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COVID-19, Income Shocks and Female Employment

Ishaan Bansal *   Kanika Mahajan†

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Abstract

Existing evidence shows that the Covid-19 pandemic has led to employed women witnessing larger losses in the labor market in India. We examine the heterogeneity that underlie these trends by studying the impact of Covid-19 induced income shocks on female employment. Using individual level panel data and a difference-in-differences strategy that exploits lockdown timing (April 2020) and accounts for seasonal employment trends, we find that women in households facing a hundred percent reduction in household male income during the lockdown were 1.5 pp (25%) more likely to take up work during the "unlockdown" months (June-August 2020). We also find these results to be predominant in poorer and less educated households. However, these positive employment trends are only transitory in nature with a reversal in female employment in these households from September 2020 onwards. 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 lockdowns across the world leading to a contraction of its GDP by 24% year-on-year during April-June 2020 with unemployment level reaching a historic high of 23.5% in April 2020 and 21.7% in May 2020.[1] and these consequences, as with any crisis, were not gender-neutral.[2] Recent studies have estimated gendered impacts of employment as a result of the Covid-19 pandemic (Desai et al., 2021; Deshpande, 2020; Alon et al., 2020; Ham, 2021). While there is increasing evidence on the gendered impacts of the pandemic induced lockdown, with larger losses borne by women, 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 women's LFP (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 COVID-19 pandemic among the urban poor. In this paper, we look at one such determinant of Female labor Force Participation (FLFP), the income effect. We aim to determine whether the pandemic induced negative income shocks led to an increase in FLFP as a result of more women being pushed into the labor force to support their families who faced income reduction.

We use the individual level panel data, collected by Center for Monitoring of Indian Economy (CMIE), namely the Consumer Pyramid Household Surveys (CPHS), to analyze the heterogeneous impacts of income losses during the lockdown in determining female labor force participation as the lockdown restrictions eased. The paper employs a strategy akin to a difference-in-differences, exploiting the variation in the months of lockdown (April-May) and unlockdown (June-August) vs pre-pandemic months (January-March), year of the pandemic (2019 v/s 2020) and the differences in income shock at the household level (negative v/s non-negative shock and the magnitude of these) to get causal estimates on the impact of

[1] Bloomberg Quint and Scroll.in
[2] UN Women.

income shocks on female employment across different categories of work in urban and rural areas. Specifically, we compare the employment rates for women post the lockdown across different phases of restrictions (lockdown vs unlockdown) to the employment rates before the lockdown, in families that faced a higher negative male income shock versus those that faced a lower male income shock, in the year 2020 over and above the same change in 2019. We control for individual level unobserved heterogeneity, monthly seasonality and yearly trends in labor market outcomes in all the specifications.

We find that the probability of overall employment for women goes up by 1.5 pp (25%) during the unlock months (June-August) if the household faces a hundred percent fall in male income during the lockdown, relative to the pre-lockdown months (January to March). For rural women, the only statistically significant increase in probability of women's work comes from casual labor at 0.9 pp (21.5%). For urban women, on the other hand, there is an increase across all categories of work including self-employed (0.41 pp or 31.6%), casual labor (0.31 pp or 40%) and salaried work (0.84 pp or 32.5%). 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 and inclusion of income shock dummy instead of a continuous variable.

Previous studies examining the cyclicity of women's work find that women's labor supply is pro-cyclical in the context of 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 implies a fall in female labor 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 income shock, like in the case of Covid-19 induced lockdown, can lead to an increase in female labor force participation in developing economies like India.

To the best of our knowledge no study thus far has examined the heterogeneous impacts of income shocks post the COVID-19 pandemic on women's employment. The underlying theoretical framework leading to counter-cyclicity 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 as a secondary worker who temporarily increases her labor supply in face of an 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 depends on income effects since substitution effects are generally small. From a lifecycle point of view, this implies that the effect only matters if the fall in 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).

Our paper has implications on how we think about female labor supply's response to the COVID-19 pandemic. These findings speak to the presence of heterogeneity in response across households, based on the income shocks suffered post the pandemic, while thinking about the gendered impacts of the pandemic. These results also show that these increases may be quite 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 developing economies like India.

2 Context

2.1 Background

The Indian government put in place one of the most stringent nation-wide shutdown to control the COVID-19 spread. It started with a one day "Janata Curfew" on 22 March, 2020, and subsequently a 21-day national lockdown was put in place on 24 March 2020. The lockdown was touted as one of the strictest across the world (Balajee et al., 2020) and was put in place when there were only 500 recorded confirmed COVID cases in the country.

The re-opening of economy (or the "Unlock" phase) was started in a phased manner from 8 June, 2020 (Unlock 1.0) permitting market-places including shopping malls, religious places, hotels and restaurants to open up. In July (Unlock 2.0) small shops were allowed to open up, and most other restrictions were lifted. August (Unlock 3.0) saw lifting up of night curfews and further ease in restrictions on economic activities and mobility.

The strict lockdowns have 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) provide a detailed discussion on how some of the key indicators like employment, incomes and consumption have changed over time and across different categories due to the pandemic in India.

2.2 Literature Review

The theoretical framework for expecting an increase in female labor supply during idiosyncratic income shocks has been expounded on by Lundberg (1985); Ashenfelter (1980); Heckman and MaCurdy (1980); Ehrenberg and Smith (2003); Borjas (2005). As discussed earlier, this framework assumes a married woman to be a secondary worker who temporarily increases her labor supply in face of an economic shock due to loss in family income due to an income effect and a substitution effect, referred to as the Added Worker Effect (AWE) in the literature.

Since substitution effects are generally small, the AWE relies on the income effects. From a lifecycle perspective this implies that women's labor supply only goes up if the fall in husband's income is a significant proportion of his lifelong income (Mincer, 1962; Lundberg, 1985). In other words, women's labor supply could be treated as an insurance mechanism for the households facing idiosyncratic shocks (Attanasio et al., 2005; Sabarwal et al., 2011). In the presence of incomplete credit and insurance markets or any other physical and financial assets, the poor households when facing a shock may resort to the one asset they are left with, labor.

In developed countries, unemployment insurance and other provisions can crowd out the need for women's labor as insurance. Empirical studies from developed countries, for example Joshi et al. (1985) for the UK, Killingsworth and Heckman (1986) for the US and Darby et al. (2001) for other OECD countries, show that female labor supply is pro-cyclical in aggregate. However, the relationship reverses in the context of developing countries. More women tend to take up work as a result of poor economy, often concentrated in the low-income households facing liquidity constraints, and the increase in jobs is also more significant in the informal sector: 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 Philippines.

In the developing economies, the absence of provisions like unemployment insurance and a great proportion of households facing subsistence constraints makes women's labor supply as a necessary asset in the hour of need to sustain family's survival needs. This tendency of women to act as a secondary worker may also be magnified due to low levels of skills and education amongst women and sociological reasons that discourage women to work in usual times, particularly so in the context of India.

COVID-19 has had substantial implications for gender equality across the world. Ongoing research indicates gendered differences in job losses, larger for women stemming from the pandemic induced lockdowns. See for example, Alon et al. (2020) for 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 the brunt of job losses more than men because the nature of industries facing closures like restaurants, retail spaces and domestic care work are the ones employing more women than men. More technically advanced jobs that allow telecommuting tend to hire less women. Seck et al. (2021) also found that in the context of Asia and Pacific, the demands for unpaid domestic and care work have increased substantially and burden of that has disproportionately fallen on women. Kabeer et al. (2021) also indicates that there is increased burden of unpaid care workload in a lot of countries, and the sectors worst-hit employ more women.

Deshpande (2020) looks at COVID-19 gendered impacts in India using CMIE-CPHS data and finds that conditional on being employed pre-lockdown, women are 20 pp less likely to be employed than men after the lockdown is lifted. Desai et al. (2021) also analyze the same question but using data collected by National Council of Applied Economic Research (NCAER) for Delhi. In contrast, they find that job losses for men were greater than women. The authors attribute this difference in result to the lack of agricultural sample in CMIE-CPHS surveys. They argue that because self-employment in agriculture and other industries was relatively well-protected as compared to wage-work which employs more men than women, the women were relatively less impacted than men due to the lockdown in India.

Another potential reason why Deshpande (2020) finds a significant fall in women labor force compared to men can also be attributed to the conditionality of the sample only including those women who were employed pre-lockdown. Hence, it does not capture the possibility that the women who were earlier not working might have been pushed into labor force. According to the AWE hypothesis, we can expect non-working women to enter the workforce after lockdown to support their families facing liquidity/ consumption constraints. In order to allow for that possibility, our paper includes the sample of all women whether working or not before the pandemic. Additionally, we complement the Deshpande (2020) and

Desai et al. (2021) paper, which only aims to understand the trend in FLFP, by analyzing the underlying heterogeneous effects of income losses on determining this trend.

3 Data

The paper uses the Consumer Pyramids Household Surveys (CPHS) by Centre for Monitoring Indian Economy (CMIE). 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). The survey collects information on individual level employment details every quarter for the set of households it follows over time. The survey is conducted across all the major Indian states and collects data on demographics of households and individuals, employment status of individuals including industry and occupation codes every quarter, income and consumption every month among other variables.[3]

We use data from January-August 2019 and January-August 2020 in our analyses. During the lockdown month i.e. April 2020, the surveys were moved from door to door in-person surveys to phone calls. The sample size reduced by almost 40% as a result. In this analysis, we therefore have to restrict our sample to the households for which we have the data during the period of lockdown, before the lockdown and after the unlock. We keep only those households for whom the survey was conducted for all the three waves in 2020 as well as 2019. We further limit data to only those households for which income data is available for the months of April and May in 2019 and 2020 which are the months we use to create the income shock measure. In our final sample, we are left with 49,849 number of households having 85,574 women aged 15 to 59 years.

[3]Households that drop over time and suitably replaced by similar households.

3.1 Income Shock Measure

To construct the measure of income shock for each household, we use monthly member income data collected in the CPHS. Data on incomes received by each member in a household are recorded in the survey. We use data across four months to construct the measure- April-May 2019 and April-May 2020. The choice of months (April-May) is because these were the months of the most severe lockdown in India and hence saw a significant income contraction. Next, we only keep the male members to calculate the income shock so that the shock measure remains exogenous to female employment status. Now we add the incomes of all male members in a household and average them for April-May in 2019 and separately for April-May 2020. Finally, we calculate the percentage change 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 there has been a greater fall in income in 2020 April-May due to the pandemic as compared to April-May 2019. The range of the shock measure lies from $-\infty$ to 100%, however, to restrict our analysis within reasonable range we restrict the negative value of the shock to be till -1000. This implies the final range of income shock lies between -1000 to 100, with a greater positive value showing a higher 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 the households where the male members in a household who were working in April-May 2019 are left jobless during April-May 2020. The peak then keeps decreasing as we move to the left representing a decreasing fall in income in 2020 as compared to 2019.

3.2 Descriptive Statistics

Table 1 shows the summary statistics of different employment outcomes considered in the analyses. The outcome variable takes a value of one if the individual is employed and zero otherwise for the variable *Employed*. Similarly, the outcome variable takes a value of one if an individual works in the given category of work (*Self employed*, *Casual labor* and *salaried*) and zero otherwise. Here *Casual labor* is defined as work done for daily wages while *salaried* is defined as work done for fixed monthly wages (it does not reflect formal work per se).

The mean employment rate for women in the sample is 5.6%, with 8.1% in the rural areas and 4.5% in urban areas.[4] In the rural areas, 4.7% women are engaged in casual labor work, while 2.7% are self-employed and only 1.3% work for fixed wages. On the other hand, in the urban areas, most women are employed in salaried employment (2.4%), followed by self-employment at 1.3% and casual labor at 0.8%.

Next, we analyze the trends in employment rate of women over different months in our sample. Figure 2 shows the overall employment rate of women by month in 2019 and in 2020. The trends show that there is a sharp drop in employment in March-April 2020 followed by a V-shaped recovery. However, the levels even in September 2020, remain below the pre-pandemic employment rate. We are interested in understanding the composition of the women whose employment increased after lockdown and if it was because of income effect.

In Figure 3 and 4 we plot employment rate for women in households which faced a negative income shock (positive sign according to the income shock measure constructed above) versus those who faced a non-negative income shock across different employment categories including total employment, self-employed, casual labor and salaried work for the

[4]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 has received criticism 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.

year 2020 for rural and urban areas respectively. The starkest trend that we see from these graphs is for the casual labor category. After a sharp dip in the lockdown months, casual labor among women picked up much more in households that faced negative income shock as compared to a non-negative income shock.

This suggests that women, in order to support the needs of the family, who faced a fall in income, have increased their casual labor work. For the outcomes of total employment and salaried work, we do not see a sharp increase in female employment rate in households with a negative income shock as compared to the non-negative shock during the unlock months. Importantly, these are descriptive trends and do not account for seasonality in outcomes. In the next section we elucidate our empirical specification to estimate the causal effect of income shocks post the pandemic induced lockdown on women's employment

4 Empirical Strategy

In order to identify the causal impact of income shocks on employment and its different categories, the paper employs a difference-in-differences strategy. We exploit the variation in pre (2019) and post (2020) during the control months of January-March compared with the treated months of April-May (lockdown) and June-August (unlockdown). We further interact this with the level of income shock constructed in section 3.1 to see the differential impact of having different levels of income shock. The following is our estimating equation:

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

The dependent variable Emp_{ihdt} is a dummy variable that takes value one for every employed individual i in a given household h in district d and time t. 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, and (iv) Salaried: =1 if an individual is engaged in temporary or permanent salaried job and zero otherwise.

Here, $unlock_m$ is a dummy variable that takes value one for the unlock months i.e. from June to August and $post_t$ is an indicator for the year 2020, as it takes value 0 for the year 2019. $lock_m$ is indicator for the lockdown months, April to May and $shock_h$ is household level measure of income shock. Our main coefficients of interest are β_1 and β_2. The coefficient β_2 on the triple interaction captures the causal impact of the income shock on female employment during the unlockdown months 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 lockdown differently across different income shock levels for the months of April to May as compared with January to March post the lockdown, again after 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.

5 Results

5.1 Baseline Results

Table 2 reports the results for the main specification (equation 2) for all India, as well as rural and urban areas separately, in Panel A, B and C respectively. 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, relative to pre-lockdown months, goes up by 1.47 pp (25% of the mean) during the unlock months (June-August) if the household faces a hundred percent fall in income. The same point estimate for rural areas is 1.32 pp (16%) and for urban areas is 1.56 pp (33% of the mean). In rural areas, the increase in probability of working for women is statistically significant only in casual labor work (0.9 pp or 21.5% of the mean). Even self-employed work and salaried work show a positive coefficient, however, the increases are not statistically significant. Urban areas on the other hand see an increase in probability of women working across all categories of work: self-employed (0.41 pp (31.6% of the mean)), casual labor (0.31 pp (40% of the mean)) and salaried work (0.84 pp (32.5% of the mean)) during the unlockdown months, in households that suffer a complete reduction in male incomes during the lockdown months.

We do not observe any overall or across categories change in urban women's employment during the lockdown months of April-May, that varies by the male income shock. This shows that no work was available during these months due to the stringent mobility restrictions placed in the country, which especially hurt the urban areas the most. Again, while rural areas see no overall effect on women's employment during the lockdown months, there is a significant fall in casual labor and a significant increase in salaried work for women in households where male income reduced during the lockdown months. This shows two things. One, that both men and women in all likelihood suffered as far as casual labor was concerned during the lockdown months in rural areas. To the extent that men and women in the same household worked as casual laborers before the lockdown, this is expected. Second, rural women moved to fixed monthly wage work in households where a higher income shock occurred during the lockdown months, perhaps reflecting a switch across the two types of work rather than any increase in employment per se.

These results concur with the earlier empirical literature for the developing countries in that it finds that a higher economic shock (lower income) leads to a higher probability of women working (Bhalotra and Umana-Aponte, 2010; Skoufias and Parker, 2006). These results, in conjunction with those by Deshpande (2020) and Desai et al. (2021) imply that while probability of women working might have fallen, there is heterogeneity in the actual impact. The households facing the most severe 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 coefficients are either negative or insignificant post August for women residing in households that suffered a higher male income shock during the lockdown. These results show that the increase in women's engagement in the labor market in households that suffered an income shock was a temporary phenomenon. Once the male incomes return back to their initial levels, women again withdraw from the work force. These results are omitted for brevity and are available on request.

5.2 Heterogeneity by women's characteristics

In order to better understand who are these women who are pushed into the workforce due to the reduction in male incomes, we examine the heterogeneity in the impact across two demographic categories. First, we sub-sample households into those that are below median income and those are above median income in 2019 and then we run the base regression on these two sub-samples separately. Similarly, we also sub-sample for women who have studied standard 10 and above (at least secondary education), and women who have studied till below standard 10 (less than secondary education). Given the theoretical foundation provided in Lundberg (1985), Mincer (1962) and Bhalotra and Umana-Aponte (2010), we expect that the results are primarily being driven by poor and uneducated women, arising out of consumption and liquidity constraints faced by these households.

5.2.1 Education

Table 3 shows the heterogeneous results by education for all areas (Panel A), rural areas (Panel B) and urban areas (Panel C). The obtained results concur with our hypothesis as we primarily see a larger and more significant increase during the unlockdown months for women with less than secondary education ('Below 10'). For rural women, in particular, less educated witness significant increases in probability of working at 2.24 pp. Not only has casual labor's impact (1.6 pp) increased for women below class 10 education but even work for fixed wages (0.4 pp) is significant for women educated below class 10.

Urban women see an increase in overall work for both categories of women, those having education below and above class 10. However, the magnitude of increase is higher for women having education below class 10 (1.85 pp) as compared to the rest of the women (1.33 pp). In self-employed work, we only see a significant increase in employment for women having class 10 education and above (0.6 pp). However, for casual labor (0.5 pp) and self employed (1.12 pp) we see increase in work coming only from women having less than secondary education.

5.2.2 Income

Table 4 shows the heterogeneous results by initial levels of income. The heterogeneous results with above and below median income in 2019 also concur with the literature expecting the income effect to be dominant in poorer households. Overall, probability of employment for women residing in below median incomes went up 1.74 pp during the unlockdown, while for above median family income it went up by 1.02 pp. For both casual labor and salaried work, again women saw a larger increase in these employment if they were residing in lower income families. For casual labor while women in both below median and above median income households see an increase, the increase is much higher in below median households (0.57 pp) than above median households (0.34 pp).

On the other hand, for self-employment, the increase comes predominantly from families that had higher initial incomes. This result might reflect the need for basic liquidity to be able to support your own business. Even for rural women, self-employed becomes slightly significant for women above median family incomes, which was earlier insignificant for the entire sample. But apart from slight significance in self-employment for above median income women, the primary increase in casual labor is driven by women in below median income households.

6 Robustness

6.1 Attrition

We check for 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.[5] 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 are presented in Table 5 and are robust to the correction for attrition in the sample.

6.2 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. We run our base regression equation with the addition of an interaction between D_d and M_m. The results are robust and are reported in Table 6. The significance do not change for any of the coefficients as presented in the main results in Table 2.

6.3 Negative Shock Dummy

We also undertake a check to see whether the results remain robust to using a dummy for the income shock measure instead of the continuous variable used in the previous specifications.

[5]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.

We create an indicator variable that takes a value for any household that lost income on the basis of the income shock measure constructed earlier. We then run the baseline regression equation 2 using this dummy variable as a measure of income shock. The results for this analysis are presented in Table 7.

The results suggest that probability of total female employment increased by 2.52 pp if a household faced a negative shock versus a household that did not face negative shock during the unlock months (June- August) as compared to the pre-lockdown months (January-March). The significance on the point estimates does not change for the most part except that it becomes slightly less significant for self-employed work overall. In the main results, the coefficient was significant at 99% significance level but now it is significant at only 90% confidence level.

7 Conclusion

In this paper we analyze the heterogeneous impacts of income shocks in the context of Covid-19 on female labor supply in India using individual panel data. Our findings suggest that women who faced a higher male income shock in their families increased their employment when the restrictions in the economy were lifted, as compared to women who faced a lower income shock. This result adds further evidence to the counter-cyclicical nature of female labor supply in the developing economies. We 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 uneducated women. However, analyzing these trends for months post-August 2020, we find the trends reversing i.e. women who earlier increased their work now move out of the work force. These results show the transitory nature of the increase in probability of women working to support their families post the initial income shock due to the lockdown.

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Tables

Table 1: Summary Statistics

Variable	Observations	Mean	Median	Standard Deviation
Panel A: Total				
Employed	387624	0.056	0	0.229
Self Employed	387624	0.017	0	0.129
Casual labor	387624	0.018	0	0.131
Salaried	387624	0.021	0	0.143
Panel B: Rural				
Employed	115115	0.081	0	0.272
Self Employed	115115	0.027	0	0.161
Casual labor	115115	0.041	0	0.198
Salaried	115115	0.013	0	0.112
Panel C: Urban				
Employed	272509	0.045	0	0.208
Self Employed	272509	0.013	0	0.113
Casual labor	272509	0.008	0	0.087
Salaried	272509	0.024	0	0.154

Note: The table uses employment data from Consumer Pyramid Household Survey 2019 & 2020 to get employment means for women across categories of work. The details for data construction of the sample is discussed in section 3. Here, salaried work included both permanent and temporary salaried work.

Table 2: Main results: Impact of Income Shock on Employment

Panel A: Total				
Variable	**Employed** (1)	**Self-Employed** (2)	**Casual labor** (3)	**Salaried** (4)
Unlock*Shock*Post	0.0147***	0.00331**	0.00501***	0.00629***
	(6.17)	(2.35)	(3.96)	(3.77)
Lock*Shock*Post	0.000551	-0.000700	-0.00256**	0.00373**
	(0.21)	(-0.38)	(-1.96)	(2.23)
Observations	249558	249558	249558	249558
R-squared	0.644	0.568	0.587	0.632
Mean Y	0.0576	0.0174	0.0180	0.0220
Panel B: Rural				
Unlock*Shock*Post	0.0132***	0.00181	0.00910***	0.00200
	(3.11)	(0.71)	(2.80)	(1.10)
Lock*Shock*Post	-0.00261	0.00129	-0.00867***	0.00474**
	(-0.56)	(0.41)	(-2.66)	(2.07)
Observations	74860	74860	74860	74860
R-squared	0.687	0.615	0.626	0.694
Mean Y	0.0827	0.0273	0.0418	0.0133
Panel C: Urban				
Unlock*Shock*Post	0.0156***	0.00414**	0.00312***	0.00835***
	(5.44)	(2.45)	(2.90)	(3.66)
Lock*Shock*Post	0.00112	-0.00146	-0.000419	0.00290
	(0.34)	(-0.65)	(-0.38)	(1.30)
Observations	174698	174698	174698	174698
R-squared	0.610	0.525	0.487	0.617
Mean Y	0.0469	0.0131	0.00781	0.0257

Note: The table uses data from Consumer Pyramid Household Survey 2019 & 2020. The details for data construction of the sample is discussed in section 3. Here, *unlock* is the indicator for unlockdown months including June-August, while *lock* is the indicator for lockdown months April-May.Here, salaried work included both permanent and temporary salaried work.

Table 3: Heterogeneity with education

Variable	Employed		Self Employed		Casual labor		Salaried	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Below 10	Pass 10	Below 10	Pass 10	Below 10	Pass 10	Below 10	Pass 10
Panel A: Total								
Unlock*Shock*Post	0.0195***	0.0118***	0.00168	0.00422**	0.0102***	0.00172	0.00765***	0.00563*
	(4.69)	(3.06)	(0.67)	(2.02)	(3.45)	(1.53)	(3.40)	(1.72)
Lock*Shock*Post	0.00359	0.00501	0.00237	-0.00211	-0.000531	-0.000453	0.00178	0.00723*
	(0.62)	(0.95)	(0.52)	(-0.61)	(-0.14)	(-0.34)	(0.74)	(1.88)
Observations	131762	97519	131762	97519	131762	97519	131762	97519
R-squared	0.665	0.682	0.593	0.596	0.611	0.638	0.635	0.676
Mean Y	0.0667	0.0508	0.0212	0.0134	0.0287	0.00511	0.0167	0.0318
Panel B: Rural								
Unlock*Shock*Post	0.0224***	0.00773	0.00225	-0.000994	0.0161***	0.00416	0.00412**	0.00358
	(3.33)	(1.17)	(0.56)	(-0.26)	(2.85)	(1.02)	(1.97)	(0.73)
Lock*Shock*Post	-0.000198	0.0122	0.00591	-0.00120	-0.00757	0.000660	0.00155	0.0124*
	(-0.02)	(1.28)	(0.91)	(-0.24)	(-1.12)	(0.13)	(0.60)	(1.74)
Observations	48512	20761	48512	20761	48512	20761	48512	20761
R-squared	0.700	0.742	0.634	0.647	0.642	0.681	0.705	0.745
Mean Y	0.0946	0.0630	0.0317	0.0188	0.0544	0.0169	0.00841	0.0266
Panel C: Urban								
Unlock*Shock*Post	0.0185***	0.0133***	0.00229	0.00583**	0.00498*	0.00116	0.0112***	0.00622
	(3.59)	(2.89)	(0.73)	(2.37)	(1.81)	(1.24)	(2.99)	(1.57)
Lock*Shock*Post	0.00499	0.00291	0.00132	-0.00232	0.00189	-0.000799	0.00179	0.00565
	(0.62)	(0.48)	(0.21)	(-0.56)	(0.44)	(-0.78)	(0.45)	(1.27)
Observations	83250	76758	83250	76758	83250	76758	83250	76758
R-squared	0.623	0.660	0.541	0.575	0.526	0.529	0.618	0.661
Mean Y	0.0504	0.0475	0.0151	0.0119	0.0137	0.00192	0.0216	0.0332

Note: The table uses data from Consumer Pyramid Household Survey 2019 & 2020. The details for data construction of the sample is discussed in section 3. Here, *unlock* is the indicator for unlockdown months including June-August, while *lock* is the indicator for lockdown months April-May. While, below 10 includes the sample of women who are educated below class 10, above 10 includes the sample of all women who have atleast graduated from class 10. Salaried work included both permanent and temporary salaried work.

Table 4: Heterogeneity with income

Variable	Employed		Self Employed		Casual labor		Salaried	
	(1) Below Median	(2) Above Median	(3) Below Median	(4) Above Median	(5) Below Median	(6) Above Median	(7) Below Median	(8) Above Median
Panel A: Total								
Unlock*Shock*Post	0.0174***	0.0102**	0.00280	0.00601**	0.00565***	0.00336**	0.00878***	0.000870
	(5.70)	(2.43)	(1.55)	(2.45)	(3.16)	(2.13)	(4.33)	(0.26)
Lock*Shock*Post	0.00391	-0.00330	0.000554	-0.00193	-0.00227	-0.00350	0.00563**	0.00163
	(0.91)	(-0.55)	(0.19)	(-0.54)	(-1.00)	(-1.46)	(2.18)	(0.36)
Observations	125127	124431	125127	124431	125127	124431	125127	124431
R-squared	0.645	0.641	0.557	0.582	0.603	0.538	0.623	0.639
Mean Y	0.0680	0.0472	0.0200	0.0148	0.0265	0.00948	0.0214	0.0226
Panel B: Rural								
Unlock*Shock*Post	0.0115**	0.0252**	-0.000478	0.0152*	0.00961**	0.00326	0.00214	0.00646
	(2.37)	(2.35)	(-0.17)	(1.83)	(2.38)	(0.54)	(1.02)	(1.27)
Lock*Shock*Post	0.00163	0.00330	0.00143	0.00728	-0.00659	-0.0131	0.00670*	0.00863
	(0.24)	(0.22)	(0.32)	(0.60)	(-1.34)	(-1.35)	(1.83)	(1.23)
Observations	47615	27245	47615	27245	47615	27245	47615	27245
R-squared	0.675	0.708	0.569	0.674	0.642	0.581	0.691	0.698
Mean Y	0.0844	0.0798	0.0241	0.0331	0.0478	0.0313	0.0123	0.0151
Panel C: Urban								
Unlock*Shock*Post	0.0209***	0.00640	0.00477**	0.00402	0.00318*	0.00288**	0.0129***	-0.000456
	(5.40)	(1.39)	(2.03)	(1.64)	(1.95)	(2.11)	(4.41)	(-0.12)
Lock*Shock*Post	0.00400	-0.00300	0.000169	-0.00258	-0.000750	-0.00130	0.00464	0.000261
	(0.73)	(-0.46)	(0.04)	(-0.75)	(-0.34)	(-0.77)	(1.35)	(0.05)
Observations	77512	97186	77512	97186	77512	97186	77512	97186
R-squared	0.617	0.600	0.547	0.491	0.510	0.408	0.603	0.629
Mean Y	0.0580	0.0380	0.0175	0.00967	0.0134	0.00337	0.0270	0.0247

Note: The table uses data from Consumer Pyramid Household Survey 2019 & 2020. The details for data construction of the sample is discussed in section 3. Here, *unlock* is the indicator for unlockdown 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. Salaried work included both permanent and temporary salaried work.

Table 5: Robustness: Attrition

Variable	Employed (1)	Self-Employed (2)	Casual labor (3)	Salaried (4)
Panel A: Total				
Unlock*Shock*Post	0.0160***	0.00392**	0.00529***	0.00665***
	(5.99)	(2.48)	(3.80)	(3.42)
Lock*Shock*Post	0.00327	0.000309	-0.00186	0.00466*
	(0.87)	(0.13)	(-1.00)	(1.83)
Observations	249558	249558	249558	249558
R-squared	0.667	0.577	0.586	0.679
Mean Y	0.0645	0.0186	0.0181	0.0275
Panel B: Rural				
Unlock*Shock*Post	0.0158***	0.00206	0.0102***	0.00321
	(3.50)	(0.75)	(2.83)	(1.52)
Lock*Shock*Post	0.00278	0.00149	-0.00602	0.00728**
	(0.44)	(0.35)	(-1.33)	(2.10)
Observations	74860	74860	74860	74860
R-squared	0.699	0.623	0.625	0.730
Mean Y	0.0877	0.0293	0.0418	0.0163
Panel C: Urban				
Unlock*Shock*Post	0.0165***	0.00497***	0.00309**	0.00834***
	(4.99)	(2.58)	(2.52)	(3.14)
Lock*Shock*Post	0.00288	0.000248	-0.000716	0.00311
	(0.62)	(0.08)	(-0.43)	(0.92)
Observations	174698	174698	174698	174698
R-squared	0.644	0.535	0.488	0.667
Mean Y	0.0546	0.0140	0.00804	0.0323

Note: The table uses data from Consumer Pyramid Household Survey 2019 & 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 unlockdown months including June-August, while *lock* is the indicator for lockdown months April-May. Salaried work included both permanent and temporary salaried work.

Table 6: Robustness: With District-specific seasonality

Variable	Employed (1)	Self-Employed (2)	Casual labor (3)	Salaried (4)
Panel A: Total				
Unlock*Shock*Post	0.0156***	0.00360**	0.00528***	0.00661***
	(6.25)	(2.46)	(3.85)	(3.78)
Lock*Shock*Post	0.00280	-0.0000840	-0.00194	0.00468**
	(0.79)	(-0.03)	(-1.07)	(2.09)
Observations	249556	249556	249556	249556
R-squared	0.649	0.573	0.595	0.634
Mean Y	0.0576	0.0174	0.0180	0.0220
Panel B: Rural				
Unlock*Shock*Post	0.0137***	0.00158	0.00911***	0.00275
	(3.13)	(0.60)	(2.58)	(1.41)
Lock*Shock*Post	0.00200	0.00175	-0.00672	0.00694**
	(0.32)	(0.41)	(-1.50)	(2.10)
Observations	74860	74860	74860	74860
R-squared	0.699	0.625	0.640	0.698
Mean Y	0.0827	0.0273	0.0418	0.0133
Panel C: Urban				
Unlock*Shock*Post	0.0161***	0.00445**	0.00310***	0.00856***
	(5.33)	(2.52)	(2.59)	(3.60)
Lock*Shock*Post	0.00212	-0.000736	-0.000751	0.00342
	(0.49)	(-0.25)	(-0.47)	(1.17)
Observations	174698	174698	174698	174698
R-squared	0.614	0.529	0.493	0.619
Mean Y	0.0469	0.0131	0.00781	0.0257

Note: The table uses data from Consumer Pyramid Household Survey 2019 & 2020. The details for data construction of the sample is discussed in section 3. Here, *unlock* is the indicator for unlockdown months including June-August, while *lock* is the indicator for lockdown months April-May. Salaried work included both permanent and temporary salaried work. To control for district-varying time trends, we have included district-month fixed effects to calculate these results.

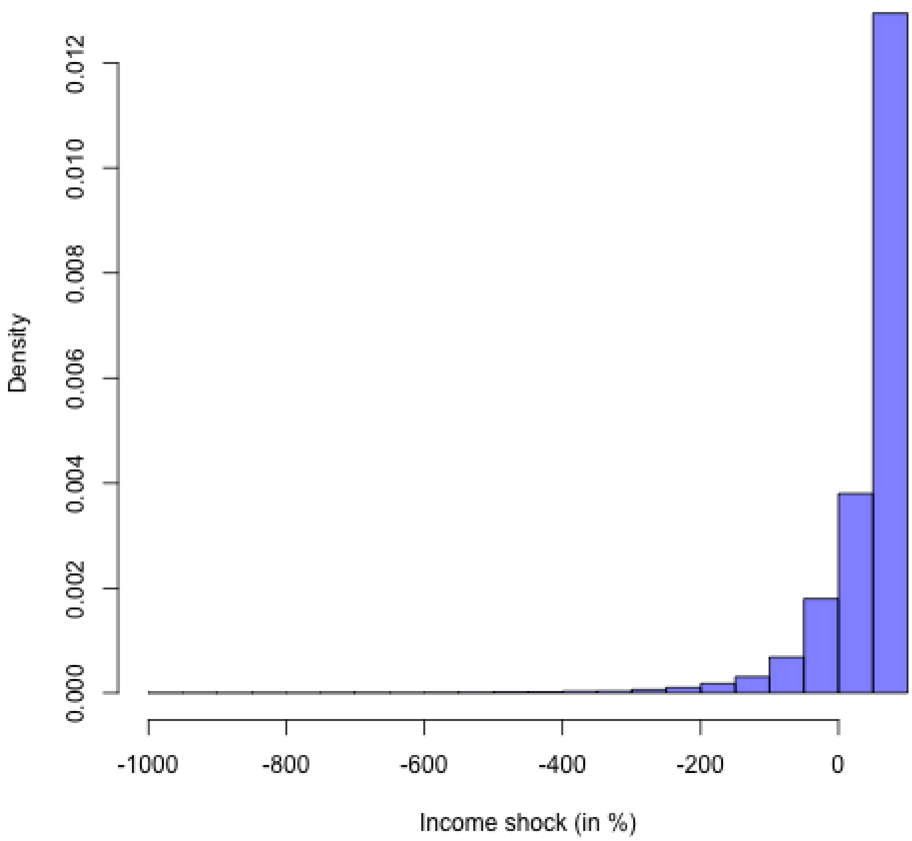
Table 7: Robustness: Negative shock dummy

Variable	Employed (1)	Self-Employed (2)	Casual labor (3)	Salaried (4)
Panel A: Total				
Unlock*Shock*Post	0.0252***	0.00470*	0.0118***	0.00856***
	(5.77)	(1.76)	(4.92)	(2.75)
Lock*Shock*Post	0.00279	-0.00109	-0.00429	0.00790**
	(0.55)	(-0.33)	(-1.57)	(2.35)
Observations	249558	249558	249558	249558
R-squared	0.644	0.568	0.587	0.632
Mean Y	0.0576	0.0174	0.0180	0.0220
Panel B: Rural				
Unlock*Shock*Post	0.0199**	-0.00269	0.0189***	0.00286
	(2.34)	(-0.46)	(3.09)	(0.70)
Lock*Shock*Post	-0.0150	-0.000458	-0.0198***	0.00506
	(-1.61)	(-0.07)	(-2.95)	(1.12)
Observations	74860	74860	74860	74860
R-squared	0.687	0.615	0.626	0.694
Mean Y	0.0827	0.0273	0.0418	0.0133
Panel C: Urban				
Unlock*Shock*Post	0.0278***	0.00811***	0.00868***	0.0111***
	(5.50)	(2.85)	(4.04)	(2.70)
Lock*Shock*Post	0.0101*	-0.000973	0.00189	0.00886*
	(1.67)	(-0.27)	(0.79)	(1.95)
Observations	174698	174698	174698	174698
R-squared	0.610	0.525	0.487	0.617
Mean Y	0.0469	0.0131	0.00781	0.0257

Note: The table uses data from Consumer Pyramid Household Survey 2019 & 2020. The details for data construction of the sample is discussed in section 3. The $shock_h$ variable in this data is a binary variable capturing whether a household faced negative shock or not instead of a continuous $shock_h$ variable. Here, *unlock* is the indicator for unlockdown months including June-August, while *lock* is the indicator for lockdown months April-May. Salaried work included both permanent and temporary salaried work.

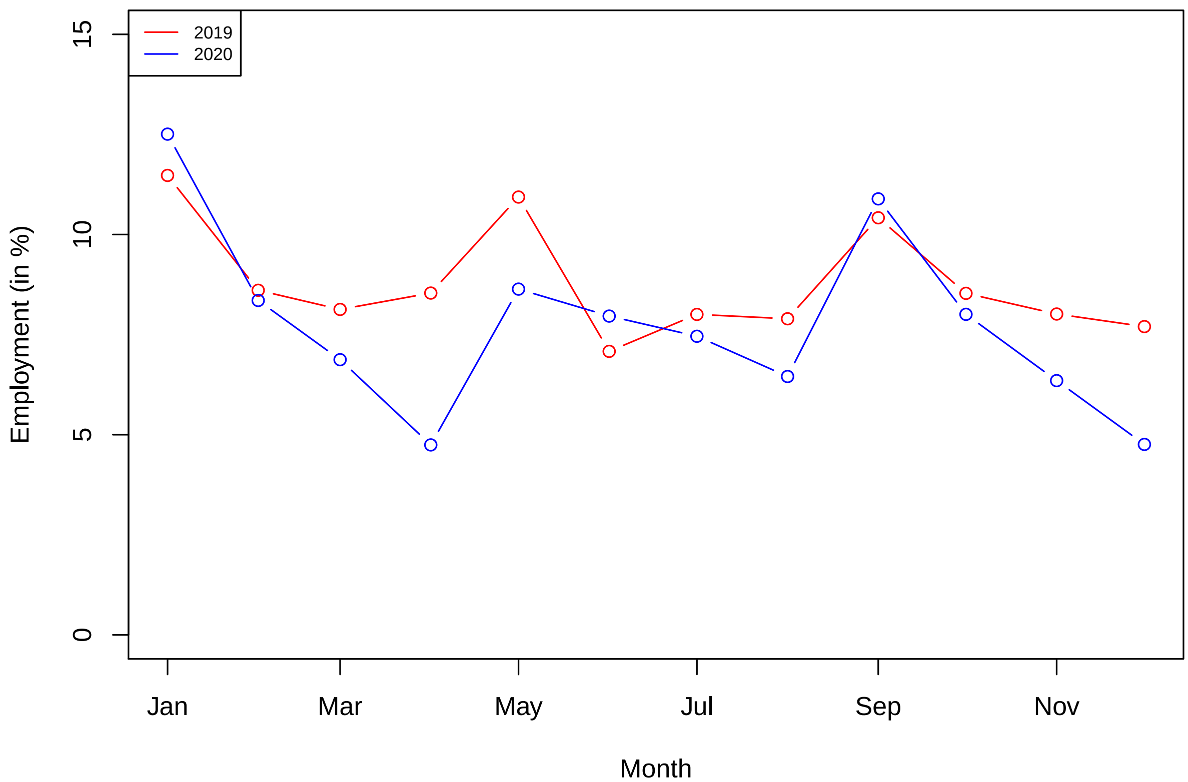
Figures

Figure 1: Income Shock Measure Distribution



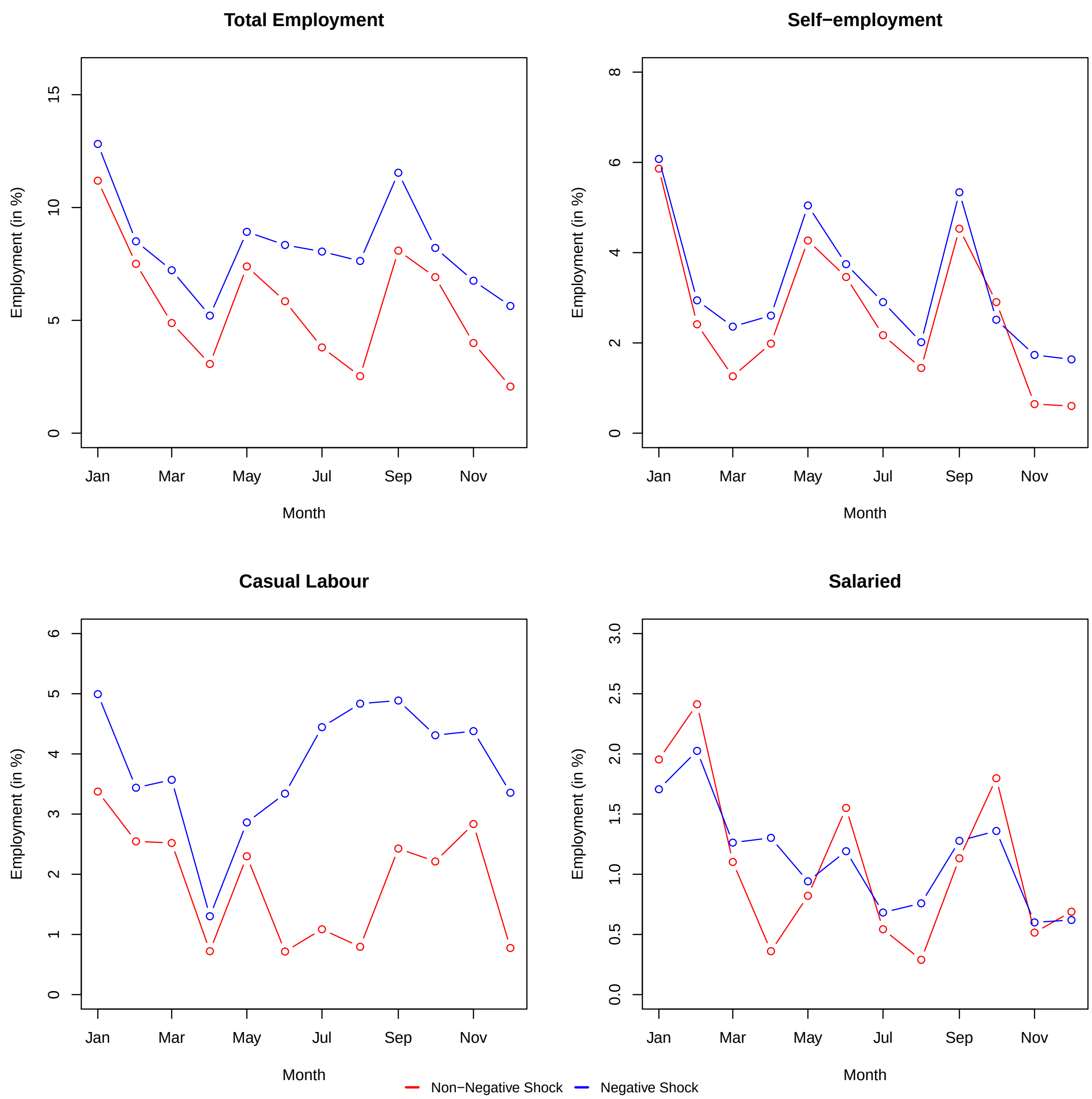
Note: The figure uses income data compiled from monthly data from Consumer Pyramid Household Surveys 2019 and 2020. Section 3.1 discusses the details on how the measure was created. A positive value here implies a fall in income in 2020 as compared to 2019. The distribution here has been restricted from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

Figure 2: Female Employment



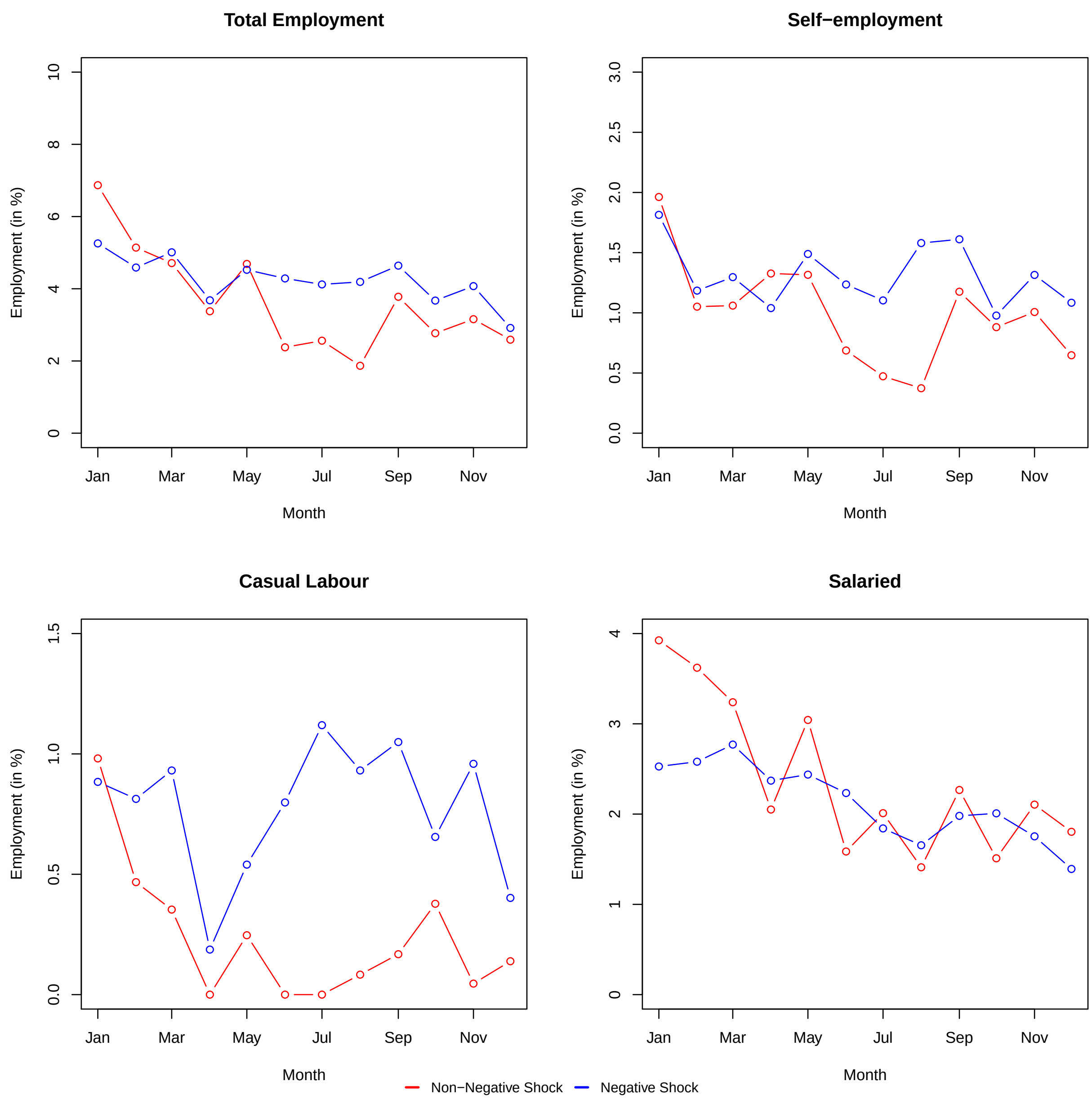
Note: The table uses employment data from Consumer Pyramid Household Survey 2019 & 2020 to get employment means for women across categories of work. The details for data construction of the sample is discussed in section 3.

Figure 3: Income Shock and Female Employment (Rural)



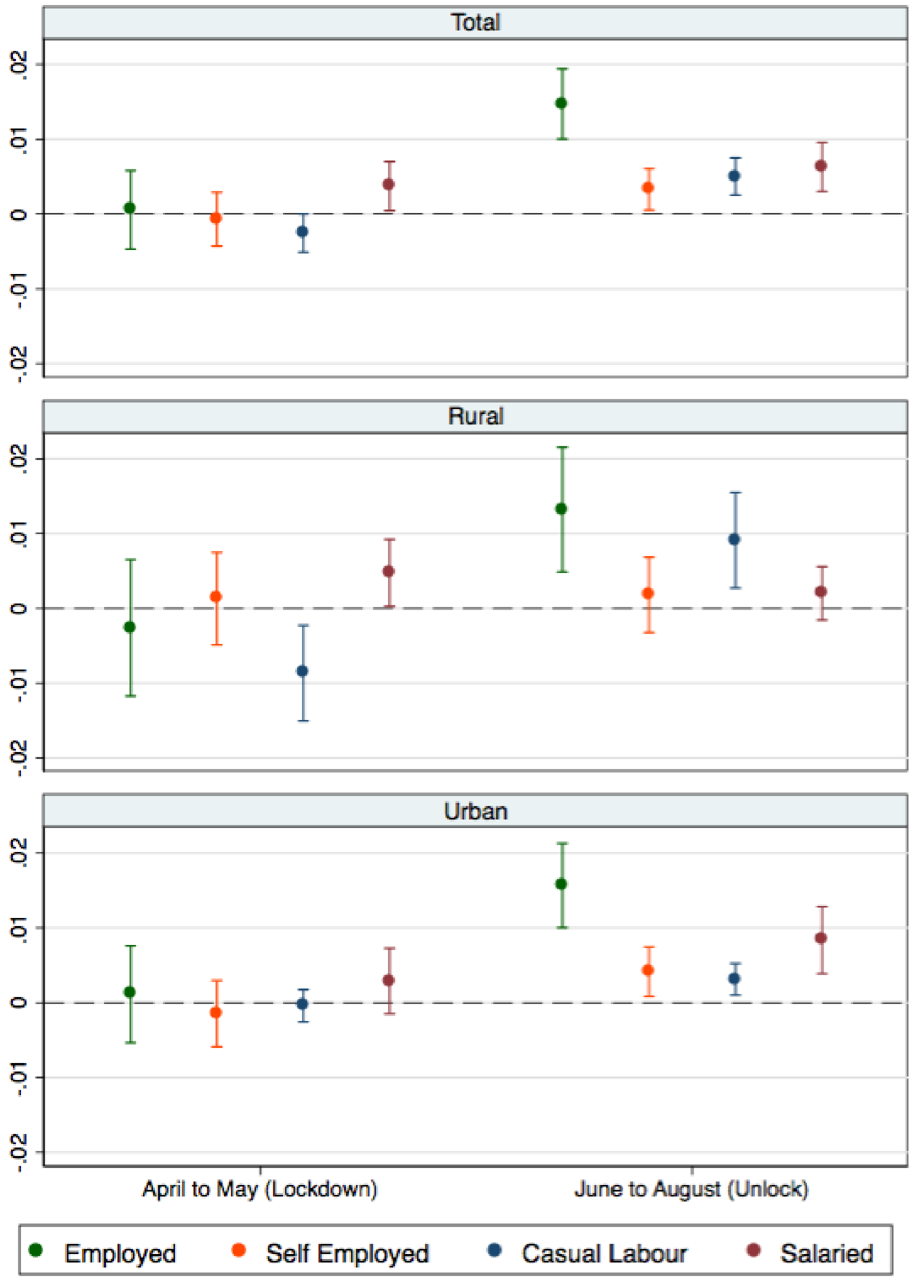
Note: The table uses employment data from Consumer Pyramid Household Survey 2019 & 2020 to get employment means for women across categories of work. The details for data construction of the sample is discussed in section 3. Negative shock sample includes all those households that saw a fall in income as compared to 2019, while non-negative sample includes households that did not face a negative shock. Here, salaried work included both permanent and temporary salaried work.

Figure 4: Income Shock and Female Employment (Urban)



Note: The table uses employment data from Consumer Pyramid Household Survey 2019 & 2020 to get employment means for women across categories of work. The details for data construction of the sample is discussed in section 3. Negative shock sample includes all those households that saw a fall in income as compared to 2019, while non-negative sample includes households that did not face a negative shock. Here, salaried work included both permanent and temporary salaried work.

Figure 5: Impact of Unlock on FLFP by type of of work



Note: The table uses data from Consumer Pyramid Household Survey 2019 & 2020. The details for data construction of the sample is discussed in section 3. Here, *unlock* is the indicator for unlockdown months including June-August, while *lock* is the indicator for lockdown months April-May.Here, salaried work included both permanent and temporary salaried work.