2$ which is the indicator for unlock months from September-December. ($\star p < 0.10, \star\star p < 0.05, \star\star\star p < 0.01$)

B Additional Tables

Table B1: Change in employment during unlock across employment categories

Variable	**Self-Employed** (1)	**Casual Labour** (2)	**Salaried Permanent** (3)	**Salaried Temporary** (4)
Panel A: Total				
Self-Employed	x	0.00168 (0.00207)	-0.00146 (0.00192)	0.000944 (0.00204)
Casual Labour	-0.00168 (0.00207)	x	-0.000734 (0.00204)	-0.00314* (0.00181)
Salaried Permanent	0.00146 (0.00192)	0.00314* (0.00181)	x	0.00241 (0.00192)
Salaried Temporary	-0.000944 (0.00204)	0.000734 (0.00204)	-0.00241 (0.00192)	x
Panel B: Rural				
Self-Employed	x	0.00809* (0.00466)	-0.00169 (0.00284)	0.000331 (0.00325)
Casual Labour	-0.00809* (0.00466)	x	-0.00776** (0.00396)	-0.00978*** (0.00368)
Salaried Permanent	0.00169 (0.00284)	0.00776** (0.00396)	x	0.00202 (0.00208)
Salaried Temporary	-0.000331 (0.00325)	0.00978*** (0.00368)	-0.00202 (0.00208)	x
Panel C: Urban				
Self-Employed	x	-0.00148 (0.00216)	-0.00155 (0.00248)	0.00117 (0.00258)
Casual Labour	0.00148 (0.00216)	x	0.00264 (0.00235)	-0.0000698 (0.00205)
Salaried Permanent	0.00155 (0.00248)	-0.00264 (0.00235)	x	0.00271 (0.00262)
Salaried Temporary	-0.00117 (0.00258)	0.0000698 (0.00205)	-0.00271 (0.00262)	x

Note: The table compares the point estimates during $unlock_m$ across different employment categories. The difference can be read as Column Value - Row value. For example, column (2) and row (1), 0.00168 is the difference between casual labor with self-employed. ($\star p < 0.10, \star\star\, p < 0.05, \star\star\star p < 0.01$)

Table B2: Impact of income shock on male employment: All India

Variable	**Employed**	**Self-Employed**	**Casual Labour**	**Salaried Permanent**	**Salaried Temporary**
	(1)	(2)	(3)	(4)	(5)
Unlock*Shock*Post	-0.0275***	0.0546***	0.0298***	-0.110***	-0.00468
	(0.00321)	(0.00486)	(0.00359)	(0.00391)	(0.00334)
Lock*Shock*Post	-0.0793***	0.00224	-0.0172***	-0.0508***	-0.0146***
	(0.00581)	(0.00661)	(0.00465)	(0.00451)	(0.00437)
Unlock*Post	-0.0254***	0.00906**	-0.0408***	0.0221***	-0.0121***
	(0.00273)	(0.00411)	(0.00320)	(0.00304)	(0.00291)
Lock*Post	-0.174***	-0.0321***	-0.106***	-0.00728*	-0.0248***
	(0.00487)	(0.00555)	(0.00429)	(0.00380)	(0.00384)
Shock*Unlock	0.00421**	0.00339	-0.000375	0.00352*	-0.00131
	(0.00181)	(0.00267)	(0.00202)	(0.00183)	(0.00183)
Shock*Lock	-0.00385	0.00559*	-0.00682***	0.00267	-0.00518**
	(0.00253)	(0.00335)	(0.00248)	(0.00225)	(0.00227)
Shock*Post	-0.00897***	0.00261	-0.000883	-0.00802***	-0.00478*
	(0.00214)	(0.00333)	(0.00249)	(0.00206)	(0.00252)
Observations	297709	297709	297709	297709	297709
R-squared	0.814	0.671	0.649	0.738	0.580
Mean Y	0.685	0.298	0.170	0.118	0.0897

Note: The table uses employment data from Consumer Pyramid Household Survey (CPHS) for the relevant time period of the sample (January to August 2019 & January to August 2020). The details for data construction of the sample is discussed in section 3. Here, *unlock* is the indicator for unlock months including June-August, while *lock* is the indicator for lockdown months April-May. ($\star p < 0.10, \star\star p < 0.05, \star\star\star p < 0.01$)

Table B3: Impact of income shock on male employment: By Sector

Variable	Employed	Self-Employed	Casual Labour	Salaried Permanent	Salaried Temporary
	(1)	(2)	(3)	(4)	(5)
Panel A: Rural					
Unlock*Shock*Post	-0.0244***	-0.00212	0.0243***	-0.0471***	-0.00916*
	(0.00631)	(0.00881)	(0.00741)	(0.00425)	(0.00478)
Lock*Shock*Post	-0.0643***	-0.0231**	-0.0149	-0.0243***	-0.00595
	(0.00897)	(0.0105)	(0.00912)	(0.00490)	(0.00535)
Unlock*Post	-0.0344***	0.0467***	-0.0537***	-0.00294	-0.0129***
	(0.00526)	(0.00750)	(0.00668)	(0.00354)	(0.00418)
Lock*Post	-0.172***	0.00520	-0.123***	-0.0214***	-0.0244***
	(0.00826)	(0.00964)	(0.00873)	(0.00453)	(0.00523)
Shock*Unlock	-0.00232	-0.00382	0.00302	0.00150	-0.000531
	(0.00346)	(0.00495)	(0.00442)	(0.00213)	(0.00255)
Shock*Lock	-0.00705	0.00108	-0.00811	0.00321	-0.00400
	(0.00447)	(0.00583)	(0.00516)	(0.00260)	(0.00307)
Shock*Post	-0.0157***	-0.00113	-0.00660	-0.00278	-0.00662*
	(0.00410)	(0.00613)	(0.00535)	(0.00213)	(0.00351)
Observations	90097	90097	90097	90097	90097
R-squared	0.813	0.700	0.655	0.721	0.577
Mean Y	0.701	0.349	0.218	0.0605	0.0562
Panel B: Urban					
Unlock*Shock*Post	-0.0285***	0.0822***	0.0323***	-0.141***	-0.00243
	(0.00368)	(0.00564)	(0.00400)	(0.00510)	(0.00433)
Lock*Shock*Post	-0.0854***	0.0196**	-0.0203***	-0.0654***	-0.0191***
	(0.00764)	(0.00833)	(0.00523)	(0.00639)	(0.00613)
Unlock*Post	-0.0219***	-0.00947**	-0.0352***	0.0349***	-0.0120***
	(0.00316)	(0.00482)	(0.00355)	(0.00398)	(0.00377)
Lock*Post	-0.174***	-0.0523***	-0.0982***	0.00186	-0.0241***
	(0.00616)	(0.00680)	(0.00474)	(0.00529)	(0.00519)
Shock*Unlock	0.00695***	0.00476	-0.00187	0.00592**	-0.00167
	(0.00210)	(0.00305)	(0.00217)	(0.00234)	(0.00238)
Shock*Lock	-0.00316	0.00397	-0.00542**	0.00485	-0.00590*
	(0.00307)	(0.00400)	(0.00270)	(0.00304)	(0.00303)
Shock*Post	-0.00620**	0.00413	0.00157	-0.0103***	-0.00399
	(0.00251)	(0.00397)	(0.00274)	(0.00276)	(0.00326)
Observations	207612	207612	207612	207612	207612
R-squared	0.815	0.656	0.643	0.739	0.578
Mean Y	0.679	0.277	0.149	0.143	0.104

Note: The table uses employment data from Consumer Pyramid Household Survey (CPHS) for the relevant time period of the sample (January to August 2019 & January to August 2020). The details for data construction of the sample is discussed in section 3. Here, *unlock* is the indicator for unlock months including June-August, while *lock* is the indicator for lockdown months April-May. ($\star p < 0.10, \star\star p < 0.05, \star\star\star p < 0.01$)

Table B4: Heterogeneity: Women's education

Variable	Employed		Self Employed		Casual labor		Salaried Permanent		Salaried Temporary	
	(1) Below 10	(2) Pass 10	(3) Below 10	(4) Pass 10	(5) Below 10	(6) Pass 10	(7) Below 10	(8) Pass 10	(9) Below 10	(10) Pass 10
Panel A: Total										
Unlock*Shock*Post	0.0189***	0.0108***	0.00136	0.00404**	0.0101***	0.00144	0.00175**	0.00137	0.00561***	0.00376*
	(0.00401)	(0.00372)	(0.00242)	(0.00205)	(0.00280)	(0.000980)	(0.000802)	(0.00240)	(0.00204)	(0.00227)
Lock*Shock*Post	0.00204	0.00234	0.00160	-0.00260	-0.000632	-0.00119	-0.000126	0.00215	0.00120	0.00373
	(0.00446)	(0.00428)	(0.00349)	(0.00295)	(0.00295)	(0.000894)	(0.000941)	(0.00258)	(0.00183)	(0.00227)
Observations	131762	97519	131762	97519	131762	97519	131762	97519	131762	97519
R-squared	0.665	0.682	0.593	0.596	0.611	0.638	0.658	0.697	0.613	0.573
Mean Y	0.0667	0.0508	0.0212	0.0134	0.0287	0.00511	0.00257	0.0205	0.0141	0.0113
Panel B: Rural										
Unlock*Shock*Post	0.0211***	0.00406	0.00165	-0.000887	0.0153***	0.00266	0.000496	0.00109	0.00354*	0.000288
	(0.00658)	(0.00607)	(0.00397)	(0.00343)	(0.00540)	-0.00342	(0.000567)	(0.00294)	(0.00188)	(0.00383)
Lock*Shock*Post	-0.00329	0.00379	0.00456	-0.000957	-0.00918*	-0.00277	0.000964	0.00211	0.000400	0.00527
	(0.00655)	(0.00739)	(0.00509)	(0.00406)	(0.00513)	-0.0038	(0.000845)	(0.00324)	(0.00170)	(0.00464)
Observations	48512	20761	48512	20761	48512	20761	48512	20761	48512	20761
R-squared	0.700	0.742	0.634	0.647	0.642	0.681	0.713	0.758	0.676	0.605
Mean Y	0.0946	0.0630	0.0317	0.0188	0.0544	0.0169	0.00177	0.0177	0.00664	0.00891
Panel C: Urban										
Unlock*Shock*Post	0.0183***	0.0129***	0.00201	0.00558**	0.00551**	0.00117	0.00290**	0.00136	0.00777**	0.00477*
	(0.00490)	(0.00445)	(0.00295)	(0.00245)	(0.00250)	(0.000832)	(0.00144)	(0.00297)	(0.00342)	(0.00269)
Lock*Shock*Post	0.00437	0.00191	0.000561	-0.00300	0.00330	-0.000771	-0.00165	0.00214	0.00215	0.00327
	(0.00632)	(0.00498)	(0.00489)	(0.00352)	(0.00325)	(0.000620)	(0.00173)	(0.00312)	(0.00333)	(0.00258)
Observations	83250	76758	83250	76758	83250	76758	83250	76758	83250	76758
R-squared	0.623	0.660	0.541	0.575	0.526	0.529	0.639	0.683	0.598	0.566
Mean Y	0.0504	0.0475	0.0151	0.0119	0.0137	0.00192	0.00304	0.0213	0.0185	0.0119

Note: The table uses employment data from Consumer Pyramid Household Survey (CPHS) for the relevant time period of the sample (January to August 2019 & January to August 2020). The details for data construction of the sample is discussed in section 3. Here, *unlock* is the indicator for unlock months including June-August, while *lock* is the indicator for lockdown months April-May. While, $below10$ includes the sample of women who are educated below class 10, $pass10$ includes the sample of all women who have atleast graduated from class 10. ($\star p < 0.10, \star\star\, p < 0.05, \star\star\star p < 0.01$)

Table B5: Heterogeneity: Women's Age

Variable	Employed		Self Employed		Casual labor		Salaried Permanent		Salaried Temporary	
	(1) 15 to 35	(2) 35+ to 59	(3) 15 to 35	(4) 35+ to 59	(5) 15 to 35	(6) 35+ to 59	(7) 15 to 35	(8) 35+ to 59	(9) 15 to 35	(10) 35+ to 59
Panel A: Total										
Unlock*Shock*Post	0.00840***	0.0194***	0.00285	0.00410*	-0.00111	0.00924***	0.00198	0.00207	0.00442**	0.00393**
	(0.00322)	(0.00352)	(0.00188)	(0.00210)	(0.00120)	(0.00210)	(0.00153)	(0.00161)	(0.00213)	(0.00169)
Lock*Shock*Post	0.00112	0.000286	-0.00152	0.000166	-0.00331**	-0.00210	0.00183	0.0000193	0.00389**	0.00219
	(0.00292)	(0.00432)	(0.00160)	(0.00318)	(0.00145)	(0.00210)	(0.00158)	(0.00192)	(0.00194)	(0.00189)
Observations	116082	129407	116082	129407	116082	129407	116082	129407	116082	129407
R-squared	0.646	0.652	0.555	0.584	0.598	0.596	0.648	0.682	0.564	0.585
Mean Y	0.0393	0.0732	0.0116	0.0223	0.00955	0.0252	0.00731	0.0117	0.0104	0.0141
Panel B: Rural										
Unlock*Shock*Post	0.00257	0.0220***	0.00318	0.000868	-0.00409	0.0205***	0.000520	0.000312	0.00237	0.000393
	(0.00443)	(0.00722)	(0.00278)	(0.00424)	(0.00279)	(0.00592)	(0.00139)	(0.00135)	(0.00276)	(0.00172)
Lock*Shock*Post	-0.00341	-0.000383	0.00104	0.00204	-0.00861**	-0.00802	-0.000149	0.00243	0.00425	0.00316
	(0.00508)	(0.00741)	(0.00305)	(0.00546)	(0.00358)	(0.00533)	(0.00120)	(0.00166)	(0.00318)	(0.00295)
Observations	36372	37268	36372	37268	36372	37268	36372	37268	36372	37268
R-squared	0.695	0.692	0.594	0.636	0.631	0.634	0.688	0.732	0.596	0.652
Mean Y	0.0523	0.111	0.0166	0.0376	0.0226	0.0596	0.00580	0.00655	0.00687	0.00738
Panel C: Urban										
Unlock*Shock*Post	0.0115***	0.0186***	0.00292	0.00551**	0.000346	0.00473***	0.00271	0.00277	0.00545*	0.00549**
	(0.00434)	(0.00397)	(0.00249)	(0.00239)	(0.00114)	(0.00167)	(0.00224)	(0.00220)	(0.00290)	(0.00228)
Lock*Shock*Post	0.00287	-0.000492	-0.00268	-0.000484	-0.00102	-0.000282	0.00268	-0.00148	0.00359	0.00175
	(0.00352)	(0.00536)	(0.00182)	(0.00393)	(0.00112)	(0.00181)	(0.00243)	(0.00274)	(0.00241)	(0.00240)
Observations	79710	92139	79710	92139	79710	92139	79710	92139	79710	92139
R-squared	0.610	0.619	0.524	0.532	0.495	0.498	0.634	0.672	0.555	0.572
Mean Y	0.0334	0.0579	0.00940	0.0161	0.00361	0.0113	0.00800	0.0137	0.0120	0.0168

Note: The table uses employment data from Consumer Pyramid Household Survey (CPHS) for the relevant time period of the sample (January to August 2019 & January to August 2020). The details for data construction of the sample is discussed in section 3. Here, *unlock* is the indicator for unlock months including June-August, while *lock* is the indicator for lockdown months April-May. While, $15to35$ represents the women aged 15 to 35, $35 + to59$ represents women aged greater than 35 to women aged 59. ($\star p < 0.10, \star\star p < 0.05, \star\star\star p < 0.01$)

Table B6: Heterogeneity: Presence of children

Panel A: Total										
Variable	**Employed**		**Self Employed**		**Casual labor**		**Salaried Permanent**		**Salaried Temporary**	
	(1) No child	(2) With child	(3) No child	(4) With child	(5) No child	(6) With child	(7) No child	(8) With child	(9) No child	(10) With child
Unlock*Shock*Post	0.0147***	0.0131***	0.00331**	0.00306	0.00501***	0.00520*	0.00219*	0.00166	0.00410***	0.00328*
	(0.00238)	(0.00406)	(0.00141)	(0.00220)	(0.00126)	(0.00268)	(0.00112)	(0.00152)	(0.00134)	(0.00191)
Lock*Shock*Post	0.000551	0.00328	-0.000700	0.000745	-0.00256**	-0.00107	0.000900	0.00133	0.00283**	0.00213
	(0.00268)	(0.00431)	(0.00183)	(0.00247)	(0.00130)	(0.00249)	(0.00125)	(0.00163)	(0.00134)	(0.00253)
Observations	249558	72496	249558	72496	249558	72496	249558	72496	249558	72496
R-squared	0.644	0.656	0.568	0.588	0.587	0.599	0.663	0.662	0.569	0.546
Mean Y	0.0576	0.0539	0.0174	0.0172	0.0180	0.0185	0.00966	0.00633	0.0123	0.0116
Panel B: Rural										
Unlock*Shock*Post	0.0132***	0.00809	0.00181	-0.000799	0.00910***	0.00740	0.000418	-0.000284	0.00158	0.00167
	(0.00424)	(0.00710)	(0.00256)	(0.00342)	(0.00326)	(0.00634)	(0.000969)	(0.00125)	(0.00161)	(0.00155)
Lock*Shock*Post	-0.00261	-0.000738	0.00129	-0.000373	-0.00867***	-0.00696	0.000989	0.00192	0.00375*	0.00470
	(0.00466)	(0.00642)	(0.00315)	(0.00375)	(0.00326)	(0.00493)	(0.00102)	(0.00143)	(0.00214)	(0.00303)
Observations	74860	23220	74860	23220	74860	23220	74860	23220	74860	23220
R-squared	0.687	0.715	0.615	0.647	0.626	0.642	0.705	0.732	0.617	0.591
Mean Y	0.0827	0.0774	0.0273	0.0265	0.0418	0.0383	0.00621	0.00534	0.00709	0.00724
Panel C: Urban										
Unlock*Shock*Post	0.0156***	0.0161***	0.00414**	0.00545*	0.00312***	0.00363*	0.00299*	0.00290	0.00536***	0.00433
	(0.00287)	(0.00488)	(0.00169)	(0.00286)	(0.00108)	(0.00189)	(0.00157)	(0.00234)	(0.00180)	(0.00292)
Lock*Shock*Post	0.00112	0.00546	-0.00146	0.00167	-0.000419	0.00259	0.000573	0.0000986	0.00233	0.000801
	(0.00331)	(0.00602)	(0.00226)	(0.00341)	(0.00110)	(0.00242)	(0.00183)	(0.00277)	(0.00170)	(0.00396)
Observations	174698	49276	174698	49276	174698	49276	174698	49276	174698	49276
R-squared	0.610	0.604	0.525	0.530	0.487	0.508	0.653	0.635	0.558	0.535
Mean Y	0.0469	0.0427	0.0131	0.0129	0.00781	0.00923	0.0111	0.00680	0.0146	0.0137

Note: The table uses employment data from Consumer Pyramid Household Survey (CPHS) for the relevant time period of the sample (January to August 2019 & January to August 2020). The details for data construction of the sample is discussed in section 3. Here, *unlock* is the indicator for unlock months including June-August, while *lock* is the indicator for lockdown months April-May. While, $Nochild$ represents the households where there is no child below the age of 6, $Withchild$ represents households with a child below the age of 6. ($\star p < 0.10, \star\star p < 0.05, \star\star\star p < 0.01$)

Table B7: Robustness: Attrition

Variable	Employed	Self-Employed	Casual labor	Salaried Permanent	Salaried Temporary
	(1)	(2)	(3)	(4)	(5)
Panel A: Total					
Unlock*Shock*Post	0.0152***	0.00338**	0.00514***	0.00225*	0.00428***
	(0.00247)	(0.00146)	(0.00130)	(0.00122)	(0.00135)
Lock*Shock*Post	0.000914	-0.000784	-0.00240*	0.00104	0.00299**
	(0.00274)	(0.00185)	(0.00134)	(0.00137)	(0.00138)
Observations	249558	249558	249558	249558	249558
R-squared	0.654	0.573	0.586	0.696	0.574
Mean Y	0.0606	0.0182	0.0182	0.0111	0.0128
Panel B: Rural					
Unlock*Shock*Post	0.0137***	0.00183	0.00924***	0.000502	0.00179
	(0.00430)	(0.00263)	(0.00331)	(0.00102)	(0.00167)
Lock*Shock*Post	-0.00205	0.00106	-0.00836**	0.00129	0.00394*
	(0.00471)	(0.00325)	(0.00325)	(0.00109)	(0.00221)
Observations	74860	74860	74860	74860	74860
R-squared	0.693	0.619	0.624	0.727	0.627
Mean Y	0.0850	0.0286	0.0416	0.00699	0.00754
Panel C: Urban					
Unlock*Shock*Post	0.0161***	0.00424**	0.00325***	0.00303*	0.00554***
	(0.00300)	(0.00176)	(0.00112)	(0.00172)	(0.00181)
Lock*Shock*Post	0.00144	-0.00143	-0.000277	0.000544	0.00250
	(0.00341)	(0.00226)	(0.00117)	(0.00202)	(0.00175)
Observations	174698	174698	174698	174698	174698
R-squared	0.624	0.531	0.487	0.689	0.562
Mean Y	0.0500	0.0138	0.00813	0.0129	0.0150

Note: The table uses employment data from Consumer Pyramid Household Survey (CPHS) for the relevant time period of the sample (January to August 2019 & January to August 2020). The details for data construction of the sample is discussed in section 3. The details for IPW used to control for data attrition is discussed in section 6. Here, *unlock* is the indicator for unlock months including June-August, while *lock* is the indicator for lockdown months April-May.
($\star p < 0.10, \star\star p < 0.05, \star\star\star p < 0.01$)

Table B8: Robustness: District-specific seasonality

Variable	Employed	Self-Employed	Casual labor	Salaried Permanent	Salaried Temporary
	(1)	(2)	(3)	(4)	(5)
Panel A: Total					
Unlock*Shock*Post	0.0150***	0.00331**	0.00517***	0.00226**	0.00419***
	(0.00239)	(0.00141)	(0.00128)	(0.00113)	(0.00134)
Lock*Shock*Post	0.00133	-0.000833	-0.00221	0.00110	0.00320**
	(0.00276)	(0.00189)	(0.00136)	(0.00130)	(0.00140)
Observations	249556	249556	249556	249556	249556
R-squared	0.649	0.573	0.595	0.665	0.571
Mean Y	0.0576	0.0174	0.0180	0.00966	0.0123
Panel B: Rural					
Unlock*Shock*Post	0.0124***	0.00157	0.00903***	0.000296	0.00123
	(0.00422)	(0.00253)	(0.00332)	(0.00100)	(0.00163)
Lock*Shock*Post	-0.00102	0.00172	-0.00689**	0.000700	0.00349
	(0.00482)	(0.00330)	(0.00346)	(0.00112)	(0.00230)
Observations	74858	74858	74858	74858	74858
R-squared	0.699	0.625	0.640	0.710	0.622
Mean Y	0.0827	0.0273	0.0418	0.00621	0.00709
Panel C: Urban					
Unlock*Shock*Post	0.0159***	0.00401**	0.00320***	0.00319**	0.00551***
	(0.00289)	(0.00170)	(0.00109)	(0.00158)	(0.00180)
Lock*Shock*Post	0.00155	-0.00193	-0.000493	0.00107	0.00274
	(0.00341)	(0.00233)	(0.00114)	(0.00188)	(0.00174)
Observations	174698	174698	174698	174698	174698
R-squared	0.614	0.529	0.493	0.655	0.560
Mean Y	0.0469	0.0131	0.00781	0.0111	0.0146

Note: The table uses employment data from Consumer Pyramid Household Survey (CPHS) for the relevant time period of the sample (January to August 2019 & January to August 2020). The details for data construction of the sample is discussed in section 3. Here, *unlock* is the indicator for unlock months including June-August, while *lock* is the indicator for lockdown months April-May. To control for district-varying time trends, we have included district-month fixed effects to calculate these results. ($\star p < 0.10, \star\star p < 0.05, \star\star\star p < 0.01$)

Table B9: Robustness: Shock dummy

		Panel A: Total			
Variable	**Employed**	**Self-Employed**	**Casual labor**	**Salaried Permanent**	**Salaried Temporary**
	(1)	(2)	(3)	(4)	(5)
Unlock*Shock*Post	0.0255***	0.00490*	0.0118***	0.00322	0.00528**
	(0.00465)	(0.00285)	(0.00260)	(0.00239)	(0.00252)
Lock*Shock*Post	0.00350	-0.000594	-0.00411	0.00319	0.00454
	(0.00663)	(0.00420)	(0.00365)	(0.00333)	(0.00357)
Observations	249558	249558	249558	249558	249558
R-squared	0.644	0.568	0.587	0.663	0.569
Mean Y	0.0576	0.0174	0.0180	0.00966	0.0123
		Panel B: Rural			
Unlock*Shock*Post	0.0208**	-0.00252	0.0187***	-0.000144	0.00405
	(0.00904)	(0.00621)	(0.00665)	(0.00298)	(0.00345)
Lock*Shock*Post	-0.0129	-0.0000844	-0.0203**	0.00291	0.00455
	(0.0124)	(0.00872)	(0.00913)	(0.00448)	(0.00493)
Observations	74860	74860	74860	74860	74860
R-squared	0.687	0.615	0.626	0.705	0.617
Mean Y	0.0827	0.0273	0.0418	0.00621	0.00709
		Panel C: Urban			
Unlock*Shock*Post	0.0279***	0.00846***	0.00868***	0.00472	0.00592*
	(0.00539)	(0.00306)	(0.00236)	(0.00318)	(0.00329)
Lock*Shock*Post	0.0102	-0.0000837	0.00190	0.00298	0.00472
	(0.00784)	(0.00460)	(0.00319)	(0.00447)	(0.00475)
Observations	174698	174698	174698	174698	174698
R-squared	0.610	0.525	0.487	0.653	0.558
Mean Y	0.0469	0.0131	0.00781	0.0111	0.0146

Note: The table uses employment data from Consumer Pyramid Household Survey (CPHS) for the relevant time period of the sample (January to August 2019 & January to August 2020). The details for data construction of the sample is discussed in section 3. Here, *unlock* is the indicator for unlock months including June-August, while *lock* is the indicator for lockdown months April-May. Here instead of continuous value of *shock* variable used elsewhere, we use a dummy value of *shock* which is 1 if the shock is negative and 0 otherwise. ($\star p < 0.10, \star\star\, p < 0.05, \star\star\star p < 0.01$)

Table B10: Robustness: Non-linear effects on female employment

Panel A: Total					
Variable	**Employed**	**Self-Employed**	**Casual labor**	**Salaried Permanent**	**Salaried Temporary**
	(1)	(2)	(3)	(4)	(5)
Unlock*Shock >50*Post	0.0315***	0.00700**	0.0141***	0.00447*	0.00564**
	(0.00466)	(0.00285)	(0.00262)	(0.00233)	(0.00251)
Unlock*Shock 0-50*Post	0.00642	-0.00318	0.00539*	0.00231	0.00171
	(0.00550)	(0.00334)	(0.00306)	(0.00276)	(0.00303)
Lock*Shock >50*Post	0.00455	-0.000711	-0.00377	0.00532*	0.00347
	(0.00619)	(0.00394)	(0.00350)	(0.00301)	(0.00327)
Lock*Shock 0-50*Post	0.00491	-0.00171	-0.00139	0.00437	0.00317
	(0.00637)	(0.00416)	(0.00340)	(0.00318)	(0.00326)
Observations	249558	249558	249558	249558	249558
R-squared	0.644	0.568	0.588	0.663	0.569
Mean Y	0.0576	0.0174	0.0180	0.00966	0.0123
Panel B: Rural					
Unlock*Shock >50*Post	0.0309***	0.00166	0.0243***	0.000470	0.00364
	(0.00909)	(0.00622)	(0.00670)	(0.00292)	(0.00342)
Unlock*Shock 0-50*Post	-0.00702	-0.0147**	0.00728	-0.00131	0.000855
	(0.0106)	(0.00721)	(0.00807)	(0.00329)	(0.00417)
Lock*Shock >50*Post	-0.00959	0.000456	-0.0177**	0.00338	0.00424
	(0.0118)	(0.00825)	(0.00894)	(0.00407)	(0.00454)
Lock*Shock 0-50*Post	-0.00959	0.00211	-0.0120	0.00340	-0.00355
	(0.0122)	(0.00914)	(0.00873)	(0.00423)	(0.00488)
Observations	74860	74860	74860	74860	74860
R-squared	0.687	0.615	0.626	0.705	0.617
Mean Y	0.0827	0.0273	0.0418	0.00621	0.00709
Panel C: Urban					
Unlock*Shock >50*Post	0.0321***	0.00960***	0.00968***	0.00620**	0.00662**
	(0.00539)	(0.00307)	(0.00239)	(0.00310)	(0.00329)
Unlock*Shock 0-50*Post	0.0126**	0.00214	0.00460*	0.00383	0.00218
	(0.00640)	(0.00362)	(0.00263)	(0.00370)	(0.00395)
Lock*Shock >50*Post	0.0101	-0.000751	0.00129	0.00574	0.00341
	(0.00728)	(0.00431)	(0.00304)	(0.00403)	(0.00433)
Lock*Shock 0-50*Post	0.0114	-0.00296	0.00320	0.00435	0.00624
	(0.00746)	(0.00439)	(0.00288)	(0.00425)	(0.00425)
Observations	174698	174698	174698	174698	174698
R-squared	0.610	0.525	0.487	0.653	0.558
Mean Y	0.0469	0.0131	0.00781	0.0111	0.0146

Note: The table uses employment data from Consumer Pyramid Household Survey (CPHS) for the relevant time period of the sample (January to August 2019 & January to August 2020). The details for data construction of the sample is discussed in section 3. Here, *unlock* is the indicator for unlock months including June-August, while *lock* is the indicator for lockdown months April-May. $Shock > 50$ indicates households where the shock range is from 50 to 100% and $Shock 0 - 50$ indicates households where the shock range is from 0 to 50%. ($\star p < 0.10, \star\star p < 0.05, \star\star\star p < 0.01$)