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Ashwini Deshpande

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ABSTRACT

The COVID-19 Pandemic and Gendered Division of Paid and Unpaid Work: Evidence from India*

Examining high frequency national-level panel data from Centre for Monitoring Indian Economy (CMIE) on paid work (employment), unpaid work (time spent on domestic work) and incomes, this paper examines the effects of the Covid-19 pandemic on the gender gaps in paid and unpaid work through the lockdown and recovery phases. The first month of the national lockdown, April 2020, saw a large contraction in employment for both men and women, where more men lost jobs in absolute terms. Employment has recovered by August 2020 for men. However, for women, the likelihood of being employed is 9.5 percentage points lower than that for men, compared to the pre-pandemic period. Men spent more time on housework in April 2020, but by August the average male hours had declined, though not to the pre-pandemic levels. Time spent with friends fell sharply for both men and women in April, to recover in August, but not to the pre-pandemic levels. The paper also examines available income data to find the sharpest contraction of incomes in the rural sector for both men and women.

JEL Classification: J1, J6, O53

Keywords: COVID-19, lockdown, employment, gender, time use, incomes, India

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1 Motivation

Contrary to global and historical trends, Indian female labour force participation has remained persistently low over decades, and has declined precipitously over the last 15 years, despite the presence of factors necessary for its rise, *viz.*, rising female education and lower fertility. The low level as well as the decline have been extensively studied; both are artefacts of a combination of factors – (mis)measurement, supply-side and demand-side issues (Deshpande and Kabeer, 2019). Historically, large demographic shocks have contributed to shifts in established gendered labour market norms. For instance, evidence suggests that the 1918 Spanish Flu epidemic in India led to a temporary increase in female labour force participation in 1921, believed to have been driven by distress labour supply by widows and rising wages (Fenske et al, 2020). Therefore, a question worth investigating is whether the first six months of the Covid-19 pandemic, which in its first month (April 2020) saw a sharp drop in employment with sustained recovery thereafter, result in changes in gender gaps in employment and labour force participation in India; and if yes, what the specific contours of these shifts were.

Early national-level estimates revealed that in the first month of the stringent nation-wide lockdown in April, in absolute numbers more men lost employment than women (104 million and 17 million respectively). However, conditional on being employed pre-lockdown, women were roughly 20 percentage points less likely to be employed in April 2020 (Deshpande, 2020b). Desai et al (2020)'s results, based on a survey in the Delhi Metropolitan Area, are similar in direction, in that the absolute loss of employment was greater for men compared to women. Kesar et al (2020), based on phone survey data in selected states till May, find that women, especially rural women, were more likely to lose employment compared to men. Chiplunkar et al (2020), using job postings on another employment portal (Shine.com) find a dramatic contraction in hiring in the first months of the pandemic, especially for young, less educated and female job seekers. They find that advertisers post fewer jobs in female dominated occupations.

While the early evidence from the lockdown does not suggest any major shifts in the gender gaps in the labour market, has this pattern changed with the steady unlocking of the economy? A recent study released by LinkedIn, based on their internal data for India, finds an increase of seven percentage points in women's participation in the labour force between April and July, 2020[1]. Their argument is that normalisation of work-from-home (WFH) and flexible hours has allowed women to enter the workforce.

An important dimension that negatively affects women's labour force participation is their predominant responsibility to get housework and domestic chores done. Across the

[1] https://www.livemint.com/news/india/work-from-home-boosted-gender-parity-in-india-s-says-linkedin-report-11601361523068.html

world, women spend more time on domestic chores and care work than men. India has amongst the most unequal gender division of household work globally. Early evidence suggests that the gender gap in average hours spent on domestic work hours *decreased* in the first month of the lockdown due to an increase in the male distribution of hours (Deshpande, 2020b). Was this shift a very short-lived blip or has this decline in the gender gap persisted beyond the first month? If it is the latter, in principle, it could set the stage for a rise in female labour supply, as suggested by the LinkedIn report. Of course, whether female employment actually increases is a function of several other factors, including demand for female labour and adequate employment opportunities.

Using nationally representative, high-frequency panel data, this paper examines the evidence from India on the impact of the Covid-19 pandemic on the gendered division of paid work (employment) and unpaid work (time spent on domestic work) and incomes. The evidence from India contributes to the rapidly emerging literature on the impact of Covid-19 on inter-group inequalities across the world. If the pandemic did, in fact, manage to shift the needle on sticky gender norms in paid and unpaid work, it would be massive silver lining to the dark phase of the pandemic and economic contraction. Any such shift in India has significant implications for livelihoods and quality of life of a third of the world's population. India has been struggling with slowing growth, rising inequality and significant persistent gender gaps and if the pandemic enables the economy to break out of persistent patterns, this would be much-needed and welcome development.

1.1 Global Evidence and Related Literature

Global evidence indicates that the slowdown and stoppage of economic activity due to the Covid-19 pandemic is disproportionately hurting women. According to the latest figures released by the US labour bureau, large numbers of women in the US are dropping out of the labour force altogether. The number of women aged 20 years or older in the labour force (including employed and unemployed women) declined by 865,000 between August and September 2020, compared to a corresponding decline of 216,000 men. There were 2.4 million fewer women in the labour force in September 2020 compared to exactly one year earlier (September 2019), compared to roughly 1.5 million fewer men[2]. This pattern is confirmed by research studies from various parts of the world which demonstrate that the first-order employment effects are more adverse for women than men (Alan et al, 2020 for the US; Andrew et al, 2020 for the UK; Farre et al, 2020 for Spain; Ikkaracan and Memis, 2020 for Turkey among others).

The impact of recessions on job losses is gendered, but not necessarily in one direction[3]

[2]https://www.bls.gov/news.release/empsit.t01.htm

[3]I have discussed this in Deshpande (2020a).

For instance, earlier recessions in the USA (2008-9) resulted in more job losses for men than women. However, this time around, women are more likely to bear the brunt because of the nature of businesses facing extended closure or possibly the threat of permanent closure (Alan et al, 2020). Restaurants, hotels, large retail spaces like malls and department stores, entertainment centres on one end, and domestic workers like maids, nannies, cleaners etc., on the other end of the workspace are large-scale employers of women.

A review of the evidence from other countries during earlier epidemics (H1N1, Ebola) reveals that increased domestic responsibilities, e.g. due to school closures, had differential effects on men and women. As their childcare burden increased, women's labour force participation fell, either in the form of reduced hours or withdrawal from paid labour altogether (Deshpande, 2020a). In the US, evidence suggests that mothers are facing a harsh dilemma due to school closures, summed up by the title of a New York Times article: "In the Covid-19 Economy, You Can Have a Kid or a Job. You Can't Have Both"[4].

As Indian women's participation in paid work is already severely constrained by unpaid work, which includes care work and domestic chores, this paper investigates how this pattern has shifted if at all. The LinkedIn India report suggests that Indian women were able to increase work participation despite school and childcare facilities being closed, due to the presence of domestic help and live-in grandparents, in addition to flexible hours and the ability to work remotely, which presumably allowed them to combine care responsibility with demands of paid work. Does national-level macro data support this evidence?

1.2 Main Results

The main results are as follows. Following a sharp drop in employment in April 2020, employment recovered through May-August 2020 for both men and women. For men the recovery is nearly back to the pre-pandemic level, as is the case for urban women. There is no evidence of an increase in female work participation over the six months of the pandemic over and above the recovery to near pre-pandemic levels.

Broken down by education levels, while highly educated women suffered the least in the job cuts in April, mean employment for this group of women is lower in August 2020, i.e. during the recovery phase than during the contraction phase. This is likely to be both due to supply side factors, i.e. due to an increase in hours spent on household work as well as due to the specific nature of recovery. This needs to be investigated more thoroughly.

Recovery in employment is different between men and women. The difference-in-differences

[4]https://www.nytimes.com/2020/07/02/business/covid-economy-parents-kids-career-homeschooling.html?action=click&module=Top%20Stories&pgtype=Homepage

estimates for the likelihood of being employed show that accounting for lagged employment, the likelihood of women being employed in August 2020 is 9.5 percentage points lower than that for men, compared to the pre-pandemic period.

The gender gap in the average hours spent on domestic work registered a decline in the first month of the lockdown (April 2020) due to an increase in male hours. However, in August male hours had declined again, though not to the pre-pandemic levels. The time spent with friends declined sharply in April 2020 and has recovered subsequently for both men and women, but is far below the pre-pandemic levels. While women spent more time with friends in the pre-pandemic months, this is now reversed, with men spending more time than women in rural areas. In urban areas, in August 2020, there is no gender gap in hours spent with friends.

The data on incomes is analysed till April 2020, as the data for August are not yet released. These show a sharp drop in incomes for both men and women consistent with the fall in employment. The sharpest drops are in the rural areas for both men and women.

The rest of this paper is organised as follows. Section 2 examines the shifts in gender gaps in paid work. Section 3 discusses time spent on domestic work (unpaid work) and with friends. Section 4 presents preliminary evidence on incomes. Section 5 contains a discussion of the main results and offers concluding comments.

2 Paid Work: Employment

2.1 Data and Summary Statistics

This paper uses data from the Centre for Monitoring Indian Economy (CMIE)'s Consumer Pyramids Household Survey (CPHS) as well as Income Pyramids member survey[5]. I use five waves of the CPHS: Wave 16 (January to April 2019), Wave 17 (May to August 2019), Wave 18 (September to December 2019), Wave 19 (January to April 2020), and Wave 20 (May to August, 2020). Since each household is surveyed three times per year, these 20 months allow up to five observations per person, subject to attrition[6] These data provide us with a pre- and post-pandemic panel of individuals, with five months in the post-pandemic period (one month in Wave 19, viz., April 2020, and 4 months of Wave 20 (May-August 2020)), which

[5]CMIE is a private data provider (with data available only to subscribers) collecting weekly data at the national level since January 2016. It is a longitudinal data set covering 174, 405 households (roughly 10,900 households per week, and 43,600 per month). Each household is followed three times per year.

[6]There is some attrition, which is to be expected in panel data. Additionally, April 2020 was a particularly disruptive month for ongoing surveys due to the complete lockdown. The CMIE shifted to phone surveys successfully; they have described the process here: https://consumerpyramidsdx.cmie.com/kommon/bin/sr.php?kall=wkb.

allows us to track changes in the status of the same individuals over time. I use income data for selected months between January 2019 and April 2020, as explained below[7].

The respondent is asked to list the employment status of all members of the household, including for household members for whom this question is not applicable, e.g. children or elderly members. If the question is applicable, the options for employment status are employed; not employed, but willing and looking for work; not employed but willing to work; and not employed, not willing and not looking for work. I have classified the latter as out of the labour force (OLF) and the middle two categories as "unemployed".

For all empirical results, I have created a panel of individuals who are observed in all the waves and for whom employment data are available[8]. Table 1 shows the mean of these three employment status categories by gender and wave: employed, unemployed and OLF for wave. We see that for ALL, the average employment for Waves 1 to 3 is roughly 40 percent. It declines to 34 percent in Wave 4, mainly due to the sharp drop in April. The monthly figures for Wave 5 show a steady recovery, as shown in Figure 1 discussed below and the average for the Wave is 38 percent. Table 1 reveals clear and sharp gender gaps, such that female employment is between 6 and 8 percent across waves and male employment is between 59 and 70 percent across waves. There is no evidence of a sharp spike in female LFP (employed plus unemployed) during the pandemic months.

Table 1 also reveals that open unemployment is low; thus, while being in the labour force (ILF) is not the same as being employed, for the purpose of this paper, employment rates and labour force participation rates are very similar. In the rest of the paper, we will focus on the impact of Covid-19 on employment[9].

Table 2 shows the occupational distribution by gender and wave for those who are in the labour force. Overall, the occupation distribution is fairly stable, with no major spikes or dips before and after the drastic fall in employment in April 2020. The proportion of women who are agricultural labourers declines sharply in Wave 4 to roughly 18 percent from the average of roughly 30 percent, but it increases again to the pre-pandemic levels by Wave 5. We see that percentage of women in self-employment increased to roughly 10 percent in the Wave 4, to decline again to roughly 7 percent average in all other waves. Proportion of women who are white-collar workers declines to 2.17 percent in Wave 5, i.e. after overall employment starts recovering. This is also seen below in the decline in employment of highly educated women not during the lockdown month, but during the period of recovery, discussed in greater detail below.

[7]The latest month for which the CMIE income data are available at the time of writing is May 2020.

[8]The total numbers are not exactly matching due to missing observations on employment status.

[9]I have done the analysis with ILF in place of employment, and the results are analogous.

2.2 Trends in total employment

Based on aggregate figures from CMIE data, Figure 1 shows the total number of employed individuals by gender and sector (rural/urban residence). The average for the pre-pandemic period January 2019-March 2020 is plotted, along with monthly figures from April to August 2020. We see a sharp dip in April 2020, followed by a sustained recovery for all categories. The average employment from January to March 2020 was 403 million, which declined to 282 million in April 2020. By August 2020, this had increased to 393 million. The comparative figures for men are 360, 256 and 353 million respectively, and for women are 43, 26 and 39 million respectively.

The male-female gaps in total employment are stark in both pre and post-pandemic periods. *Prima facie*, national level estimates do not support the evidence of a sharp increase in female employment, as suggested by the LinkedIn survey. If anything, these numbers suggest an increase in the urban male-female employment ratio from 9.04 in May 2020 to 10.58 in July 2020. For rural areas, the male-female employment ratio was 8.5 in August 2020, an increase from the pre-pandemic average of 7.91.

The initial drop in employment (between March and April 2020) was higher in urban areas (33 percent) compared to rural (29 percent), i.e. employment figures for April 2020 were 67 and 71 percent of the average employment during the preceding year (March 2019 to March 2020), for urban and rural areas, respectively. This was to be expected because sectors that shut down completely included manufacturing and services, which are mostly urban based. Rural women's employment suffered the largest fall at 57 percent of the previous year's average. This ratio was 73 percent for rural men, 69 percent for urban women and 67 percent for urban men. The decline in female LFPRs since 2004-5 has been driven by a decline in LFPRs of rural women. The pandemic-induced suspension of economic activity revealed a similar pattern.

Figure 1 reveals that the overall recovery in employment by August 2020 has been substantial, relative to the drop in April 2020, but it is not fully back to the pre-pandemic average (January 2019 to March 2020). All-India employment in August 2020 is 97 percent of the pre-pandemic average. Male employment (total, rural and urban) is 98 percent, whereas female employment is 91 percent of the pre-pandemic average (91 and 92 percent for rural and urban areas respectively). Thus, the recovery in female employment is roughly 7 percentage points lower than the recovery in male employment.

We should note that the CMIE employment and labour force participation figures for women are lower than those available from other widely used surveys such as the official National Sample Survey (NSS), or the publicly available India Human Development Survey

(IHDS)[10]. Leaving aside the considerable issues related to the (lack of) accurate measurement of women's work, the differences are attributable to definitions used by the various surveys. Very briefly, the CMIE rate is comparable to the the "current weekly status" (CWS) definition used by the NSS, and not the principal or usual status definition which measures the majority time in the year, or time spent in any 30-day period in employment. For CWS, a person is considered employed if the person has worked for at half a day in the past seven days. CMIE takes the status as of the day of the interview and not the past seven days. If a person is employed for four hours or more on that day, she is considered employed. The CMIE definition is more stringent and therefore the estimates are lower than those obtained via the NSS. For the purpose of this paper, what matters is that the definition remains consistent over time, and we are able to measure increases or decreases accurately.

2.3 Pre and Post-Pandemic Panel

In order to examine the main effects of the pandemic, we can begin by examining the overall change between the pre-pandemic months (January 2019 to March 2020), and post-pandemic months (April to August 2020). We will call them "pre" and "post" respectively. We can estimate a difference-in-differences equation:

$$Emp_{it} = \alpha + \beta female + \gamma post + \delta female * post + indFE + \epsilon_i \tag{1}$$

where Emp_{it} is a dummy for the employment status of individual i in period t, which takes the value 1 if employed. $female$ is the dummy variable for women. $post$ is a binary variable that takes the value 1 for April 2020 onwards, and zero otherwise, and $female * post$ is the interaction term which gives the coefficients of interest, the DID estimate of the effect of the pandemic on women's employment relative to men. This is estimated with individual fixed effects, with standard errors clustered at the district level for all individuals 15 years and older.

We estimate the same equation adding interactions, first with sector (rural/urban residence), and then with education levels. Equation 2 shows the interactions with education level ($edlow$), which is a binary variable taking the value 1 for those with upto 10 years of education and 0 for those with education level greater than 10 years.

[10] The most recent round of the former are only available for 2017-18, and for the latter for 2011-12. Thus, the CMIE data are currently the only national-level source for assessing changes in employment in real time, especially if we want to assess the immediate effect of the national lockdown which started in the last week of March, 2020.

$$Emp_{it} = \alpha + \beta female + \gamma post + \theta edlow + \delta female * post + \zeta female * post * edlevel \\ + indFE + \epsilon_i \quad (2)$$

Here ζ is the coefficient of interest, which gives us the DID estimate of the differential effect of the pandemic on the employment probability of men and women by their education levels. It allows us to see if the effect of the pandemic varied by low versus high education level.

Figure 2 shows the marginal effect of the pandemic, separately for men and women, based on estimates from Equation 1 in Panel A, and from Equation 2 for *edlevel* in Panel B[11]. For ease of interpretation, Panel B shows the marginal effects in two smaller sub graphs, one for each level of education.

Panel A of Figure 2 reveals that the gender gap in the probability of employment was 12.5 percentage points in the pre-pandemic period. This declined significantly in the post pandemic period (April to August 2020) to 7 percentage points. However, we should note that this decline is due to the lower probability of male employment, rather than due to an increase in the probability of female employment.

Panel B of Figure 2 reveals that male employment declined in both categories of education, but was sharper for men with lower levels of education (i.e. less than 10 years). For this category of men, the probability declined from 49 to 38 percent, whereas for men with higher education levels, it declined from 42 to 38 percent. Thus, despite overall recovery in employment, the effect of the pandemic has been to significantly lower the employment probability of men with lower education levels.

A binary division of the entire time period between "pre" and "post" pandemic is useful to see the larger picture, but given the month-by-month changes in the post-pandemic period (Figure 1), it is worth investigating changes over shorter intervals to understand the contours of the shifts in paid and unpaid work. Also, the strongest determinant of employment in any one period is lagged employment (employment in the previous period). With only two periods (pre and post), we are not able to introduce lags, but an analysis over shorter time intervals allows us to estimate a dynamic lagged model, as Section 2.4 proceeds to do.

[11] The results by sector are similar to that for the whole sample, i.e. the change between pre- and post-pandemic between male and female employment do not vary significantly by sector, hence not being reproduced here.

2.4 The Lockdown Panel

Figure 1 demonstrates that the contraction in employment happened in one month, *viz.*, April 2020. Subsequent months have seen a recovery in employment. We can define a "lockdown panel" of individuals surveyed in April 2020 and compare their outcomes in the pre-pandemic period as well as in the unlockdown or the recovery phase. Most of the April 2020 respondents were interviewed in April 2019 in Wave 1; August 2019 in Wave 2; December 2019 in Wave 3 and in August 2020 in Wave 5. Examining the changes in employment status for this panel of individuals will allow us to explore the full impact of the the lockdown and subsequent recovery.

Education and Employment

Figure 3 plots the marginal effects for the probability of employment for the lockdown panel by gender and educational attainment following an ANOVA estimation. For each education level, in all months for the lockdown panel, the probability of male employment is higher than that for female. Men in all educational categories registered a fall in probability of employment in April 2020, with a steady recovery in subsequent months. Consistent with the larger picture presented in Figure 2, we see that the drop in male employment was sharpest for illiterate men (from 88 to 34 percent between April 2019 and April 2020), and the recovery in August 2020 (at 65 percent) is below the pre-pandemic levels.

Female employment pattern differs from male in one noteworthy dimension. In April 2020, highly educated women (PG and above) not only did not suffer job losses, on the contrary, their probability of employment increased from 9 percent in April 2019 to 33 percent in April 2020. This was the only category of workers that registered an increase in the probability of employment during lockdown. But as the economy unlocked, May and August 2020, as workers in all other educational categories registered an increase in employment, this category of women registered a decline in the probability of employment to 12 percent, which is higher than the pre-pandemic months, but less than half of the peak in the previous quarter.

As Table 2 shows, the proportion of women in white-collar jobs declined clearly in Wave 5. The overwhelming majority of the highly educated women are white collar employees, with a small fraction in self-employment. Examining changes between April and August 2020, the fraction of PG women in white collar jobs fell from 78 to 71 percent, whereas the fraction in self employment increased from 13 to 21 percent. This indicates that nature of work done by highly educated women changed through the recovery phase, as some of them moved out of paid salaried work, and shifted to self-employment.

As most women with PG+ education are in white-collar jobs, the decline in female employment in this category could be a combined effect of demand and supply factors. It could be the case that the closure of schools and childcare for prolonged periods, combined with the pressures of balancing WFH and domestic work, might have led women to opt out of paid work, very similar to the experience of women in advanced industrial economies such as the US. Alternatively, it could be because of the specific nature of labour demand during the recovery phase.

Marriage and Children

In the case of women especially, marriage and childcare responsibilities affect their participation in paid work. To check for the role of marriage and children in employment, Figure 4 plots mean employment by marital status (not married, currently married and ever married, i.e. single now but were once married) and the presence of children (no children under 18, very young children below five years and older children between 6 and 18 years). For men, we see that employment rates of currently married men are the highest in August 2020, almost fully recovered to the pre-pandemic levels. For women, employment rates of ever married women are higher than those for currently married. The employment rate for this category of women has almost recovered to its pre-pandemic level. The male-female differences among those with young children are the analogous. Men with young children have the highest employment rates in all periods, with substantial recovery to the pre-pandemic levels by August 2020.

Table 3 shows average employment by presence of children, education levels and gender by month for the lockdown panel. For women with very young children, there is virtually no recovery: in April 2019, mean employment was 7.8 percent and in August 2020, for this category, the mean employment is 3.5 percent, after dropping to 2.9 percent in April 2020.

Table 3 also throws some light on the trends in employment for PG+ women. Between April and August 2020, employment PG+ with children between 6-18 years, i.e. school-going children dropped drastically (from 56 to 27 percent), whereas for men it increased from 69 to almost 90 percent. Between the pre-pandemic quarter of December 2019 and the lockdown month of April 2020, we see the employment for PG+ women with very small children drops from 25.6 percent to zero, whereas that for women with 6-18 children increases from 17 to 56 percent.

Social Identity

An examination of social groups (SC, ST, OBC, higher-ranked castes) and religion categories can be seen in Figure 5, which reveals differences between these groups within men and women for each month, with a drop in employment across the board in April 2020, but relatively more for SC men relative to upper caste men. However, the recovery in August 2020 seems to have re-established the pre-pandemic pattern. A comparison between three major religions: Hinduism, Islam and Christianity: reveals that for men the relative ranking of these three religion in terms of mean employment remained the same across the period.

For women, the drop in employment in April 2020 did not alter the relative ranking of social groups: ST women with the highest employment and upper caste women the lowest; Christian women the highest and Hindu women the lowest employment rates. Thus, we see that the pandemic and its aftermath have neither upset, nor reversed or flattened traditional hierarchies across gender-social group matrix.

2.5 DID estimates on the Lockdown Panel

This section runs regressions similar to Equations 1 and 2, but on the lockdown panel, i.e. individuals who are observed in April 2020. The time variable is “month", instead of “pre" and “post". Variables such as employment, wages, earnings are strongly path dependent, in that the likelihood of being employed in any period is strongly associated with employment in the previous period. Thus, the question that arises is whether we should run a time invariant fixed effects model (as in Equation 1) or a lagged-dependent variables model, i.e. do a dynamic panel data estimation. Angrist and Pischke (2009) highlight the dilemma of choosing between the two models, as including both fixed effects and lagged dependent variables introduce a bias, and estimating a time invariant fixed effects model will not estimate the true effect of time varying trends, viz., past employment. Given that the two models are not nested, one cannot estimate one and treat the other as a special case.

Angrist and Pischke (2009) show that using fixed effects when lagged-dependent variables matter will produce a treatment effect that is “too big". On the other hand, using a lagged-dependent dynamic panel data model will produce a treatment effect which will be “too small", as individual fixed effects will not be controlled. Thus, one option is to estimate both models and take the estimates as bounding the causal estimate we are trying to estimate (p. 184).

Accordingly, we estimate a fixed effects model, as in Equation 1 above, on the lockdown panel, with month dummies capturing the time trends, instead of a binary pre/post time dummy. For the dynamic panel estimation with lagged dependent variable, we estimate Equation 3 to get the D-I-D estimates to account for the effect of being previously employed. By including a one-period lag, we lose one month of observations.

$$Emp_{it} = \alpha + \beta.female + \gamma.month + \delta.female * month + \phi.Emp_{it-1} + \epsilon_i \tag{3}$$

where Emp_{it-1} is the lagged employment and all other terms are the same as in Equation (1). δ is the DID coefficient of interest. This does not include time invariant individual fixed effects. We include district fixed effects and standard errors are clustered at the state level.

The results are shown in Figures 6 and 7 respectively. Figure 6 with individual fixed effects shows that there was no significant change in the likelihood of being employed in August and December 2019 compared to April 2019. Post-pandemic, in April 2020, for men employment dropped by 23 percentage points compared to April 2019. By August 2020, male employment was 1.9 percentage points lower than in April 2019. The male female gaps did not change in the pre-pandemic months of August and December 2019. In April 2020, the gender gap in the likelihood of being employed reduced by 20 percentage points. By August 2020, the gap was back to the pre-pandemic level.

The results of the dynamic panel data model can be seen in Figure 7, based on estimating Equation (3). Accounting for lagged employment, we see that the drop in employment in April 2020 is 24 percentage points (compared to August 2019, since April 2019 gets omitted. However, we know from Figure 5 that the likelihood of being employed in August 2019 is the same as in April). By August 2020, accounting for lagged employment, the likelihood of men being employed is 11 percentage points higher than the pre-pandemic period. For women, after a 22 percentage point convergence in April 2020, the likelihood of being employed in August 2020 is 9.5 percentage points lower than that for men. This indicates that the gender gap in the likelihood of being employed has widened relative to the pre-pandemic level.

It is important to note that the decline in the gender gap is due to the decline in male employment, rather than an increase in female employment, as we had noted in Figure 2. Figure 8 shows that more clearly as it plots the marginal effects from the $female * month$ interactions for each month.

For those with desk jobs, work during lockdown shifted from the workplace into the home. A key dimension of "Work from Home" (WFH) is having to juggle multiple demands. Andrew et al (2020), using data for England, are able to examine the quality of time at work, which is critical for productivity and learning. As the authors emphasise, this could impact future earnings and career progression. They find that mothers and fathers doing paid work used to be interrupted during the same proportion of their work hours before the crisis; after the crisis, mothers are interrupted over 50% more often. These data are not available for India, and hence we cannot examine this question, but it is an important gender difference that is likely to be present in several contexts outside England, quite possibly in India.

3 Unpaid Domestic Work and Time with Friends

The large demand-side constraint to women's participation in economic activity is the (non-) availability of suitable jobs, which appears to have been worsened by the pandemic, according to the analysis in Section 2. A question actively being investigated in diverse parts of the world in the context of this massive exogenous shock in the form of pandemic is this: did the lockdown, which forced everyone to stay at home, and the need for social distancing which has resulted in the widespread adoption of WFH, shift the sharing of domestic work towards greater gender equality?

South Asia (India and Pakistan in particular) and MENA (Middle East and North Africa) regions have among the most unequal gender norms in terms of sharing of household chores and domestic work, including care work. While these regions are at one end of the spectrum, women everywhere spend more time doing household chores compared men. The social norm of women being primarily responsible for housework is one of key constraints to their being able to access paid work from the supply side (Deshpande and Kabeer, 2019).

Since the pandemic is still ongoing, and countries are expected to go in and out of lockdowns till a vaccine is found, there cannot be a definitive answer to this question until we emerge out of the pandemic decisively and have data covering the entire period. However, an analysis of the early evidence on this issue is both pertinent and interesting.

The CHPS data has included a question on "time spent on domestic work" in half-hour increments, starting with zero hours, since Wave 18 (September-December 2019). My previous estimates (Deshpande, 2020b), comparing gender gaps in self-reported time spent on domestic work by men and women, revealed a decline in the average gender gap in time spent on housework, due to an increase in male hours men in the lockdown month of April 2020, compared to December 2019. the period of strict lockdown was marked by an absence of domestic helpers, integral to the lifestyles of a large number of Indian families. Anecdotal accounts suggest that men stepped up their contributions to housework in this extraordinary situation. Did the pattern persist with unlockdown as domestic helpers returned to work, and men returned to their paid jobs?

Figure 9 presents the marginal effects of gender on the predicted mean housework hours from ANOVA estimates. We see that by August 2020, men's time spent on housework had again declined from the April high, though not to the pre-lockdown level of the December 2019 average. Thus, while the the green shoots of gender equality within the household, seen in the clear decline in the gender gap in the time spent on housework in April, did not get further enhanced in August, the good news is that men did not relapse completely into their pre-lockdown habits.

Part of the reason for the change in time spent on housework in April could lie in the change in type of paid work (full or part time). Table 4 shows the type of employment for men and women in the labour force by month for the lockdown panel. We see that the proportion of both women and men working full time declined in April 2020 (from 68.46

to 39.34 percent for women, and from 93.11 to 61.11 percent for men between December 2019 and April 2020). This was not due to full time workers shifting to part time work; the decline in full time workers was matched by an increase in the category “not applicable", which would be relevant for unemployed workers. By August 2020, these proportions had reverted to their pre-pandemic December 2019 levels.

Overall, it appears that there was some change in the time spent on housework in the post-pandemic months, compared to the pre-pandemic months. We can look at the broad picture by comparing the average time spent on housework, pre and post pandemic, and break it down by education level, number of children and gender. Table 5 presents the average time by these categories.

Men with small children (0-5 years) increased the hours spent on housework within each educational category. Men with school-going children reveal two different patterns: illiterate and primary educated men (i.e. with zero or very low levels of education) increased time spent on domestic work post-pandemic. More educated men with school-going children did not show a similar increase. Similarly, men with education levels upto secondary school with no children increased the hours spent on housework post-pandemic, whereas higher educated men did not. Thus, we see that men's time spent on housework is shaped by their education levels, with less educated men having increased their time post-pandemic.

For women, the post-pandemic change shows a different pattern. UG women with no children show a clear rise. Women with small children overall show no significant change, and women with school-going children also do not show a major change. Thus, overall taking the entire pre and post period into account, which includes the spike in domestic work in the month of lockdown in April, and then a fall to the pre-pandemic levels, most women continued spending roughly 6 hours per day on domestic work, with men spending between half and one-third that amount.

3.1 Time Spent with Friends

I examine another dimension of time allocation, time spent with friends. This is an important indicator, as it not only signifies leisure but also the possibility of de-stressing with someone outside the family, very important for emotional well-being. Figure 10 presents the marginal effects of gender on the predicted mean hours spent with friends, separately for rural and urban areas, from ANOVA estimates. Here I have used the available data for all the months, not just for the lockdown panel. We see that time spent with friends went down significantly in April for both men and women, but relatively more for women. Thus, in addition to the pressure of decreased employment, women had to bear the brunt of less time with their friends.

There has been a recovery in time spent with friends for both men and women in rural as well as urban sectors. However, the time spent with friends in August 2020 remains far lower than the pre-pandemic average. The recovery in urban areas is slower than that for rural areas. The other noticeable feature is that while women spent more time with friends than men in the pre-pandemic period, in the post pandemic period, the relative position has reversed. In urban areas, in August 2020, the gender gap appears to have closed.

4 Incomes

CMIE generates data on incomes from all sources via the Income Pyramids dataset. Unlike the employment data that are realeased by Wave, income data are released monthly and with a lag (at the time of writing, income data till May 2020 are available). Small surveys indicate that while livelihoods are recovering through the unlockdown, incomes are not necessarily recovering in tandem. Since the CMIE data for the unlockdown months are not fully released, this question will have to examined in detail when more data become available. This section contains a preliminary examination the trends in average income for the lockdown panel till Arpil 2020.

Estimation of a linear model similar to Equation (1) with log income as the dependent variable reveals that overall, income contracted by 28 percentage points in April 2020, compared to April 2019. This is higher but in the same order of magnitude to the contraction in GPD reported in June 2020 quarter.

Figure 11 represents the mean income separately for men and women for the lockdown panel. The January 2019 figure is shown for comparison. We note that the average of wage income is very close to the average of total income for men, indicating that wage or salary incomes comprise the bulk of male incomes. In the case of women, the means coincide, indicating that female incomes almost exclusively come from their wage or salaried work.

In accordance with the evidence on employment, we see that in April 2020 incomes dropped to half their December 2019 levels, as employment contracted. Again, given the gender gaps in employment, the decline for male incomes was greater compared to female.

Figure 12 shows the marginal effects from a triple interaction of month*gender*sector, following an ANOVA estimate with 95% confidence intervals. The male-female income gap is clear, as is the rural urban gap for both sexes. The decline of urban male incomes is the sharpest, in accordance with drop in employment.

Figure 13 shows results of the ANOVA estimates by gender and occupation, where we can see the change across occupations and how that varied by gender. For women, the rural occupations: big and small farmers show among the sharpest drops between December 2019 and April 2020, as expected given that rural women experienced a sharper fall in paid work in April 2020. The topmost earning category is a combination of top management positions, legislator positions. For women, the incomes for this group are volatile across time, and the drop is sharp between December 2019 and April 2020.

For men, virtually all categories of workers show a drop. The sharpest drop is for the big farmers, followed by blue collar and small farmers. The flat line for small traders and hawkers for both men and women is an artefact of the Y-axis scale, as their incomes are minuscule compared to other categories of workers with substantially higher incomes.

5 Discussion and Concluding Comments

The Covid-19 pandemic has often been described as a great leveller. In several countries, early evidence suggests that regardless of which sections of the population are more vulnerable to the disease, the impact of the lockdown and economic shutdown, which is the key pandemic control strategy everywhere, has been highly uneven, hitting the already vulnerable groups much harder than. In this sense, the pandemic has exposed the many fault lines that lay beneath the surface across the world.

India, home to a third of the world's population, is no exception to this global pattern. Using five waves of longitudinal national data for roughly 55,000 individuals, this paper presents estimates for differential effects of the lockdown as well as recovery on employment on men and women.

Due to the pre-existing significant and widening gender gaps in labour force participation rates and employment, the absolute number of men who lost employment is larger than the absolute number of women who lost employment in the first month of the lockdown. However, even though pre-lockdown employment was the strongest predictor of post-lockdown employment, its effect was different for men and women. Accounting for lagged employment, women are 9.5 percentage points less likely than men to be employed in August 2020, compared to the pre-pandemic levels.

5.1 Time Use

India has amongst the most unequal gender division of household work globally. Time Use Surveys, conducted by the Central Statistical Organisation of the Ministry of Statistics and

Programme Implementation, provide a reference point against which the CMIE data can be assessed, while we note that the data sources are not comparable. The previous NSS survey in 1998-1999 across six states in India was considered a pilot; the latest national survey is for 2019, i.e. after a gap of two decades. The statistics from these surveys are not comparable, but instructive. The 1998-99 survey found that men spent significantly more time on income earning and personal care (including leisure) activities compared to women. However, women spend 10 times as much time on household work, including unpaid work on family enterprises, compared to men (CSO, 1999).

The main results from the nationwide 2019 survey indicate that consistent with labour force statistics, women spend significantly less time than men in “employment and related activities". However, consistent with other evidence of women's involvement in unpaid economic work, they spend more time in “production of goods for own final use" compared to men. In “unpaid domestic service", women's participation rate is roughly four times that of men, and they spend about three times more time compared to men. Women spend roughly twice the time in unpaid care work, compared to men. Prima facie, this indicates that the gender gap in unpaid domestic and care work might have reduced over the last two decades. However, we have to note that the 2019 survey is not comparable to the 1998-99 one. We need at least two comparable surveys in order to accurately gauge change over time.

In this paper, comparing hours spent on domestic work pre- and post-lockdown, I find that for both men and women, the gender gap in average hours spent on domestic work hours decreased in the first month of the lockdown. This was due to an increase in male hours on domestic work. However, by August 2020, the male hours had again dropped, but not to the pre-pandemic levels. If this shift persists or gets accentuated, it would indicate a clear shift in gender norms.

5.2 What Does History Tell Us?

Severe shocks can shift social norms defining gendered labour force patterns, which in turn could have an impact on the gendered division of domestic chores. For instance, the years after World War II resulted in a rise in female labour force participation in OECD countries (Long, 1958). This was also a time when the division of domestic chores shifted towards greater equality.

Specifically in the context of this pandemic, Alon et al (2020) find that beyond the immediate crisis, work norms which normalize work from home as well as the norms of fathers participating in childcare might “erode erode social norms that currently lead to a lopsided distribution of the division of labor in house work and child care". For India, we would need to examine the evidence over a longer time period, as such changes unfold slowly over several years; a month-long lockdown is certainly no proof of the magnitude and persistence of shifts.

Sabarwal et al (2010) discuss the first and second-order effects of the 2008 financial crisis. They find that the loss of employment for women already in the labour force - the first-order effect- depended on the sector of employment. However, economic crises can lead women outside the labour force to enter the workforce ("added worker effect") in response to declining family incomes. The evidence presented above shows an adverse first-order effect on women of the lockdown. The analysis presented above, with data till August 2020, does not reveal the positive second-order effect.

While women have suffered disproportionately more job losses, risky, hazardous and stigmatized jobs are exclusively their preserve. All frontline health workers, the trinity that forms the backbone of the primary healthcare system - ASHA (Accredited Social Health Activists), ANM (auxilliary nurse and midwife) and Anganwadi workers (the ICDS or Integrated Child Development Scheme workers) are women. Thus, for a very large number of women, the choice seems to be between unemployment and jobs that put them at risk of disease and infection and make them targets of vicious stigma.

Pandemics have implications for women's and children's health outcomes which, in addition to being important in themselves, have implications for women's ability to participate in paid work. For instance, school closures for prolonged periods, combined with the fact that women bear a disproportionate brunt of child-rearing responsibility, would negatively impact women's labour force participation. Minnardi et al (2020) examine evidence from earlier epidemics (Ebola and H1N1) and outline the multiple negative costs of school closures: lack of school meals which are a vital source of nutrition especially for disadvantaged children; disruption of education can increase the risk of child labour, early marriage, teen pregnancies and genderual assaults.

Thus, lessons from earlier disruptions (wars or pandemics) point towards both negative and positive effects on women's ability to participate in paid work, as well as their role as sole providers of unpaid care work. For the Indian case, evidence so far seems to indicate the presence of most of the negative effects (lower employment, greater care burdens, increased domestic violence), but barring a small shift in gender division of domestic work, none of the positive effects.

India's economy has "suffered even more than most" as a result of the lockdown (Economist, 2020). India's growth rate has been faltering over the last six years, decelerating each year since 2016, to reach 3.1 percent in the first quarter of 2020 (January to March), just before the Covid-19 pandemic hit India. Recent figures reveal that in the June 2020 quarter, India's GDP contracted by 24 percent, making it the worst performer among its peers. This has led to expectations of a large contraction over 2020, if not for longer[12].

Despite the recovery in employment, the evidence of GDP contraction suggest that the unemployment challenge is massive. To sustain the momentum in employment generation in the coming months, we need to see strong policies to provide employment and boost demand, in the absence of which job losses might mount, worsening the employment crisis. The results of this paper indicate that in addition to overall unemployment, pre-existing inequalities along gender lines are likely to get reinforced, unless the specific contours of disadvantage are recognised and addressed.

[12]https://www.livemint.com/news/india/gdp-contraction-sets-india-behind-em-peers-11600760017416.html

6 Figures

Figure 1: Total Employment, By gender and Sector, India

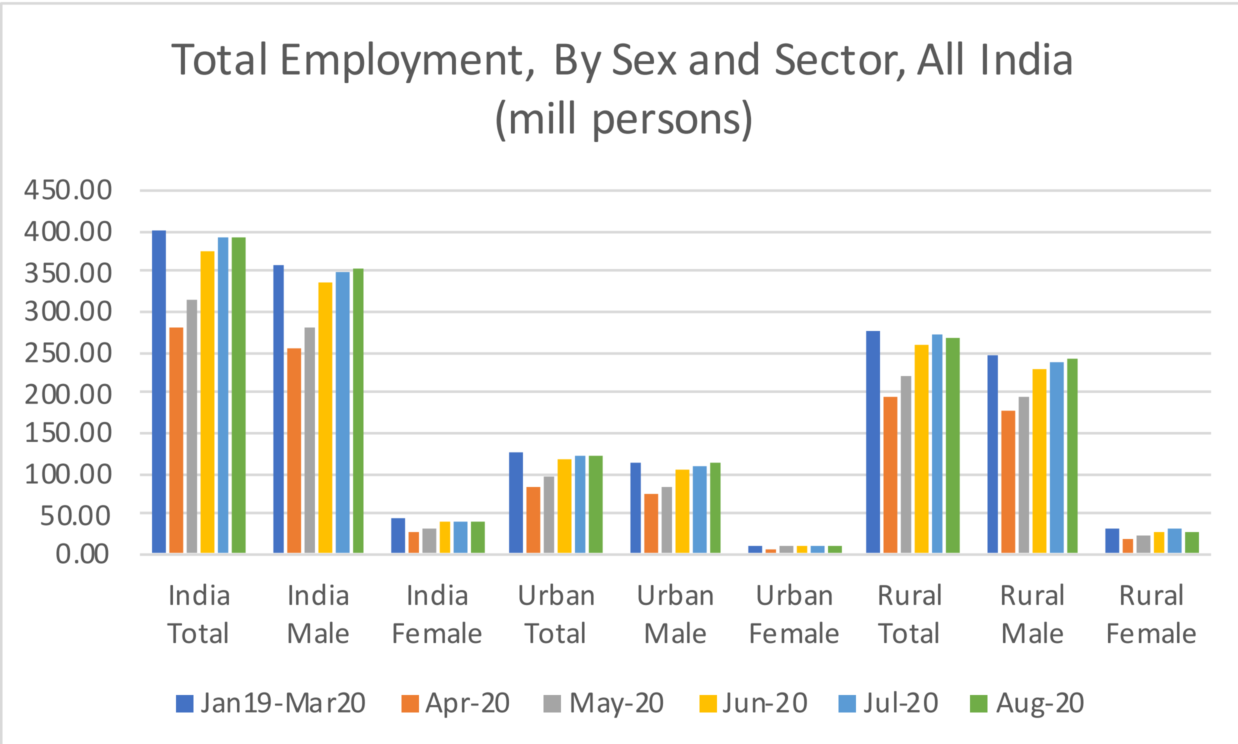


Figure 2: Change in Employment by Gender, Post-Pandemic, India

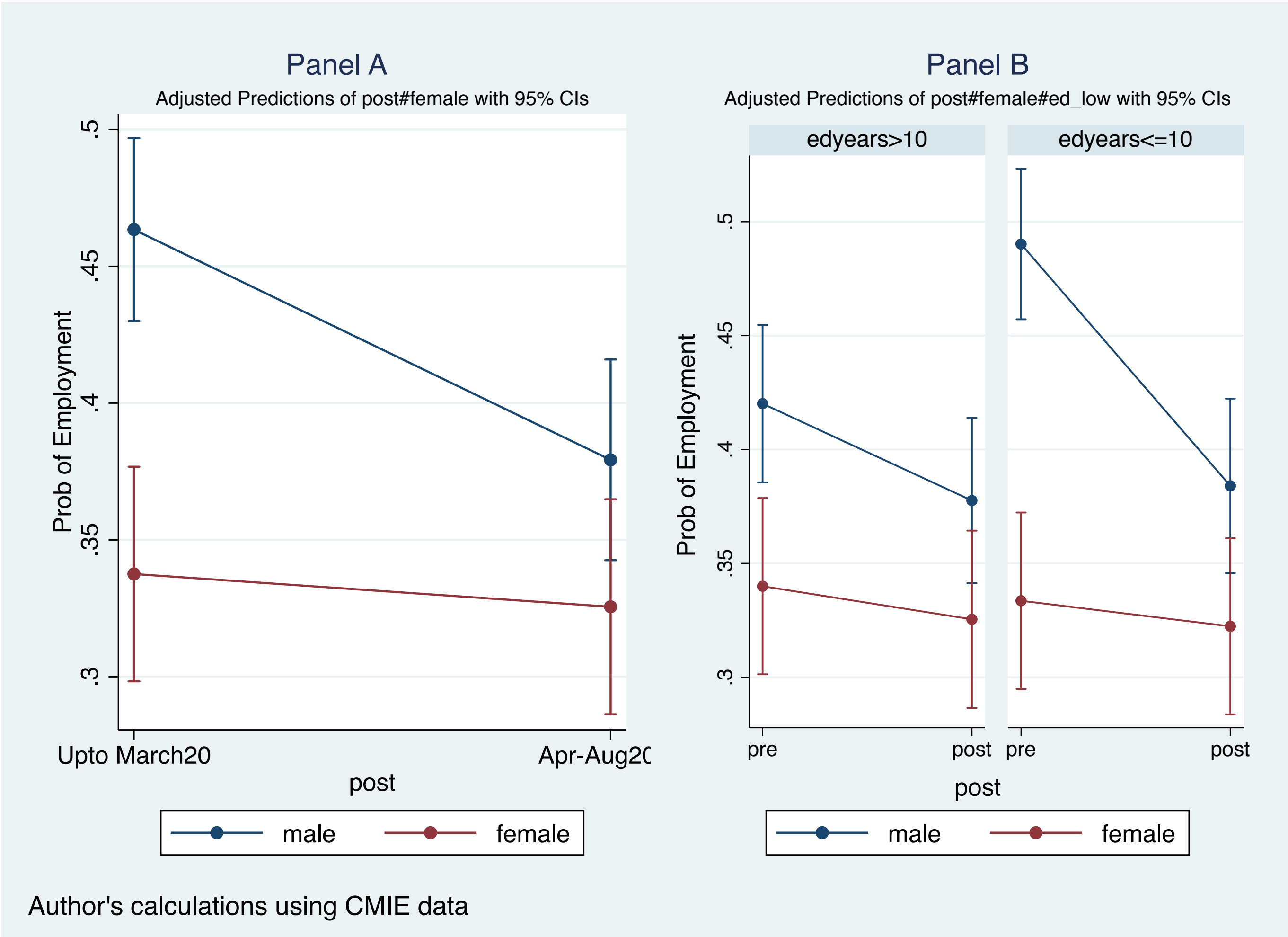


Figure 2 presents the marginal effects of the pandemic from the estimation of Equation 1. N=277,296. The Panel A shows the estimation over the whole panel; Panel B shows the results of interaction with two education levels, low and high.

Figure 3: Change in Mean Employment by Gender and Edu Level, 15 yrs older, India

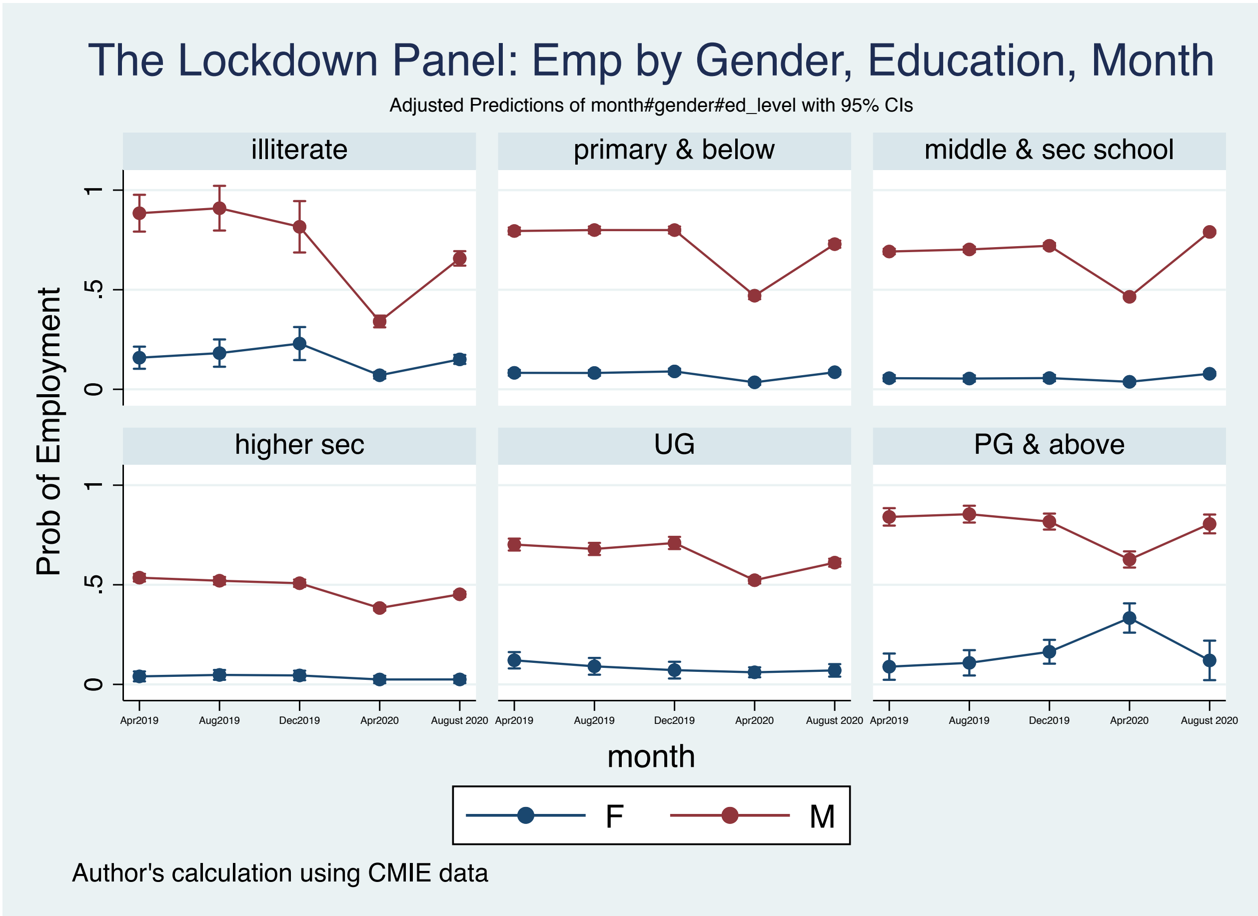


Figure 4: Mean Employment by Marital Status & Children, India

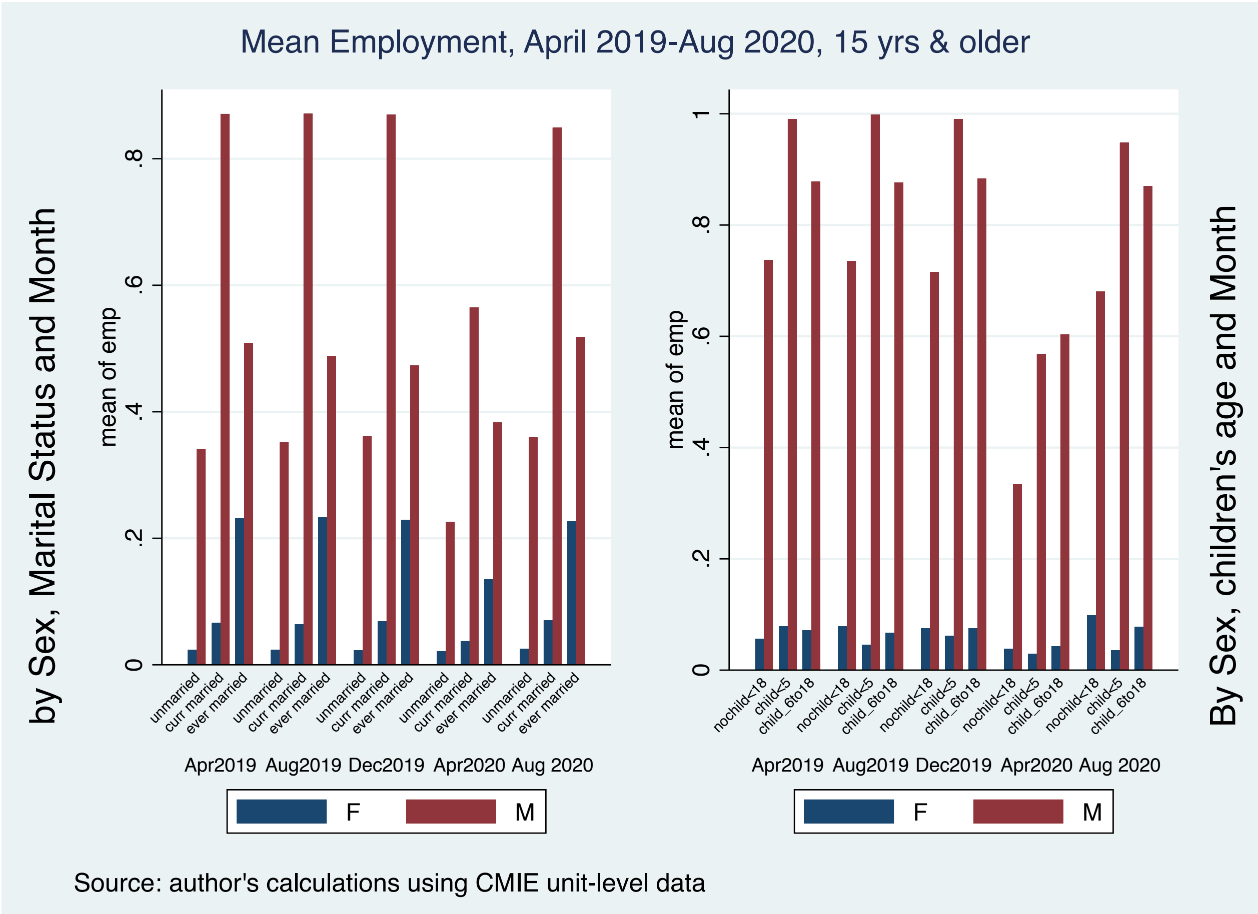


Figure 5: Mean Employment by Social Groups, India

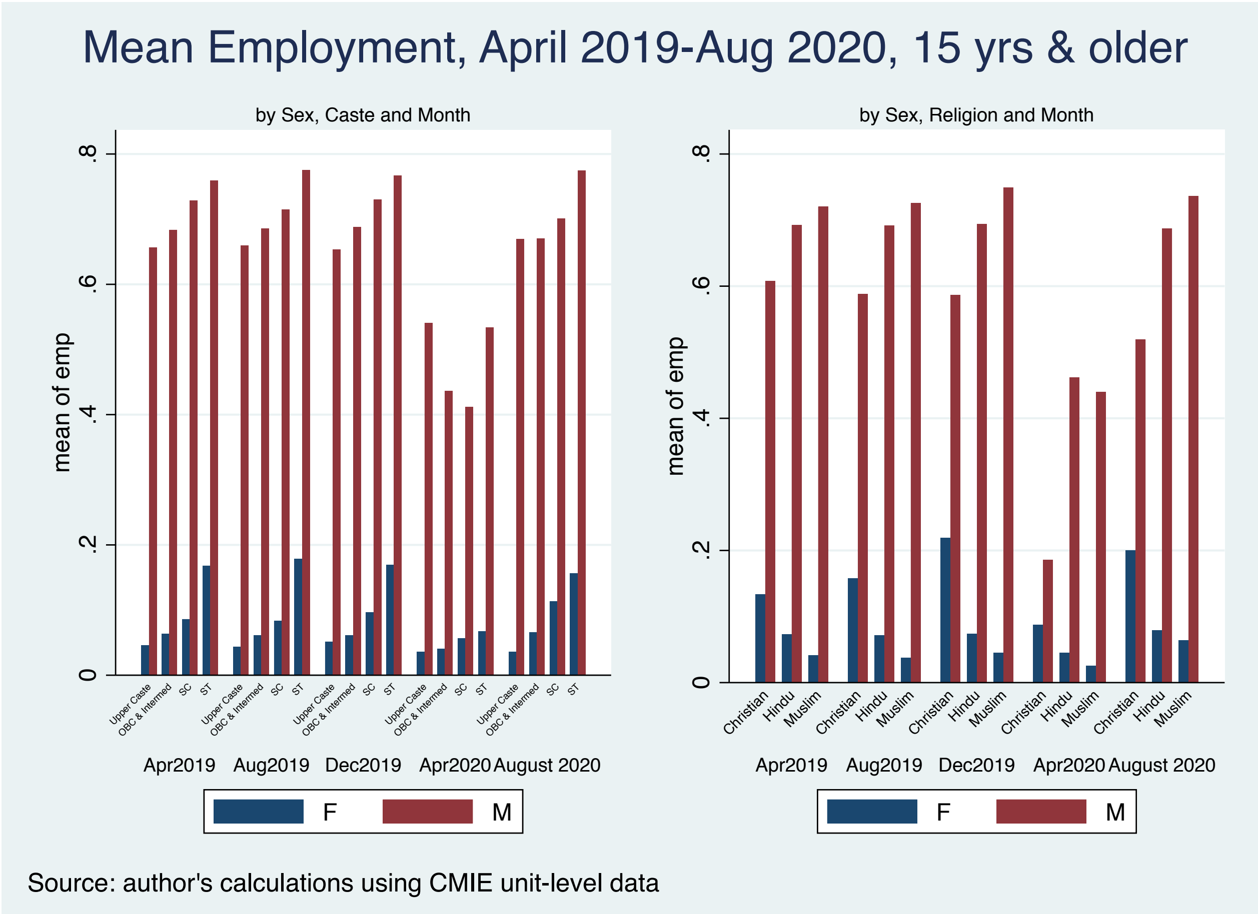
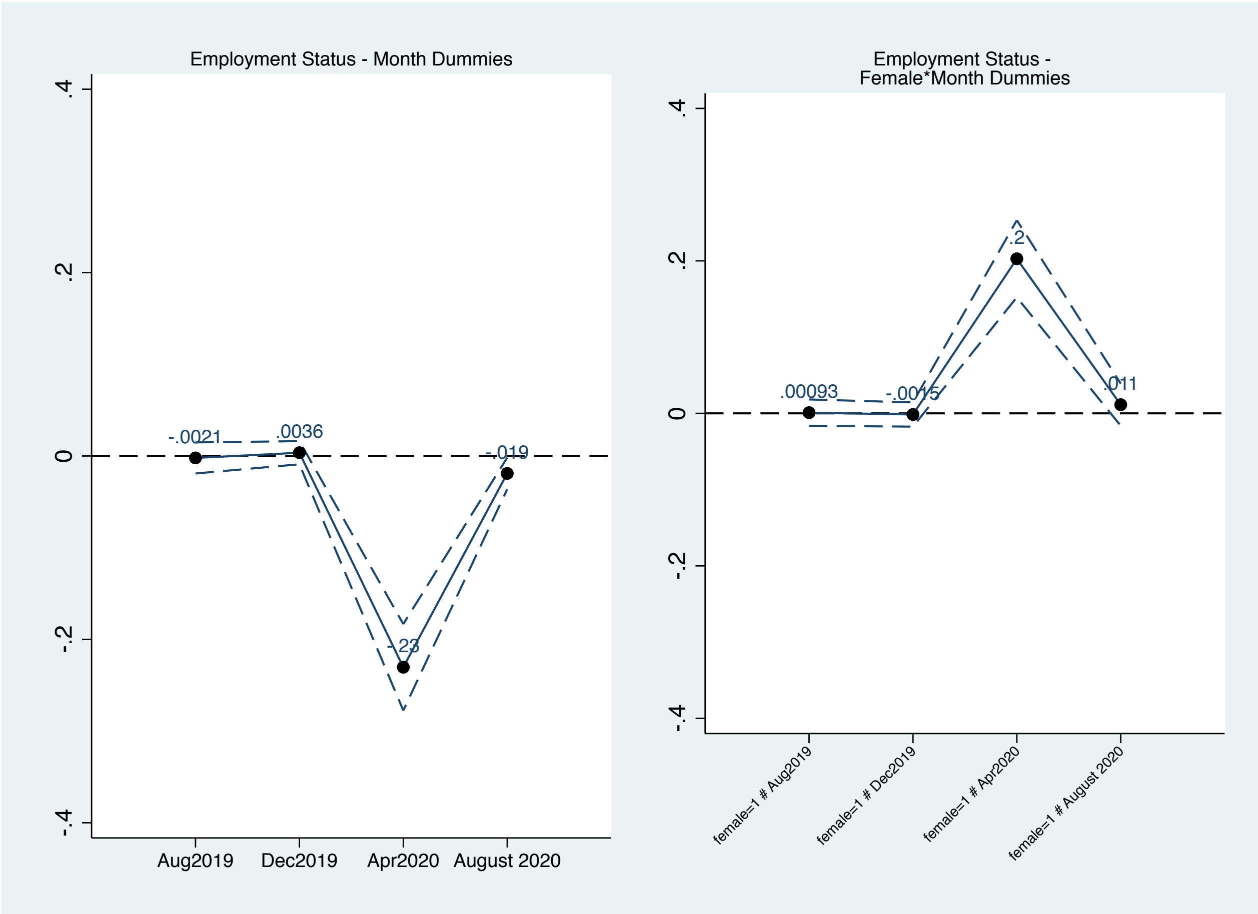
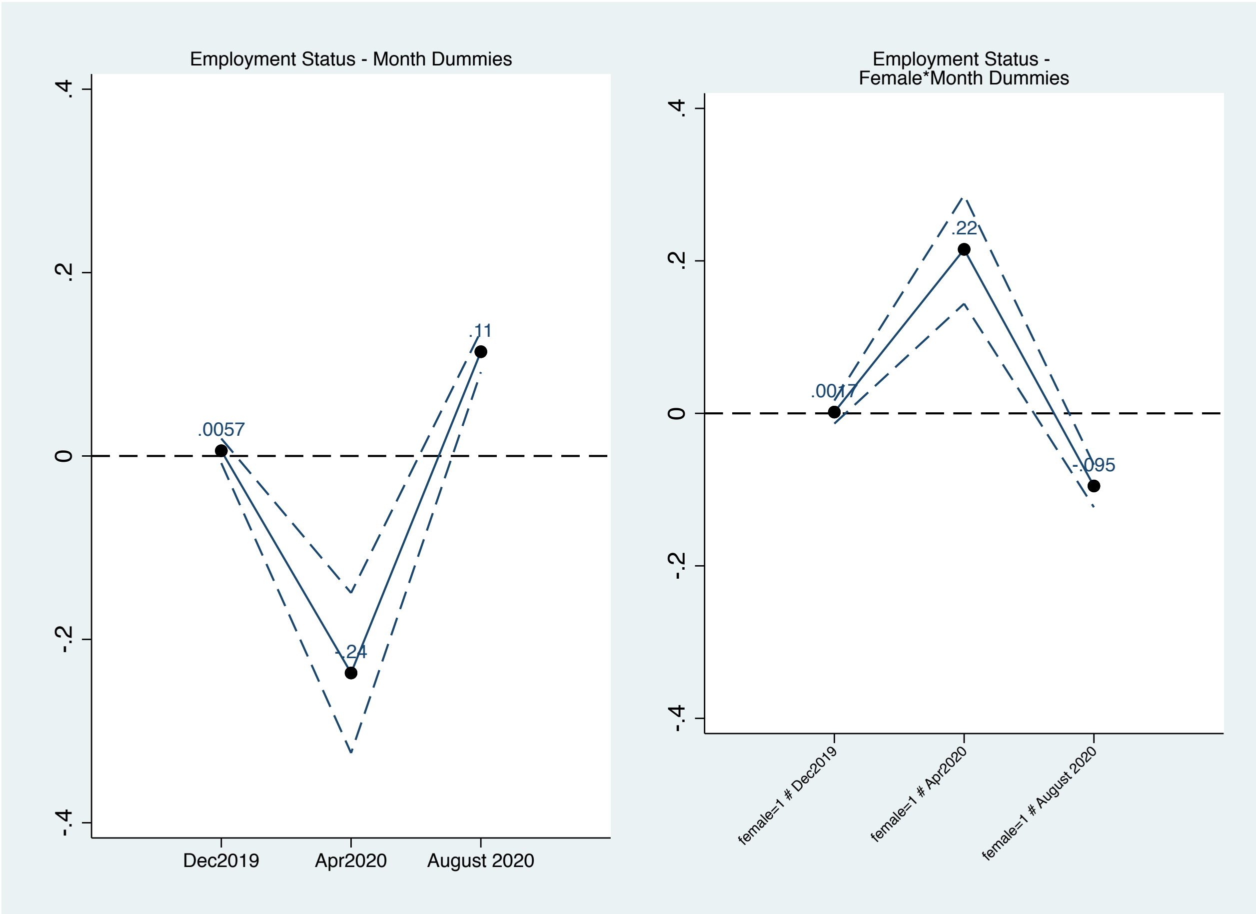


Figure 6: D-I-D estimates for Lockdown Panel by Month and gender



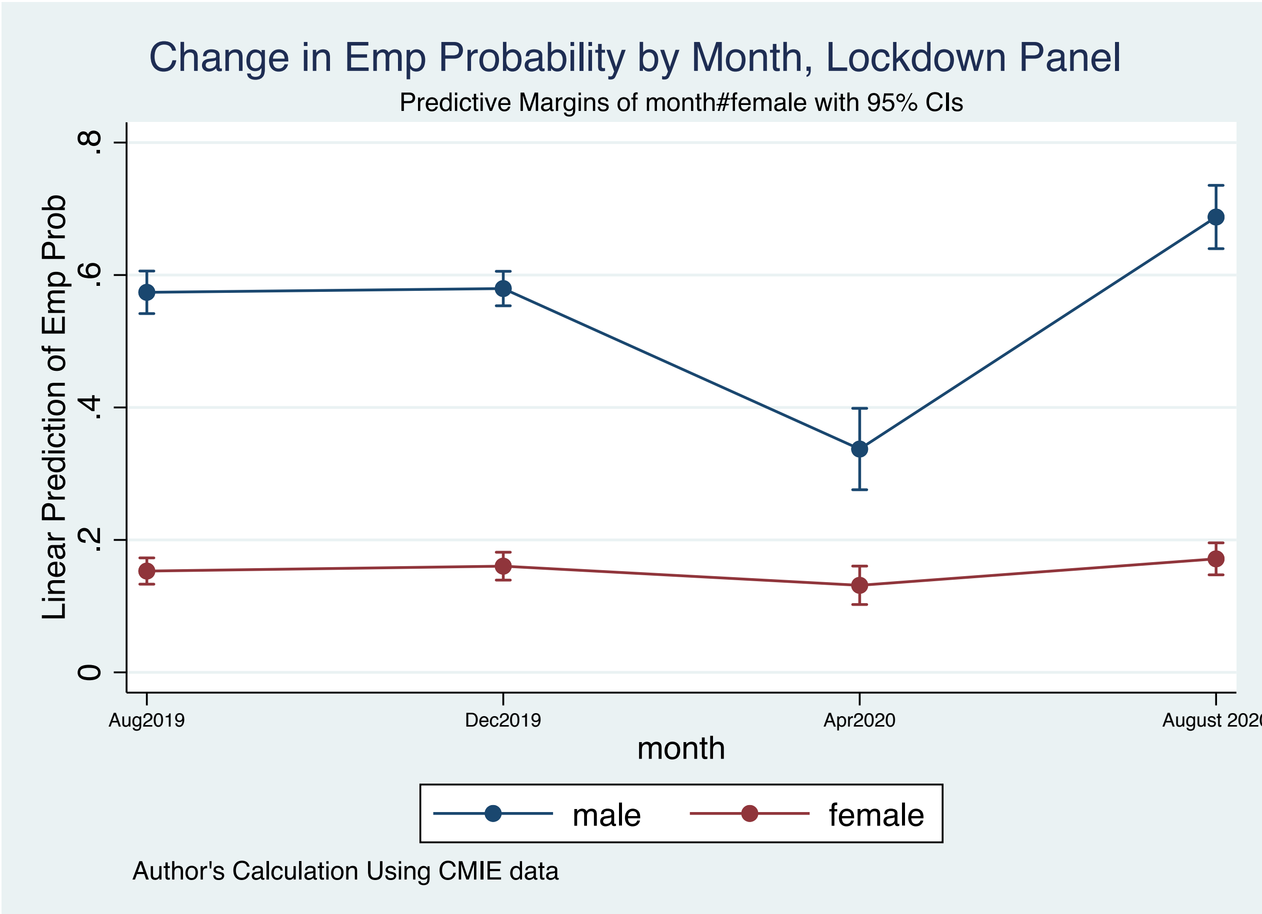
This figure plots the D-I-D estimates by month arising from estimating Equation 1 on the Lockdown Panel. The dependent variable is a dummy for being employed in period t. N=88,625. Intercept=0.5. The omitted month is April 2019

Figure 7: D-I-D estimates for Lockdown Panel with Lagged Employment



This figure plots the D-I-D estimates for the lockdown panel arising from estimating Equation 3. The dependent variable is a dummy for being employed in period t. N=70,900. Intercept=0.977. The omitted month is August 2019. The first month, April 2019, drops out because of the inclusion of lags.

Figure 8: Marginal Effects, DID estimation with Lagged Emp, Lockdown Panel



This figure plots the marginal effects of month*gender from the D-I-D estimates for the lockdown panel arising from estimating Equation 3. The dependent variable is a dummy for being employed in period t. N=70,900. The omitted month is August 2019. The first month, April 2019, drops out because of the inclusion of lags.

Figure 9: Average Hours Spent on Housework, by gender, India

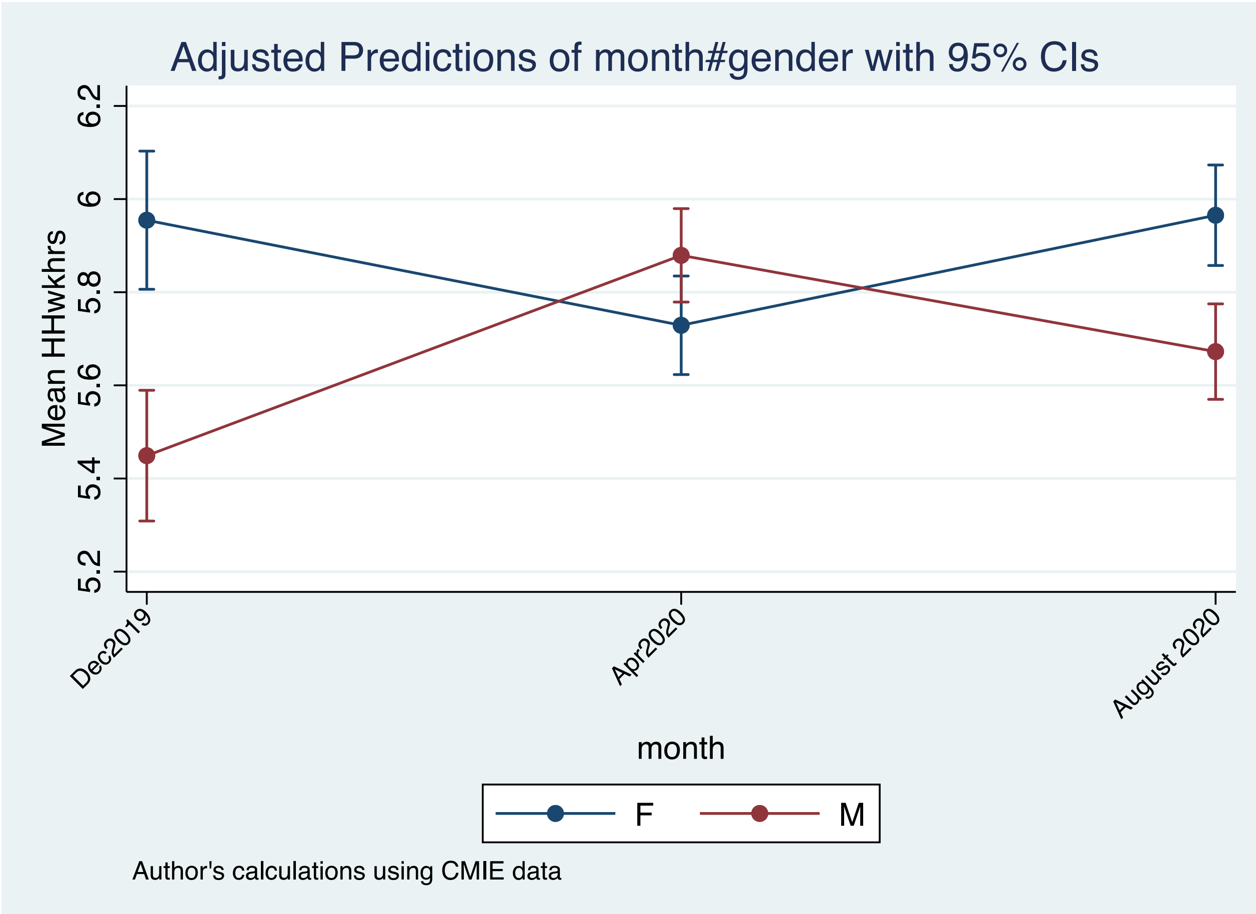


Figure 10: Average Hours Spent with Friends, by gender and Sector, India

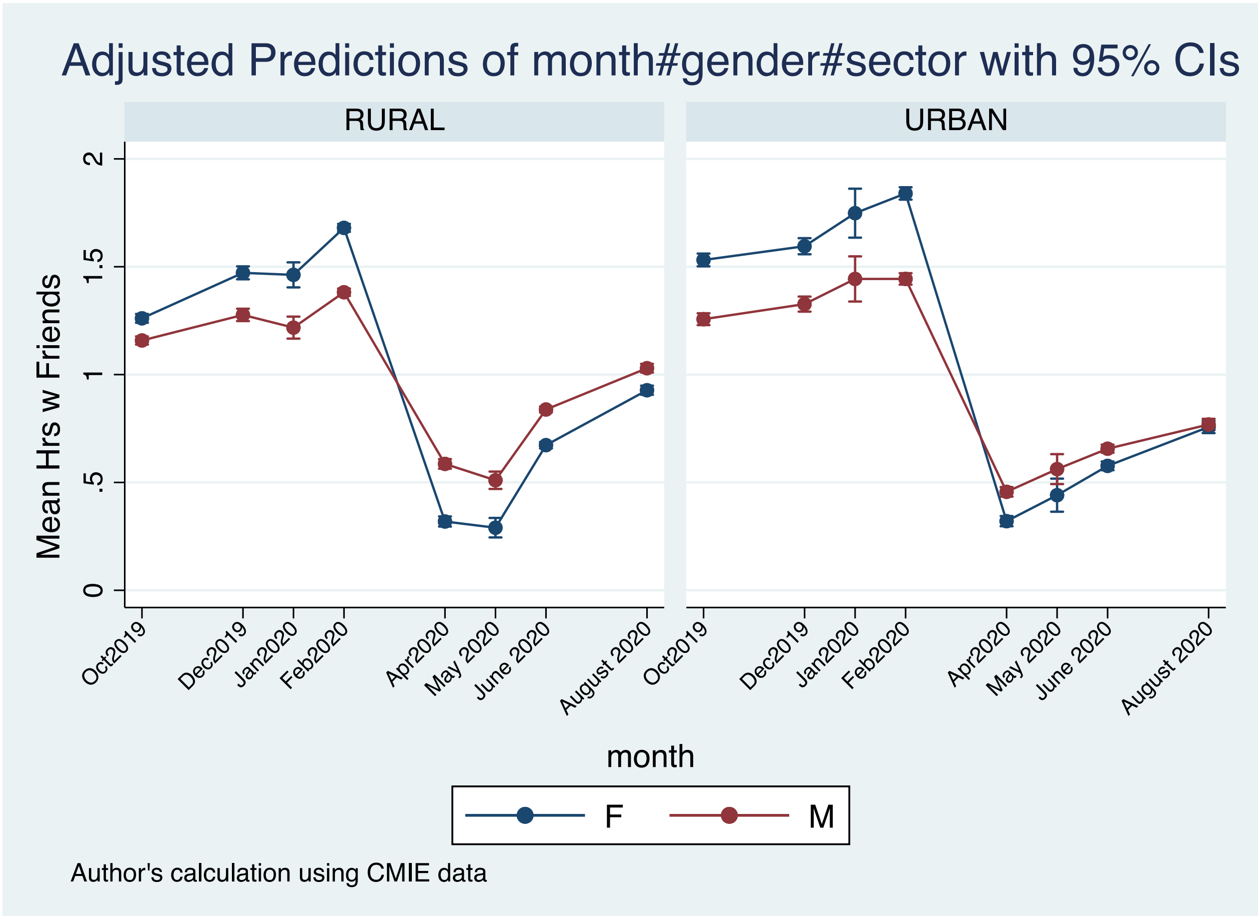


Figure 11: Income from all sources Jan 2019 to April 2020, India

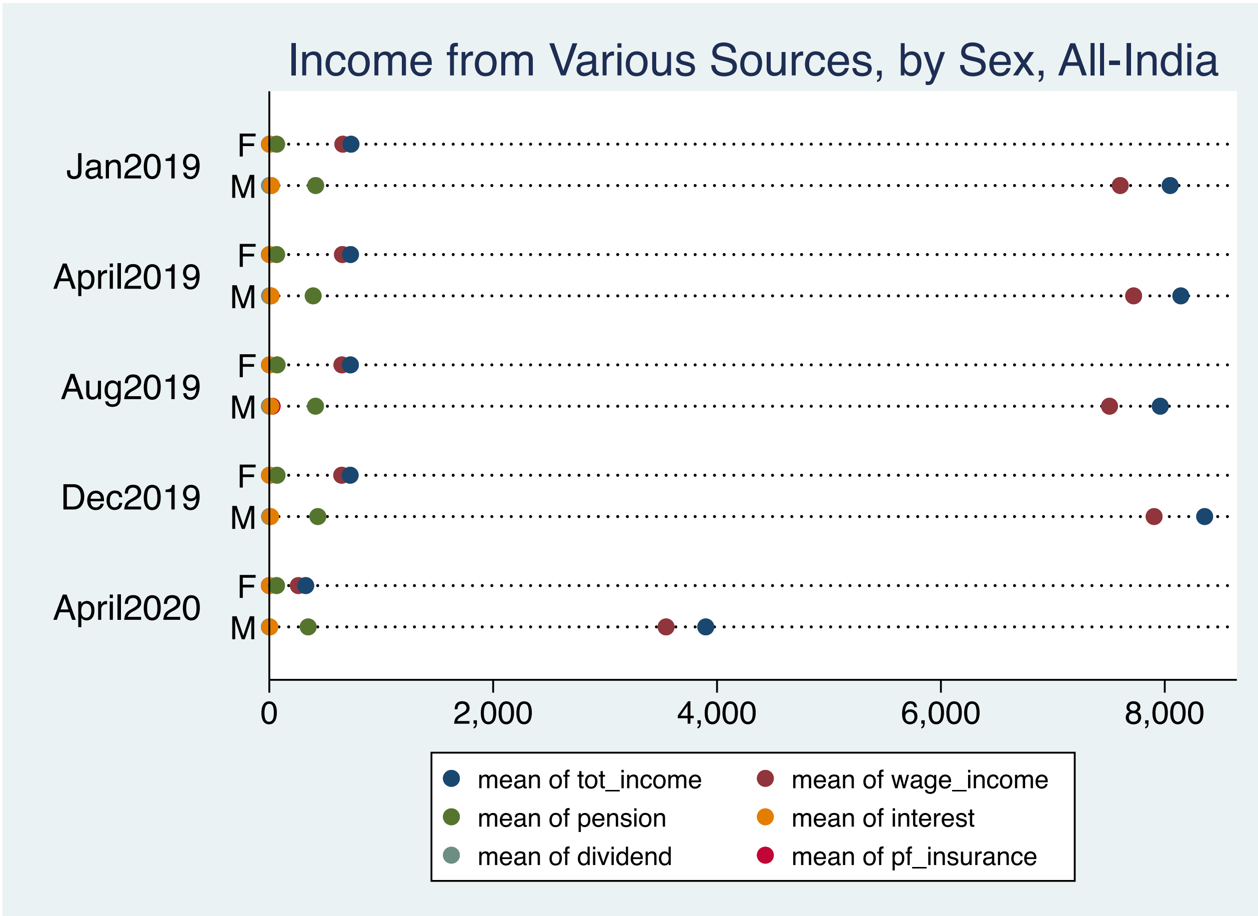


Figure 12: Change in Income by Gender and Month, India

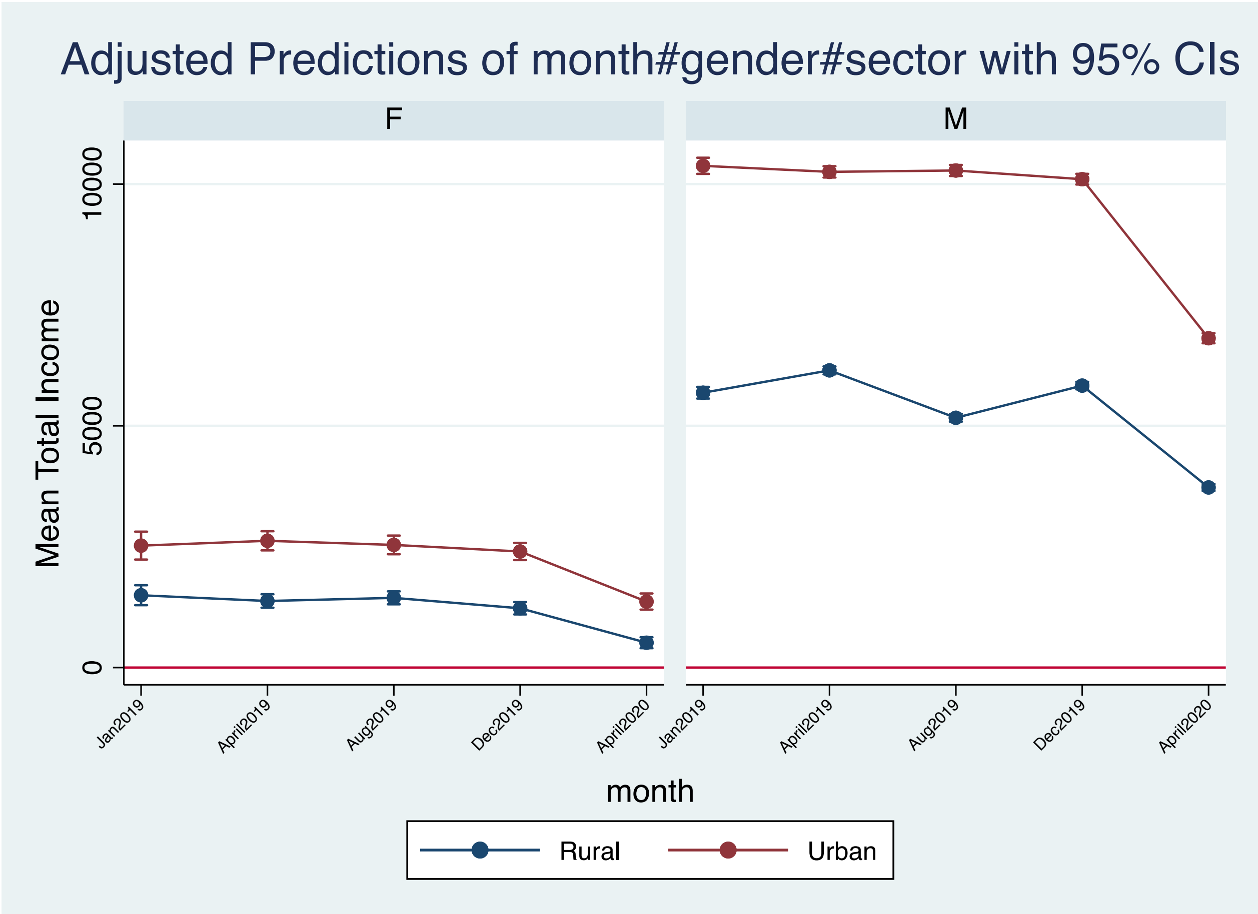
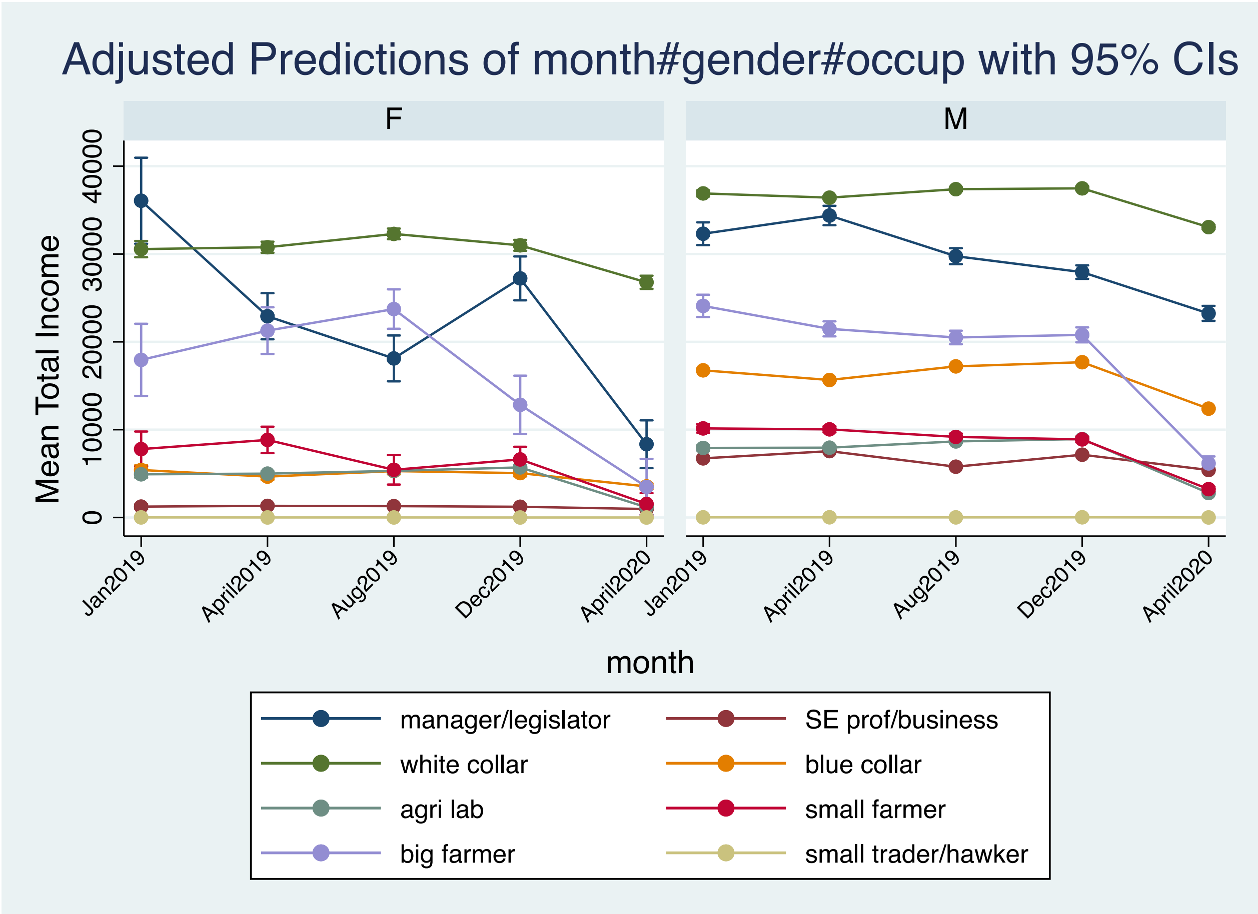


Figure 13: Income by Occupation and gender, Jan 2019 to April 2020, India



7 Tables

Table 1: Employment Status by Wave and gender, India

	(1)		(2)		(3)		(4)		(5)	
	Fem:Jan-Apr19		May-Aug19		Sep-Dec19		Jan-Apr20		May-Aug20	
	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
employed	0.08	0.26	0.07	0.26	0.07	0.26	0.06	0.24	0.08	0.27
unemployed	0.03	0.17	0.03	0.18	0.03	0.18	0.04	0.20	0.04	0.19
OLF	0.89	0.31	0.90	0.30	0.89	0.31	0.90	0.31	0.88	0.32
Observations	26001		24923		24914		26030		27124	
	(1)		(2)		(3)		(4)		(5)	
	Male:Jan-Apr19		May-Aug19		Sep-Dec19		Jan-Apr20		May-Aug20	
	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
employed	0.69	0.46	0.69	0.46	0.70	0.46	0.59	0.49	0.64	0.48
unemployed	0.06	0.23	0.06	0.24	0.06	0.24	0.16	0.36	0.09	0.29
OLF	0.25	0.43	0.24	0.43	0.24	0.43	0.25	0.43	0.27	0.44
Observations	29939		28613		28622		29910		31220	
	(1)		(2)		(3)		(4)		(5)	
	ALL:Jan-Apr19		May-Aug19		Sep-Dec19		Jan-Apr20		May-Aug20	
	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
employed	0.40	0.49	0.40	0.49	0.41	0.49	0.34	0.48	0.38	0.49
unemployed	0.05	0.21	0.05	0.22	0.05	0.21	0.10	0.30	0.07	0.25
OLF	0.55	0.50	0.55	0.50	0.55	0.50	0.55	0.50	0.55	0.50
Observations	55940		53536		53536		55940		58344	

	Wave 1			Wave 2			Wave 3			Wave 4			Wave 5		
	F	**M**	**Total**	**F**	**M**	**Total**	**F**	**M**	**Total**	**F**	**M**	**Total**	**F**	**M**	**Total**
manager/legislator	0.33	0.22	0.23	0.67	0.23	0.28	0.4	0.34	0.35	0.18	0.57	0.53	0.04	0.25	0.22
SE prof/business	7.99	21.96	20.52	6.73	20.06	18.62	7.26	22.54	20.81	9.73	22.2	20.81	6.72	22.06	20.14
white collar	6.21	6.79	6.73	5.82	6.54	6.46	5.67	6.89	6.75	6.24	6.24	6.24	2.17	5.1	4.74
blue collar	21.26	31.11	30.1	19.96	29.05	28.07	21.42	30.69	29.64	24.59	28.41	27.98	22.03	27.14	26.5
agri lab	30.58	4.92	7.57	28.66	5.71	8.18	27.88	4.79	7.4	18.42	6.73	8.04	28.5	4.81	7.79
small farmer	5.41	17.03	15.83	3.62	19.07	17.41	5.62	16.83	15.56	7.92	16.75	15.76	10.68	21.15	19.83
big farmer	3.85	8.03	7.6	3.83	8.66	8.14	2.65	9.29	8.54	3.26	7.34	6.88	5.14	10.78	10.08
small trader/hawker	0.71	2.36	2.19	0.98	2.36	2.21	0.9	1.84	1.73	2.54	3.79	3.65	2.04	2.76	2.67
notworking	23.67	7.57	9.23	29.74	8.32	10.63	28.19	6.79	9.21	27.13	7.98	10.12	22.68	5.94	8.04
Total	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Table 2: Occupational Distribution by Wave and gender

Note: This table shows the occupational distribution for those in the labour force.

	No Child			**Child<5 yrs**			**Child 6-18 yrs**		
	Women	Men	Total	Women	Men	Total	Women	Men	Total
Apr-19									
illiterate	0.176	0.934	0.464	0	1	0.64	0.125	0.861	0.364
primary	0.06	0.802	0.364	0.053	1	0.41	0.07	0.857	0.391
middle-sec	0.047	0.714	0.416	0.107	0.988	0.568	0.054	0.888	0.491
highersec	0.007	0.862	0.529	0.05	0.996	0.581	0.084	0.895	0.599
UG	0.043	0.495	0.331	0.116	1	0.622	0.168	0.904	0.624
PG+	0.044	0.564	0.403	0.057	0.907	0.639	0.07	0.891	0.633
Total	0.056	0.737	0.395	0.078	0.99	0.524	0.071	0.878	0.466
Aug-19									
illiterate	0.185	0.921	0.436	0	1	0.454	0.108	0.914	0.389
primary	0.077	0.834	0.396	0.018	1	0.392	0.065	0.856	0.383
middle-sec	0.07	0.691	0.407	0.053	0.997	0.541	0.056	0.887	0.491
highersec	0.107	0.849	0.587	0.116	1	0.634	0.086	0.875	0.575
UG	0.018	0.409	0.257	0.061	1	0.718	0.114	0.883	0.589
PG+	0.139	0.546	0.41	0.114	1	0.618	0.084	0.919	0.667
Total	0.079	0.735	0.404	0.045	0.999	0.51	0.067	0.876	0.462
Dec-19									
illiterate	0.207	0.689	0.406	1		1	0.058	0.959	0.434
primary	0.092	0.813	0.396	0.008	1	0.406	0.074	0.856	0.388
middle-sec	0.049	0.677	0.389	0.075	0.979	0.512	0.061	0.907	0.505
highersec	0.024	0.736	0.519	0.098	1	0.667	0.09	0.894	0.581
UG	0.025	0.487	0.295	0	1	0.709	0.118	0.884	0.583
PG+	0.093	0.565	0.425	0.256	1	0.77	0.172	0.865	0.65
Total	0.075	0.715	0.398	0.062	0.99	0.512	0.075	0.883	0.471
Apr-20									
illiterate	0.079	0.384	0.168	0.032	0.458	0.128	0.048	0.345	0.123
primary	0.028	0.399	0.176	0.005	0.515	0.137	0.023	0.512	0.207
middle-sec	0.018	0.295	0.172	0.044	0.473	0.273	0.036	0.588	0.343
highersec	0.016	0.45	0.259	0.042	0.692	0.448	0.063	0.765	0.512
UG	0.063	0.23	0.164	0.01	0.967	0.61	0.095	0.814	0.594
PG+	0.194	0.756	0.677	0	0.563	0.548	0.561	0.693	0.658
Total	0.038	0.334	0.187	0.029	0.568	0.288	0.042	0.603	0.318
Aug-20									
illiterate	0.317	0.892	0.519	0	0.651	0.37	0.119	0.627	0.276
primary	0.084	0.653	0.289	0.016	0.994	0.393	0.064	0.779	0.305
middle-sec	0.026	0.715	0.426	0.049	0.968	0.473	0.083	0.905	0.536
highersec	0.101	0.635	0.487	0.032	0.865	0.607	0.039	0.909	0.585
UG	0.01	0.252	0.195	0	1	0.595	0.086	0.896	0.646
PG+	0	0.428	0.391	0	1	0.684	0.272	0.895	0.815
Total	0.098	0.681	0.391	0.035	0.948	0.478	0.077	0.87	0.469

		Full-time	Not app	Part-time	Total
Apr-19	F	73.74	23.48	2.78	100
	M	92.46	7.42	0.12	100
	Total	90.57	9.04	0.39	100
Aug-19	F	68.53	29.39	2.08	100
	M	91.77	8.07	0.16	100
	Total	89.31	10.33	0.37	100
Dec-19	F	68.46	28.62	2.92	100
	M	93.11	6.73	0.16	100
	Total	90.38	9.16	0.46	100
Apr-20	F	39.34	55.91	4.75	100
	M	61.22	38.09	0.69	100
	Total	58.81	40.05	1.14	100
Aug-20	F	66.6	30.44	2.96	100
	M	92.35	7.35	0.3	100
	Total	89.2	10.18	0.62	100

Table 4: Type of Employment by gender and Month, %

	No Child			Child<5 yrs			Child 6-18 yrs		
	Women	**Men**	**Total**	**Women**	**Men**	**Total**	**Women**	**Men**	**Total**
Pre-pandemic									
illiterate	5.5	1.86	4.23	4.45	2.06	3.37	5.48	1.72	4.21
primary	5.45	2.05	4.03	6.11	1.68	4.32	5.71	1.73	4.07
middle-sec	5.69	2.49	3.89	6.1	1.76	3.86	5.97	1.84	3.78
highersec	5.96	2.07	3.54	6.3	1.78	3.91	5.93	1.89	3.47
UG	5.66	2.63	3.61	6.25	2.11	3.79	6.01	1.81	3.25
PG+	5.52	2.54	3.55	7.02	2.02	3.93	5.98	2.08	3.33
Total	**5.56**	**2.28**	**3.91**	**6.15**	**1.78**	**4.02**	**5.83**	**1.82**	**3.84**
Post-pandemic									
illiterate	4.5	2.47	3.85	5.21	2.89	4.29	4.48	2.27	3.82
primary	5.3	2.38	4.19	6.2	2.35	5	5.46	2.06	4.26
middle-sec	5.5	2.93	4.07	5.74	2.19	3.96	5.55	1.99	3.62
highersec	5.82	2.27	3.47	5.33	2.02	3.03	5.82	1.96	3.21
UG	6.45	3.57	4.55	6.07	2.26	3.65	5.81	2.03	3.12
PG+	5.25	2.64	3.05	6.9	2.66	4.16	5.96	2.2	2.99
Total	**5.35**	**2.78**	**4.05**	**5.82**	**2.23**	**4.05**	**5.41**	**2.02**	**3.73**

Table 5: Average Hours Spent on Domestic Work, by Children and Education Levels

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