Final report

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Livelihoods and mental well-being during COVID-19: A study using matched husband-wife-friend data in urban India*

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Abstract

This study estimates the immediate and near-term impact of the COVID-19 crisis on the gendered aspects of employment and mental health of urban informal sector workers in India. We report three key findings. First, men's 'current working status' declined by 89 percentage points (pp) post pandemic relative to baseline. We interpret this as both temporary and permanent loss of work. In contrast, women did not experience any significant impact on employment post pandemic, as reported by their husbands. Second, we document very high levels of mental stress, with wives reporting worse mental health than husbands. Third, social networks mitigate stress levels for husbands but exacerbate the same for wives. This effect can be explained by the home-based friends of wives and is consistent with the sociological literature that documents the perverse effects of social networks of women who may feel compelled to expend scarce mental resources in helping their friends, or spreading anxiety among each other or the loss of support of home-based friends due to social distancing during the lockdown.

JEL Classification: J16, J22, J23, O14, O17
Keywords: Covid19, informal sector, wage employment, mental health, social networks, gender, India

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1. Introduction

With its 1.3 billion population, of which vast numbers are self-employed informal sector workers and daily wage earners who lack access to social security measures, India faces significant policy challenges, both humanitarian as well as economic, in the wake of the COVID-19 crisis and the subsequent nationwide lockdown. Specifically, many of these workers faced job and income losses, food shortages and require direct support in terms of cash and food. It is also becoming increasingly apparent that significant mental health concerns have arisen in the face of the COVID-19 crisis and the nationwide lockdown, both due to the economic uncertainty as well as due to the social distancing measures put in place to control the spread of the diseases, but which has put pressure on our social fabric and feeling of community connectedness.

This study aims to provide direct evidence on how India is dealing with these various challenges, especially in case of vulnerable segments of the population in overcrowded, urban centres. In particular, we estimate the immediate and near-term impact of the COVID-19 crisis on the livelihoods of urban informal sector workers in India, as well as analyze the effects of the pandemic on the mental health of these vulnerable groups. In addition, we focus on the gender differences in impact of the COVID-19 crisis, and the role of social networks therein, in times of social distancing. These findings can contribute to our understanding of the processes needed for response, recovery and building resilience against such devastating and widespread shock among vulnerable groups more broadly.

Our data come from two rounds of surveys: a pre-pandemic survey in May 2019 for over 1600 women and their husbands living in households in urban clusters of Delhi, and a follow-up post-pandemic phone survey just around the peak of the Covid-19 health crisis, in April and May 2020.

Our main findings are that men's working status was more impacted than women's due to the Covid19 shock. In particular, men's self-reported working status declined by 89 percentage points (pp) post pandemic. This is primarily driven by wage and casual labourers who experienced nearly 91 pp reduction in 'currently working' status, followed by the self-employed and salaried workers. We interpret these numbers as reflecting both temporary and permanent loss of work. In contrast, women (wives) did not experience any significant impact on employment as a result of the pandemic, as reported by their husbands. This is consistent with the emerging Covid19 literature that overall, men's employment has been more impacted than women's ((Deshpande 2020);(Afridi, Mahajan and Sangwan 2021);(World-Bank 2020). This finding is also consistent with the role of women's jobs as insurance (Sabarwal, Sinha and Buvinic 2011), wherein number of scholars have documented the counter cyclicality of women's labour force participation during the debt crises of the Latin American countries in the 1990s ((Parker and Skoufias 2006); (Francke 1992); (Leslie et al 1998)).

In terms of mental health effects, we find very high levels of mental stress due to the pandemic among our study sample, driven primarily by financial (90%) and health (85%) concerns. While this is true for both men and women, the latter report relatively greater mental stress. In particular, women report 0.06 standard deviations greater mental stress compared to men. The biggest contributor to women's stress appears to be anxiety and nervousness, followed by depression, health worries and sleeplessness. Therefore, despite not facing job losses women seem to be more

anxious than men. A plausible explanation for this could be the greater social pressures exerted on women at home, at a time when their spouses are also at home (increasing pressure) during crises. This conclusion has been reinforced by other studies on India e.g. (Gopal et al 2020).

To investigate the potential drivers of such gendered effects, we analyse the mediating role of social networks on mental health outcomes. We exploit rich social network data that we collected during our pre-pandemic survey, to show that the size of the social network, as measured by total number of friends, lowers mental stress for men, but increases the same for women. In particular, we find that men with larger social networks report 0.059 standard deviations lower mental stress compared to those without. But this pattern is reversed for women, such that women with larger social networks report on average 0.039 standard deviation *higher* mental stress than those without. In other words, social networks appear to have a mitigating effect on men's mental health, but an exacerbating effect on women's mental health, especially in times of crisis.

We also attempt to unpack the factors that may explain such a gender-specific role of social networks in mediating mental health, by disaggregating by *type* of social network. We find that the positive marginal network effect for women appears to be driven by the *home-bound* nature of their networks. While for men, having an additional "home-friend" lowers their mental stress by 0.057 standard deviations, for women, it *increases* their mental stress by an additional 0.042 standard deviations. A similar pattern is observed for "neighbourhood-friends" in terms of effect size and direction, although the estimated effect for men is no longer statistically significant. In contrast, "work-friends" lower mental stress for *both* men and women, although neither is statistically significant. Hence, our findings provide support in favour of the "stress-contagion" role rather than the "stress-buffering" role of social ties in affecting mental health in times of crisis, particularly with regard to women. The sociological literature (Berkman and Kawachi 2001) suggests that this is likely due to increased pressures on women from their social networks. In our context, this could be driven by their *home-bound* friends as opposed to *workplace* friends. One might expect the latter to provide some non-redundant information about jobs, while home-bound friends either cause contagion in stress levels or require more intensive caregiving by women, but not by men. It may also be due to the highly integrated nature of home-bound friends, whose support may have weakened due to the social distancing measures imposed during the pandemic, more for women than men.

The rest of the paper is organized as follows. Section 2 presents a brief summary of the literature. Section 3 describes the data, variables and estimation strategy. Section 4 presents the employment results, while Section 5 presents the mental health results. Section 6 concludes.

2. Literature Review

The Covid-19 pandemic has had a massive, negative impact on economies and labour markets across the world due to shutdowns and social distancing measures. Studies document employment (Kesar, et al. 2020, Gupta and Kudv 2020), income and consumption losses in India (Bertrand, Krishnan and Schofield 2020) due to the severe lockdown that began on March 24th 2020 but eased from June 2020 onwards. As a consequence of the lockdown, the impact on economic activity

across the country was catastrophic and the country entered a recession. India's GDP contracted by 23.9% during April-June and 7.5% in the second quarter (July-September) of the 2020-21 fiscal year as opposed to 5% growth in the GDP in 2019-20[1].Thus the effects of the shutdown on the economy persist and are likely to have longer-term implications for employment and wage earnings of the labour force in India. Furthermore, while employment losses occurred across the board, there is evidence of differentiated labour market impacts by demographic groups –gender, caste, age and residence in India (Deshpande 2020, Afridi, Mahajan and Sangwan 2021, World-Bank 2020). In contrast, we find significant employment and earnings losses for men, but not women. This is in keeping with the literature on the counter-cyclicality of women's labour force participation during the debt crises of the 1990s.

Sabarwal, Sinha and Buvinic (2011) review how women weather economic crises differently from men. The strongest evidence of women's response in terms of labour force participation comes from the debt crises in the Latin American countries of the 1990s, where a number of scholars document that women's employment among low-income households is counter cyclical and rises during crises. They basically substitute for men's higher unemployment by joining the labour force. The counter cyclical effect is concentrated in middle-aged married women rather than younger single women employed in higher income jobs. These findings contrast with what has been found in developed countries. For example,[2]Alon, et al. (2020) show that for the first time in a recession, in the US, UK, Spain, Canada women's employment losses were much higher than men's in the 2020 pandemic. They attribute this to the sectoral composition of jobs with women being employed in hospitality and service sectors as well as the increased childcare responsibilities. In contrast, our study is focused on households where women were mostly involved in childcare even pre-Covid19, and where they were working from home.

Existing research suggests that the impact of economic shocks is dynamic and may differ by occupations. For instance, Hall and Kudlyak (2020) distinguish between recall and jobless unemployment. While the former is temporary and can recover relatively quickly, the latter can get aggravated due to economic recession. Indeed, evidence suggests that casual jobs were lost disproportionately more in the early phase of the lockdown in India (April-May). However, formal sector employment witnessed a decline with economic recession and as demand receded in 2020 in India (Lahoti, et al. 2020). Hence job losses may have been either temporary or permanent for different segments of the labour force. These job losses were significantly higher in urban areas relative to rural areas during the initial phase of the pandemic (April-May) in India (Afridi, Mahajan and Sangwan 2021). Similar to these papers we also find differential impacts on different categories of labour.

Unanticipated, large losses to income may also affect mental well-being. Using exogenous variation in the interview dates of the 2008 Health and Retirement Study of the US, McInerney, Mellor and Nicholas (2013) compare the changes in wealth and health for respondents interviewed before and after the October 2008 stock market crash. They find that the crash reduced wealth and increased depressive symptoms – a loss of $50,000 of non-housing wealth increases the likelihood of feeling depressed by 8%. Indeed, early research on the psychological effects of the Covid-19

[1] https://economictimes.indiatimes.com/news/economy/indicators/india-q2-gdp-live-news-november-27/liveblog/79439880.cms

[2] https://econofact.org/impact-of-the-covid-19-crisis-on-womens-employment

pandemic indicates significant increases and stress levels in developed countries with a larger negative impact on women's emotional well-being. Using Google trends data, (Brodeur, et al. 2020) find a substantial increase in the search for boredom, loneliness, worry and sadness in Europe and the US.

In addition, there is substantive evidence of differential gender impacts on emotional well-being. Adams-Prassl, et al. (2020) use real time survey data from the US to show that state-wide stay-at-home orders lowered mental health by 0.085 standard deviations, driven entirely by the impact on women and unexplained by increased financial or childcare concerns. Thus, the pandemic increased the existing gender gap in mental health by 66%.Etheridge and Spantig (2020) document similar gender differences in UK and suggest that a larger social network before the pandemic is a strong predictor of well-being declines after the pandemic's onset. Interestingly, women reported more close friends before and greater loneliness after the pandemic.

In the developing country context, particularly India, while the focus of the research so far has been on economic losses due to the pandemic, there is virtually no data on its psychological impacts (see report by (YourDOST 2020), as an exception). deQuidt and Haushofer (2016) theoretically contend that depression can cause individuals to have pessimistic beliefs about the returns to her effort, and a decrease in labour supply, which can result in a poverty trap. From a gender perspective, Ghosal, et al. (2020) find that psychological empowerment interventions can break such a trap and lead to positive behaviour change, including improvement in savings choices and health-seeking behaviour. (Baranov, et al. 2020) shows that a reduction in maternal depression improves women's intra-household empowerment with potentially better educational outcomes for their children in rural Pakistan. These studies, thus, underline the salience of psychological well-being in influencing the longer-term effects of the Covid-19 pandemic on poverty and gender inequality.

The paper is also related to studies of how social networks mediate aggregate shocks. Makridis and Wang (2020) for e.g., show how consumption is affected by the information on the effects of the pandemic gleaned from geographically distant but connected (via social media) friends. The sociology literature (Berkman and Kawachi 2001) has documented gender differences in the effects of social networks on psychological wellbeing–social networks of women may paradoxically increase the psychological distress among women due to the higher pressures to provide support to others. A gender gap in support during times of crisis provided between spouses with women giving more support has also been shown to increase demoralisation and depression. There may be "stress contagion" through social networks when the participants are facing similar shocks. Women's networks, when they are composed of others similar to them in terms of low resources, do not help them with upward mobility and may often exact emotional or physical penalties (Belle 1990).

In keeping with the existing literature discussed above, our study focuses on the urban poor, along with an emphasis on the gender disaggregated impacts of emotional well-being.

3. Data, Variables and Estimation

3a. Data description

Pre-pandemic survey:

With the aim of studying factors driving low female labour force participation in urban India, we started with a survey across 5 districts of Delhi-NCR in early 2019.[3]Within these 5 districts, we chose 10 assembly constituencies with concentration of light industries, from which 108 primary sampling units PSUs were randomly selected (see Figure 1). From each PSU, 15 eligible households were randomly chosen to participate in this study. A household was considered eligible if there was at least one married couple in the age group of 18-45 years.

The baseline (pre-pandemic) survey consisted of two surveys: a household survey and an individual survey. The household survey comprised of 1613 households and provided us with information regarding household composition, socioeconomic characteristics, assets owned etc. The questionnaire was supposed to be answered by the household head, but in case of unavailability, any knowledgeable adult was allowed to give the answers. Following the household survey, the youngest couple of the household[4] (between 18-45 years of age) was interviewed as part of the individual survey, where we were able to collect information for 97% of our target sample. The husband and wife were interviewed individually.

Next, we created a combined pre-pandemic sample containing both household and individual characteristics. After fuzzy matching the household head's name from the pre-pandemic household survey with husband's name from the pre-pandemic individual survey, we retained 1034 pre-pandemic households, in which the husband was the main respondent for both individual (male) and household surveys at baseline.[5]

Post-pandemic survey:

The Indian government ordered a stringent 21-day national lockdown to deal with the COVID-19 pandemic, on 24 March 2020 until April 14, which was later extended to May 30, 2020 with some easing of mobility restrictions thereafter. Hence, we were unable to conduct in-person follow-up surveys. Instead, we conducted a post-pandemic phone survey in two phases. In Phase 1 (03 April – 19 April 2020) that coincided with the initial, stringent lockdown, 458 households were surveyed. In Phase 2 (20 April – 09 May 2020) when some of the restrictions were lifted, an additional 966 households were surveyed. The date of survey for our respondents was randomly selected. Hence, as Appendix Table A1 shows, those who were interviewed earlier (Phase 1) are mostly similar in socio-economic characteristics to those who were interviewed later (Phase 2).

[3] For the baseline sample, we first drew a list of electoral board (EB) wards around planned industrial estates of Delhi, concentrated in 5 (North, North-West, West, North-East and Shahdara) of the 11 districts of Delhi. Dropping wards that comprised of only planned, 'regularised' colonies (and hence are relatively economically better off compared to unauthorised settlements and slum dwellings), EB wards were mapped to census wards. These census wards were contained within 10 Assembly constituencies (AC). In each AC, 10 polling stations (PS) were randomly sampled and 15 households within each PS through systematic random sampling. 8 additional polling stations were randomly sampled to address interview refusals. Thus, our final sample consists of 108 polling stations and 1613 households therein. The PSs form our primary sampling units.

[4] This was in case there were multiple couples in this age group in the household.

[5]The remaining 579 households (1613 – 1034) were dropped because of a matching score of < 0.4.

This allows us to compare the experiences of the samples in Phase 1 and Phase 2 and attribute any differences in their responses to the length of their exposure to the lockdown.

Since most women in our sample do not own a personal phone, the main respondent of our phone survey was the husband for all the questions, including employment and mental health. However, we also separately asked their wives questions on mental health. This provides us with matched husband-wife data for mental health outcomes, which gives us a unique insight into the gendered experience of the crisis in this context. Thus, our post-pandemic sample consists of 745 households out of the 1034 pre-pandemic households, where the same individual was interviewed in both surveys.[6] See Figure 2 for more details on the process of sample creation.

Our sample data for the employment results comes from both pre-pandemic and post-pandemic surveys, and hence constitutes a panel dataset of 1779 household observations, comprising of 1034 pre-pandemic and 745 post-pandemic households. In contrast, our sample data for the mental health results is only obtained from the post-pandemic survey, and therefore constitutes the cross-sectional dataset of 745 households. The total number of individual observations in our mental health sample is 1266, out of which 737 observations correspond to husbands and remaining 529 to wives.

Table 1(a) presents the summary statistics of household characteristics of our sample. The average household has 5.16 members, with an average of 2.5 children. Nearly all households live in *pucca* houses, with two-thirds owing the house they live in. 61% possess ration cards, while 76% belong to lower castes. 83% are Hindu. Two-thirds of the household heads have native homes outside. Delhi.

Table 1(b) presents descriptive evidence on the individual characteristics of our sample, differentiated by gender. The average adult male in our sample is 35 years old, and typically 4 years older than his wife. They have almost 8 years of formal schooling on average, compared to 6.7 years in case of their wives. 63% of the males in our sample are daily wage earners in factories and construction, or self-employed in the informal sector (e.g., small retail shops), with an average monthly income of Rs. 12,282. This demographic group is particularly vulnerable to economic and health shocks and may be expected to need significant support through public transfers to tide over loss of livelihoods. They live in clusters of households–which include both *jhuggi-jhopri* (JJ) clusters and resettlement colonies–with very high density that makes social distancing particularly challenging. Furthermore, assessments by the Central Pollution Control Board (CPCB) point out that these clusters are critically polluted and do not meet air, water or soil pollution safety parameters, all of which may make these residents particularly vulnerable to the virus.(Wu, et al. 2020)

Moreover, as Table 1(a) shows, although our respondents are not short-term or seasonal migrants but has been residing in Delhi for over 28 years on average, over 65% of the respondents' original state of residence is outside Delhi, primarily UP (over 40%) and Bihar (9%). Hence, the earnings

[6]We exclude 166 households where the husband was unavailable for the phone survey, and the wife or some other adult member was the main respondent for all the questions, as there might be systematic differences between these households and the rest of the sample. 123 households could not be surveyed in the post-pandemic survey.

and incomes of these families may have implications not just on their own welfare but also for their rural relatives through remittances.

Finally, Table 2 show that there is little selective attrition between the pre-pandemic and post-pandemic samples., with the exception of religion, asset and husband's education. All our results presented below are robust to the inclusion of these and other baseline characteristics as controls.

3b. Outcome variables

Our main outcome variables of interest are current working status and mental health. As mentioned in Section 3a. above, we collected self-reported employment data in both the pre-pandemic and post-pandemic surveys, while we collected mental health data only in the post-pandemic survey. Section 3c below discusses the implications of this data structure for our estimation methods.

Employment:

Our first outcome variable of interest is employment. In both the pre-pandemic (individual) and the post-pandemic surveys, the male respondents were asked to report their main occupation in months prior to the date of interview.[7] Based on their responses, the employment variable for males is constructed as a binary variable that equals 1 if the male respondent reports that he is currently working during the relevant reference period, and zero otherwise.

In contrast, the employment variable for females is constructed based on the responses provided by their spouses and is not self-reported. In the pre-pandemic survey, a woman is considered employed if her spouse reported her as being employed in the pre-pandemic household survey. In the post-pandemic survey, a woman is considered employed only if her spouse reported her as being employed in the pre-pandemic individual survey and her spouse did not report her as having lost her job in the post-pandemic survey. As for males, the employment variable for females is also constructed as a binary variable which equals 1 if the female was reported as employed during the relevant reference period, and 0 otherwise.

Mental Health:

The second outcome variable of interest is mental health. In contrast to employment data, we directly collected mental health data from both our male and female respondents, but only in the post-pandemic survey. Respondents were asked questions about five different aspects of their mental health. Specifically, they were asked: "To what extent do you agree or disagree with the following statements":

Nervous/Anxious: "I feel nervous when I think about the current circumstances";
Health worry: "I am worried about mine and my family's health";
Financial stress: "I feel stressed about mine and my family's financial situation";
Depressed: "I am feeling down, depressed or hopeless";
Sleep disorder: "I am having sleeping troubles (too much or too little)."

[7]In particular, we asked respondents to report their main occupation *over the last 12 months* in the pre-pandemic survey and *before lockdown was imposed on March 24th* in the post-pandemic survey.

The response scale for each of these statements was: “1-Strongly agree", “2-Agree", “3-Indifferent", “4-Disagree", “5-Strongly disagree”. For each of these five statements, a binary variable is created that equals 1 if the answer is either 1 or 2, and zero if the answer is 3, 4 or 5. These five binaries are aggregated to generate a mental stress index between 0 and 1, and then converted into a standardized z-score by subtracting the mean and dividing by the standard deviation. Higher values of the index, therefore, indicate worse mental health

3c. Other constructed variables

Social network variables:

In addition to the impact of the pandemic on mental health, we also examine the role of social networks in mediating mental stress during this crisis. In the pre-pandemic individual survey, all the respondents were asked to name two friends/close relatives to whom they could reach out in case of each of eight hypothetical situations.[8] These situations are as follows:

(i) whom would they borrow Rs 400-500 from for a day in case of emergency;
(ii) whom would they contact if in needed to rush to the hospital/doctor;
(iii) whom would they contact to borrow food items like cooking oil, sugar etc immediately from the neighbourhood;
(iv) whom would they like to go for a walk or chat with in free time;
(v) whom would they would go for shopping or local market to buy groceries etc;
(vi) whom would they approach for attending social functions or religious events like going to temple/mosque etc. together;
(vii) whom would they have lunch with or spend free time with at work; and
(viii) who are their preferred friends to travel to work with.

The responses were categorised as: “parent”, “uncle/aunt”, “cousin/siblings”, “in-laws”, “friends”, “co-workers”, “neighbour/friend from nearby lane/block”, “neighbour/friend from previous locality” and “neighbour/friend from native home” and “others”. Adding up answers for all these questions gave us total number of *friends* for each individual, with values ranging from 0 to 16.[9]

To further analyse the differential impacts by *type* of social networks, we aggregated the total number of friends into three categories:

(i) home-friends comprised of “parent”, “uncle/aunt”, “cousin/siblings”, “in-laws”, “friends” and “others”[10];
(ii) neighbourhood-friends comprised of “neighbour/friend from nearby lane/block”, “neighbour/friend from previous locality” and “neighbour/friend from native home”; and
(iii) work-friends comprised of “co-workers”.

We calculated the total of each of *home-friends*, *neighbourhood-friends* and *work-friends* for inclusion in the regression analysis. As Table 1(b) shows, women report nearly twice as large

[8]These friends/close relatives were not people residing in the same house as the respondent.
[9]We use the term “friends” throughout to denote both friends and close relatives
[10]The answers under “others” were classified into home-friends since most of the detailed answers included under this category were related to home friends.

social networks (6.1 friends on average) than men (3.77 friends on average), but almost all of women's friends are within their home or neighbourhood. Men too report more home-based friends, but around 5% of their friends are from their workplace.

3d. Estimation

In order to estimate the impact of the Covid19 pandemic on employment, we conduct a before-and-after analysis using the following OLS regression specification:

$$y_{it} = \alpha + \beta PostCovid_t + \gamma Z_i + \varepsilon_{it} \qquad (1)$$

where y_{it} indicates the dependent variable of interest for individual i in time period$t$. $PostCovid_t$ is a binary variable equal to 1 if the observation relates to the post-pandemic time period, and zero if it refers to the pre-pandemic time period. The coefficient β captures the average impact of the Covid19 pandemic on employment. Z_i a vector of pre-pandemic individual and household socioeconomic characteristics such as age, education, occupation, and religion, years of residence, type of house, no. of children, no. of household members, caste, native state etc. We run this regression specification separately for male and female employment.

We further explore the differential impact of the pandemic on male and female employment by pre-pandemic occupation type. In particular, we examine three types of occupations: wage employment, self-employment and salaried employment. We estimate the following specification as an extension of (1):

$$y_{it} = \alpha + \beta PostCovid_t + \gamma Z_i + \delta_1 Wage_i XPostCovid_t + \delta_2 Self employed_i XPostCovid_t + \delta_3 Salaried_i XPostCovid_t + \varepsilon_{it} \qquad (1a)$$

where the coefficient δ_1 captures the differential impact of the pandemic on employment of casual workers/daily wage earners, δ_2 captures the same for the self-employed and $\delta_3$captures the same for salaried workers. The omitted group is workers in other sectors.Z_i includes the level effects of the occupation types. We run this regression specification separately for male and female employment.

In order to analyse the gender difference in the mental health experience of the Covid19 pandemic, we conduct a cross-sectional analysis using the following OLS regression specification:

$$m_i = \alpha + \delta Wife_i + \rho Z_i + \varepsilon_i \qquad (2)$$

where m_i indicates the standardized mental stress variablefor individual i. $Wife_i$ is a binary variable equal to 1 if the individual is the female partner in the couple and zero if male partner. The coefficient δ captures the differential impact of the Covid19 pandemic on mental health of women relative to men. $Z_i$constitutes a vector of post-pandemic individual and household socioeconomic characteristics such as age, education, occupation, and religion, years of residence, type of house, no. of children, no. of household members, caste, native state etc.

We further explore the role of social network in mediating gender differences in mental health outcomes by estimating the following OLS regression specification as an extension of (2):

$$m_i = \alpha + \delta Wife_i + \pi Friends_i + \mu Wife_i XFriends_i + \rho Z_i + \varepsilon_i \qquad (2a)$$

where $Friends_i$ indicates the total number of friends/close relatives reported by an individual i. The coefficient π on $Friends_i$captures the impact of social network size on mental stress reported by men, while the coefficient on the interaction term μcaptures the differential impact of social networkson mental health of women relative to men. We also explore an extension of equation 3(a) using the disaggregated $Friends$ variables by *type* of social network (as discussed in Section 3c above).

4. Impact on Employment

4a. Men

We find that the Covid19 pandemic and subsequent lockdown led to a massive shock to the livelihoods and wage earnings of our study participants (see Figure 3). As expected, the vast majority of the workers in these residential areas (approx. 90% of the men) were completely unable to work, and this situation did not improve over time, as suggested by the responses in Phase 2, even after the easing of some restrictions. Consistently, around 85% of the respondents did not earn *any* income from their main occupation during this period. The proportion reporting non-receipt of full wages is 14 percentage points higher in Phase 2 than in Phase 1.

Examining the occupational distribution of this colossal employment shock in Figure 4, we find that wage labourers (e.g., those employed in a specific sector such as manufacturing) and casual labourers (daily wagers not attached to one specific sector) were by far the most adversely affected (100%), followed by the self-employed in informal sector (90%) and salaried workers (90%), in terms of loss of livelihoods. We document a marginal decline in reported unemployment among the self-employed and salaried workers in Phase 2 relative to Phase 1, but not among wage and casual labourers. This indicates that the most vulnerable among the working population continued to bear the biggest brunt of the pandemic in terms of their livelihoods and economic well-being, and the easing of restrictions did not address the situation. Moreover, among those who were gainfully employed before March 24th and reported some days of work post lockdown, the daily earnings declined by 78% for the entire sample across both phases - from an average of Rs. 378 to Rs. 84 per day.

These descriptive patterns are also borne out in our regression analysis. We find that men's self-reported employment status declined by 89 percentage points (pp) post pandemic relative to baseline (see Column 1, Table 3). This is primarily driven by wage and casual labourers who experienced nearly 91 pp reduction in employment, followed by the self-employed and salaried workers (see Column 3, Table 3). We interpret the reported decline in employment as both temporary and permanent loss of work due to the strict lockdown imposed from March 24 2020 onwards, since we are unable to disentangle the two. We hope to be able to quantify the extent of temporary versus permanent loss so in subsequent survey rounds.

Many of the respondents surveyed reported relying on friends and family to tide over temporary setbacks. We asked about job losses among their social networks as this would presumably lead to higher levels of stress than otherwise. 76% reported loss of job in their family while over 73% within their network of friends and relatives (see Appendix Figure A1). More respondents reported loss of job within their social network (family, relative and friends) in Phase 2 (77%) compared to Phase 1 (67%). A majority of respondents initially perceived the job losses as temporary (see Appendix Table A2), but over time there was an increase in the proportion who perceived the job losses in their social network as permanent – from 12% in Phase 1 to 20% in Phase 2, suggesting that as the duration of the lockdown increased, more workers began to perceive their current unemployment status as a permanent job loss.

4b. Women

Next, we study the impact of the pandemic on female employment to examine the gendered dimension of the crisis. As discussed in Section 3, the husbands reported their wife's employment status in our pre-pandemic and post-pandemic surveys. In contrast to the large negative impact on men's employment, we do not find any significant change in reported women's employment post pandemic (see Figure 5, and Table 4, column 1). Comparing across occupations, we find that the estimated post-pandemic coefficients for female casual/wage workers and self-employed workers are negative (see Table 4, column 3) but not statistically significantly different from the omitted group in a consistent way.

5. Impact on Mental health

Emerging evidence points to significant increase in mental and emotional stress across the world as a result of the Covid19 pandemic – some purely arising from the stress due to physical isolation and others related directly to more fundamental concerns about physical and financial well-being. However, given that much of this evidence is focused on developed countries like UK, US and European nations (Etheridge and Spantig 2020, McGinty, et al. 2020, Pierce, et al. 2020, Banks and Xu 2020, Kuan-Yu, et al. 2020, Proto and Quintana-Domeque 2020) we know little about the implications of the pandemic for mental health outcomes among people living in developing countries. In this section, we attempt to shed light on this important issue.

We document very high levels of mental stress due to the pandemic among our study sample, driven primarily by financial (90%) and health concerns (85%). Consistent with emerging evidence (Etheridge and Spantig 2020, Banks and Xu 2020, Proto and Quintana-Domeque 2020), women appear to be suffering from greater mental stress than men (see Figure 6). For example, 90% of women report feeling worried about the physical health of their families compared to 85% of men. 66% of men report feeling depressed about their situation while 70% of women do. Strikingly, both men and women worry more about their family's financial adequacy than about their health, though the difference is not significant. Almost 82% of women felt anxious or nervous about the current situation compared to 64% of men and more than 1/3rd of both women and men have trouble getting adequate sleep.

The overall descriptive patterns are also borne out in our regression analysis that attempts to systematically examine the gender difference in the mental health experience of the Covid19 pandemic in our sample. We find that women appear to be bearing a greater burden of pandemic-induced mental stress relative to men, which corroborates our descriptive evidence from Figure 6. Women report 0.043 standard deviations greater mental stress compared to men (Column 1, Table 5), although the coefficient is not statistically significant. The biggest contributor to women's stress appears to be anxiety and nervousness, followed by depression, health worries and sleeplessness (see Appendix Tables A3(a)-A4(e)).

5a. Role of networks

Theoretical evidence from existing sociological literature has pointed to the role of social networks in mediating psychological stress, but the evidence is mixed. On the one hand, Cohen and Wills (1985) discuss the positive effects of social networks. In particular, they highlight the "stress-buffering" role of networks for individuals in crisis, through the provision of economic and psychological support. On the other hand, (Berkman and Kawachi 2001) analyse the potential negative impacts of social networks, arguing that they may paradoxically increase psychological distress owing to higher pressures of providing support to others ("stress-contagion"). They emphasize that these negative effects might be especially true for women, who tend to exhibit greater empathy for others' pain than men (Christov-Moore and Iacoboni 2018).

Given such theoretical ambiguity, we directly test for gender differences in the impact of social networks on mental stress during the pandemic in our sample. For this purpose, we exploit rich social network data that we collected at baseline, as described in Section 3c. We find that the size of the social network, as measured by total number of friends, lowers mental stress for men. Men with larger social networks report 0.059 standard deviations lower mental stress compared to those without (Column 2, Table 5). But this pattern is reversed for women, such that women with larger social networks report on average 0.039 standard deviation *higher* mental stress than those without. In other words, social networks appear to have a mitigating effect on men's mental health, but an exacerbating effect on women's mental health, especially in times of crisis.

Looking further, we attempt to unpack the factors that may explain such a gender-specific role of social networks in mediating mental health, by disaggregating by *type* of social network, as discussed in Section 3c. We find that the positive marginal network effect for women appears to be driven by what we label as the "home-bound" nature of women's networks, in particular "home friends" (Column 3, Table 5). While for men, having an additional "home-friend" lowers their mental stress by 0.057 standard deviations, for women, it *increases* their mental stress by an additional 0.042standard deviations. A similar pattern is observed for "neighbourhood-friends" in terms of effect size and direction, although the estimated effect for men is no longer statistically significant. In contrast, "Work-friends" lower mental stress for *both* men and women, although neither is statistically significant. On the one hand, our findings provide support in favour of the "stress-contagion" role rather than the "stress-buffering" role of social ties in affecting mental health in times of crisis, particularly with regard to women. On the other hand, the increase stress on women may have been due to the social distancing measures imposed during the lockdown, lowering the psychological support from 'home-friends' for women.

5. Conclusion

We use data from poor households and individuals in urban India, before (May-July 2019) and after (April-May 2020) the Covid-19 pandemic struck to document the impacts on their employment and mental well-being. We assess how these impacts differ by gender by analysing husband-wife matched data on self-reported employment status and the intensity of psychological effects. In addition, using detailed pre-pandemic data on the social networks of husbands and wives, we study whether and how the psychological impact of the crisis is mediated by the size and nature of social networks.

In line with the existing evidence, we estimate a large negative shock on men's current employment status immediately following the shutdown of economic activity, relative to the pre-pandemic period. In contrast, women did not experience any significant impact on employment post pandemic, as reported by their husbands. We find evidence of significant psychological impacts due to the financial and health related concerns surrounding the pandemic, but higher amongst women than men, which increased with the extension of the lockdown for women. Surprisingly, the larger the social network, the lower the adverse emotional impact of the pandemic on men but higher for women. This result appears to be driven by the "stress-contagion" role rather than "stress-buffering" role of social networks closer to home in affecting mental health in times of crisis with regard to women.

Our findings highlight the relevance of understanding the psychological effects of this unprecedented crisis and their potential long-term impacts on economic recovery and labour productivity in developing countries.

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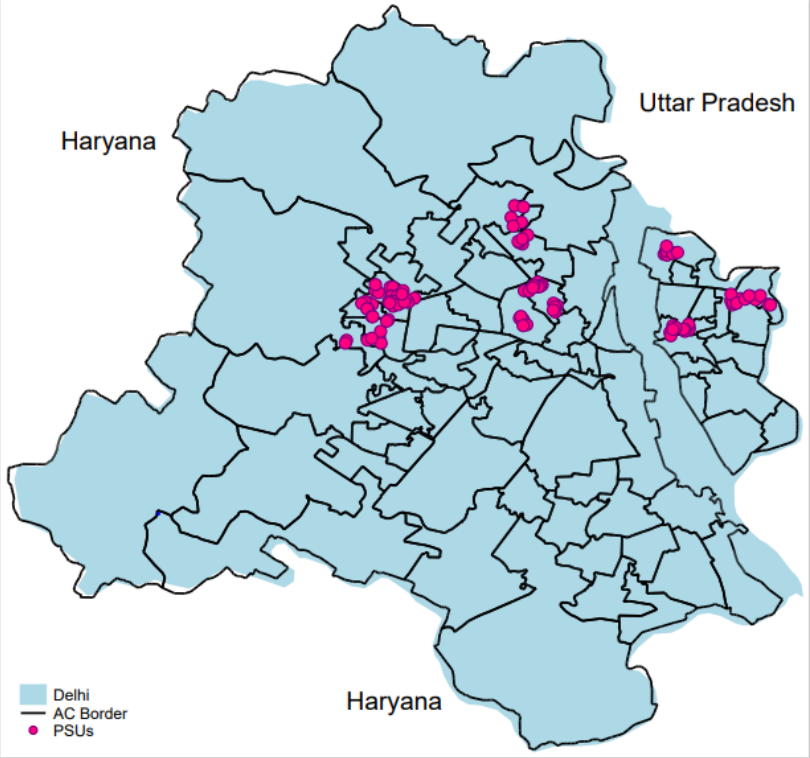
Figure 1: Sample selection – 108 Primary Survey Units



Notes: This figure is a graphical representation of our sample area for this study. Area shaded in blue represents entire Delhi region, and pink dots denotes the 108 primary survey units chosen through systematic random sampling for conducting the survey. The map is based on census (2001) shape files of districts and assembly constituencies of Delhi, and geographical coordinates collected via survey to represent the PSU's.
Source: Census (2001) and Authors' calculations based on pre-pandemic data.

Figure 2: Flowchart on Sample Creation

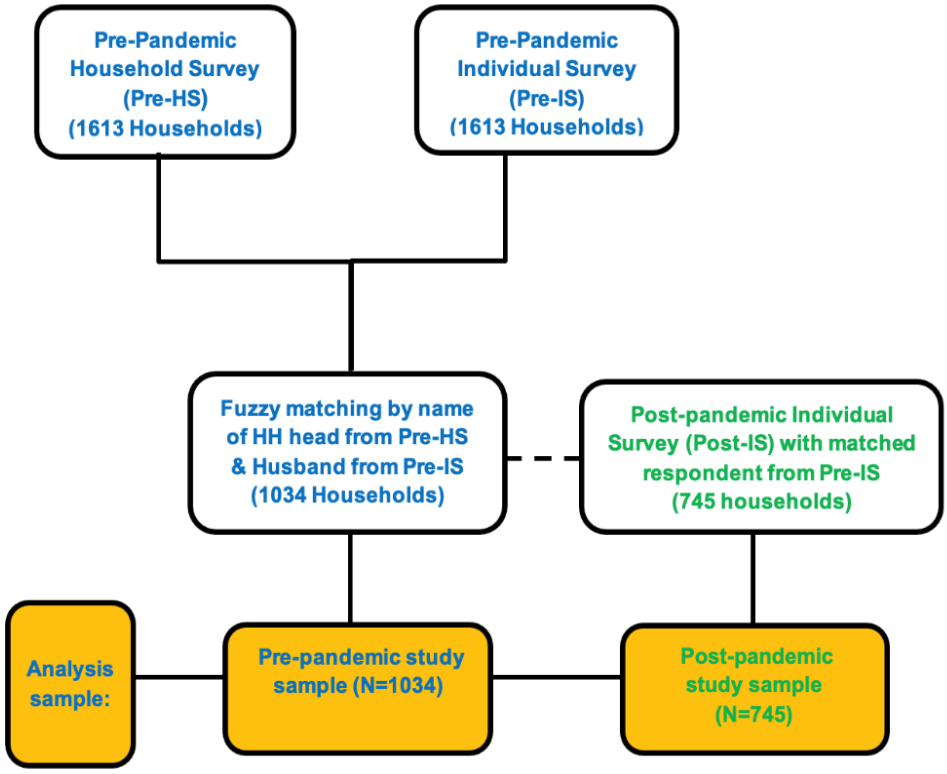
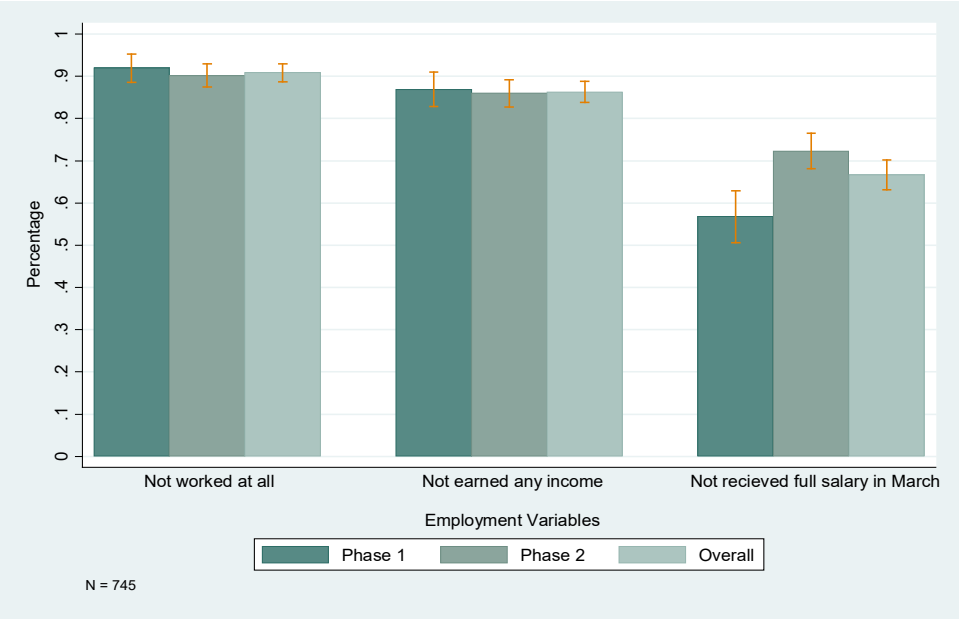
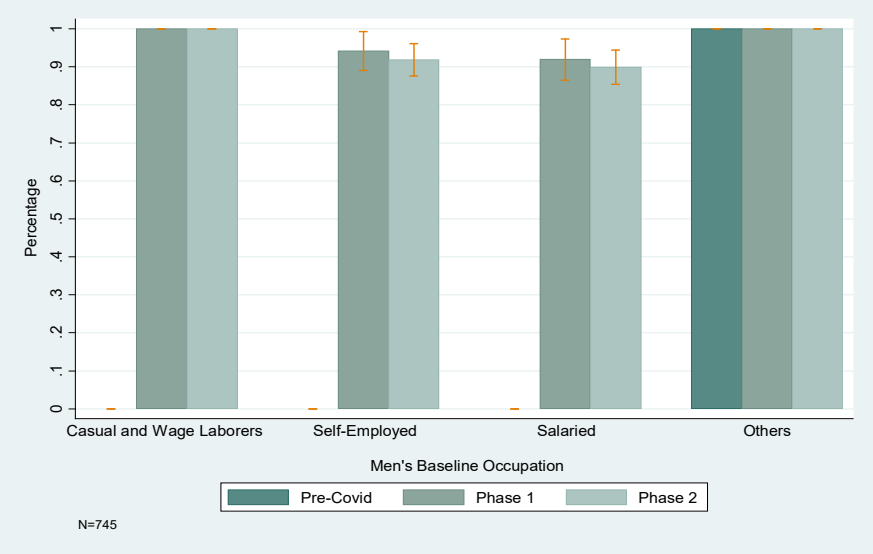


Figure 3: Men's Employment Status during Covid19



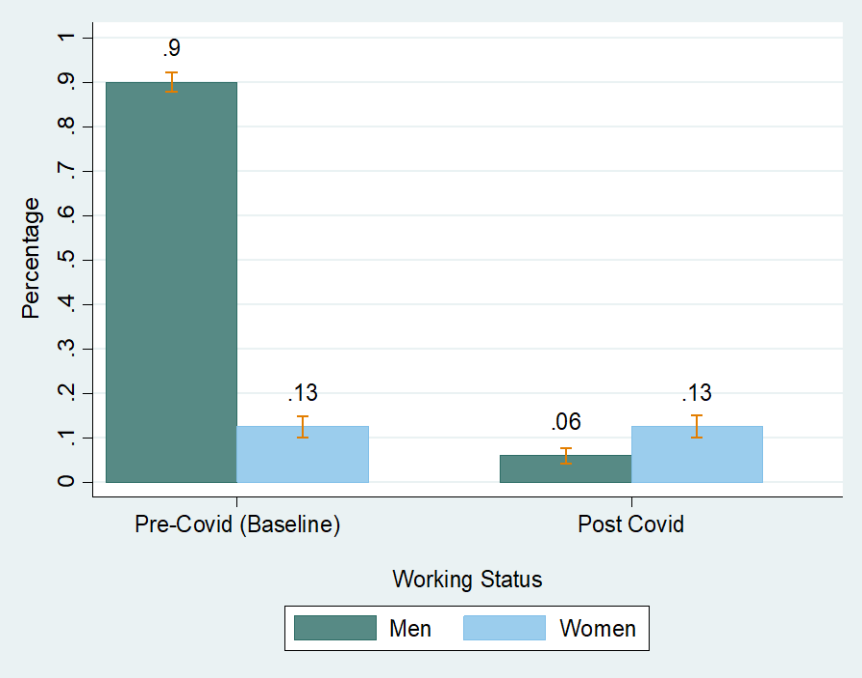
Notes: This figure depicts employment status of men during the lockdown based on three aspects; not worked at all, not earned any income during lockdown (beginning 24thMarch, 2020) and not received full salary in the month of March. The overall sample covers the period from April 3rd-May 9th. Phase 1 refers to respondents surveyed between April 3rd-April 19th and Phase 2 refers to respondents surveyed between April 20th - May 9th. The phase 1 consists of 268 data points, whereas this count is 477 for the phase 2. The reference period for all respondents was from March 25th until the date of survey.

Figure 4: Men's Unemployment Status during Covid19, by Pre-Covid Occupation



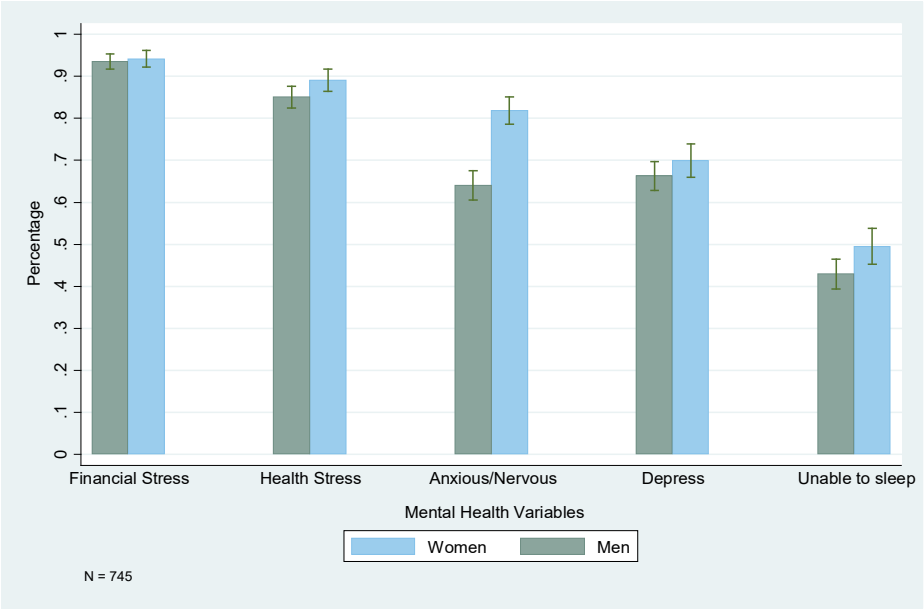
Notes: This figure illustrates percentage of men unemployed pre-pandemic and during the lockdown by their pre-pandemic (baseline) occupational categories. The pre-Covid sample represents employment status before the pandemic. Phase 1 refers to respondents surveyed between April 3rd- April 19th and Phase 2 refers to respondents surveyed between April 20th - May 9th. The phase 1 consists of 268 data points, whereas this count is 477 for the phase 2. The reference period for all respondents was from March 25th until the date of survey for post pandemic survey.

Figure 5: Employment Status before and during Covid19, by gender



Notes: This figure illustrates the percentage of men and women employed (working) before and after the Covid19 pandemic.

Figure 6: Mental health outcomes, by Gender

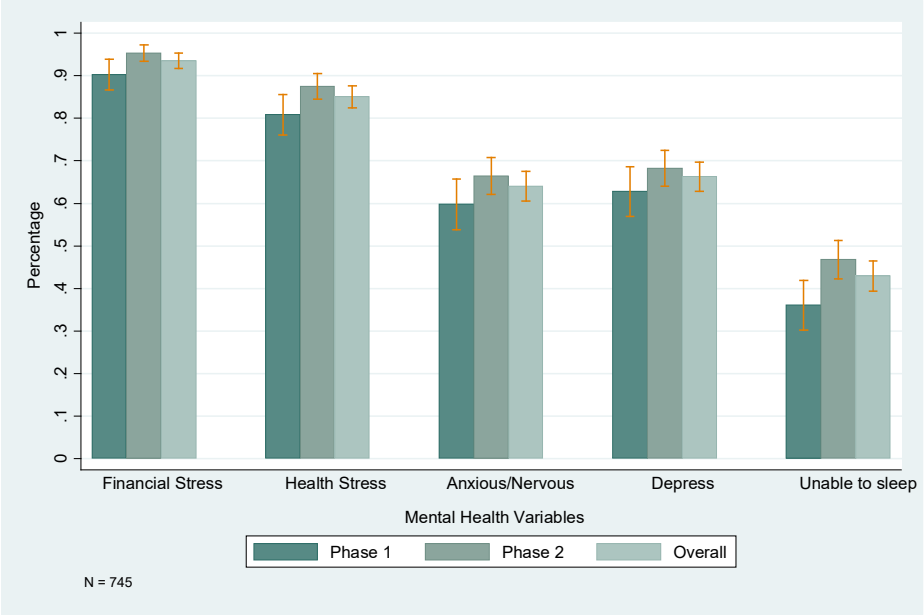


Notes: This figure shows the participants' responses to the different mental health questions as discussed in Section 3b, by gender. The overall sample covers the period from April 3rd-May 9th. The sample sizes for women and men are 529 and 741 respectively. The reference period for all respondents was from March 25th until the date of survey.

Figure 7: Mental health outcomes: Females, by Phases

Notes: This figure depicts women's response to the different mental health questions as discussed in Section 3b, by phases. The overall sample covers the period from April 3rd- May 9th. Phase 1 refers to respondents surveyed between April 3rd- April 19th and Phase 2 refers to respondents surveyed between April 20th-May 9th. Phase 1 consists of 268 observations and Phase 2 consists of 477 observations for females. The reference period for respondents was from March 25th until the date of survey.

Figure 8: Mental health outcomes: Males by Phases



Notes: This figure indicates men's response to the different mental health questions as discussed in Section 3b, by phases. The overall sample covers the period from April 3rd- May 9th.Phase 1 refers to respondents surveyed between April 3rd- April 19th and Phase 2 refers to respondents surveyed between April 20th-May 9th. Phase 1 consists of 268observations and Phase 2 consists of 477 observations for males. The reference period for all respondents was from March 25th until the date of survey.

Table 1(a): Baseline Household Characteristics

	N	mean	se
No. of household members	745	5.16	0.06
No. of years in current location	745	28.29	0.5
No. of children	657	2.48	0.04
Has pucca house (0/1)	745	0.96	0.01
Owns house (0/1)	745	0.66	0.02
Has ration card (0/1)	744	0.61	0.02
Caste	738		
Scheduled caste		0.41	0.02
Scheduled tribe		0.02	0.01
Other backward caste		0.33	0.02
General		0.24	0.02
Hindu (0/1)	745	0.83	0.01
Mean asset index	745	1.81	0.02
Mean asset index of bottom 25th percentile	745	0.91	0.02
Mean asset index of top 25th percentile	745	2.59	0.02
Household head from Delhi (0/1)	745	0.35	0.02

Notes: This tables presents the pre-pandemic household characteristics of the 745 households common in pre-pandemic and post pandemic survey. A fuzzy matching using household head's name from pre-pandemic household survey and husband's name from pre-pandemic individual survey created the pre-pandemic sample of 1034 households. Out of these 1034 households, same individual was interviewed in 745 households during the post-pandemic survey.The assets index was constructed using Principal Component Analysis. The variable considers 14 assets: own flat/house, box tv, LCD/LED, fridge, clock, stove, cycle, bike, car, fan, cooler, AC, computer, mobile and sewing machine. Further, on the basis of this continuous assets index, we constructed a categorical variable which divides the population into four cohorts i.e., below 25^{th} percentile, below 50^{th} and between 50^{th} - 75^{th} and below 75^{th} percentile.

Table 1(b): Baseline Individual Characteristics

		Women			Men	
	N	mean	se	N	mean	se
Age (years)	723	31.1	0.22	740	35	0.22
Education (years)	722	6.69	0.16	739	7.89	0.14
Occupation	723			740		
Wage Labourer		0.08	0.01		0.24	0.02
Self-Employed		0.08	0.01		0.33	0.02
Salaried		0.04	0.01		0.37	0.02
Housewives		0.78	0.02		-	
Others		0.02	0.01		0.06	0.01
Currently working (0/1)	723	0.20	0.40	701	0.95	0.01
Current monthly income (in Rs)	130	4,215	322	666	12,282	760
Total friends	745	6.06	0.09	745	3.77	0.06
Total home friends	745	4.68	0.1	745	2.9	0.06
Total neighborhood friends	745	1.35	0.07	745	0.66	0.04
Total work friends	745	0.03	0.01	745	0.2	0.02

*Notes:*This tables presents the pre-pandemic individual characteristics of the 745 households common in pre-pandemic and post pandemic survey. A fuzzy matching using household head's name from pre-pandemic household survey and husband's name from pre-pandemic individual survey created the pre-pandemic sample of 1034 households. Out of these 1034 households, same individual was interviewed in 745 households during the post-pandemic survey.

Table 2: Attrition Checks by Baseline Characteristics between Pre- and Post-PandemicSurveys

	PRE-PANDEMIC			POST PANDEMIC			DIFFERENCE	
	N	mean	se	N	mean	se	Mean	se
Household characteristics								
No. of household members	1034	5.2	0.05	745	5.16	0.06	-0.04	0.03
No. of years in current location	1034	28.56	0.43	745	28.29	0.5	-0.25	0.28
No. of children	915	2.48	0.04	657	2.48	0.04	0.00	0.03
Has pucca house (0/1)	1034	0.96	0.01	745	0.96	0.01	0.00	0.00
Owns house (0/1)	1034	0.65	0.02	745	0.66	0.02	0.01	0.01
Has ration card (0/1)	1034	0.62	0.02	745	0.61	0.02	-0.01	0.01
Caste	1022			738				
Scheduled caste		0.43	0.02		0.42	0.02	-0.01	0.01
Scheduled tribe		0.02	0.00		0.02	0.00	0.00*	0.00
Other backward caste		0.32	0.01		0.33	0.01	0.01	0.01
General		0.23	0.01		0.24	0.01	0.01	0.01
Hindu (0/1)	1034	0.82	0.01	745	0.83	0.01	0.01**	0.01
Mean Asset Index	1034	1.78	0.02	745	1.81	0.02	0.03**	0.01
Assets in bottom 25th percentile	264	0.89	0.02	171	0.91	0.02	0.02	0.03
Assets in the top 25th percentile	254	2.61	0.01	180	2.59	0.02	-0.02	0.02
Household head from Delhi (0/1)	1032	0.35	0.02	743	0.35	0.02	0.00	0.01
Individual characteristics								
Wife's age (years)	1006	30.97	0.19	723	31.1	0.22	0.11	0.13
Husband's age (years)	1028	35	0.19	740	35	0.22	0.00	0.14
Wife's education (years)	1006	6.69	0.14	723	6.69	0.16	0.00	0.01
Husband's education (years)	1028	7.54	0.12	740	7.88	0.14	0.34***	0.01
Wife's occupation	1006			723				
Wage labourer		0.08	0.01		0.08	0.01	0.00	0.01
Self Employed		0.09	0.01		0.08	0.01	-0.01	0.01
Salaried		0.05	0.01		0.04	0.01	-0.01	0.00
Housewife		0.76	0.01		0.78	0.02	0.02	0.01
Other		0.03	0		0.02	0.01	-0.01	0.00
Husband's occupation	1028			740				
Wage labourer		0.25	0.01		0.24	0.02	-0.01	0.01
Self Employed		0.33	0.02		0.33	0.02	0.00	0.01
Salaried		0.37	0.02		0.37	0.02	0.00	0.01
Other		0.05	0.01		0.06	0.01	0.00	0.00
Wife’s monthly earning (Rs)	198	4,540	306	130	4,215	322	-325	238
Husband’s monthly earnings (Rs)	923	12,307	686	666	12,282	760	-25	479
Wife is employed (0/1)	219	0.9	0.02	147	0.88	0.03	-0.02	0.03

Husband is employed (0/1)	976	0.95	0.01	701	0.95	0.01	0.00	0.00

Notes: The above figure shows the balance tests for household and individual characteristics used as baseline controls in the regression analysis. Significant at ∗10%, ∗∗5%, and ∗∗∗1%.

Table 3: Male employment effects, by occupation

	(1)	(2)	(3)
	Men's self-reported employment		
Post Covid	-0.891***	-0.890***	-0.226***
	(0.013)	(0.013)	(0.079)
Husband is labourer at baseline		0.547***	0.928***
		(0.025)	(0.035)
Husband is self-employed at baseline		0.568***	0.927***
		(0.026)	(0.035)
Husband is salaried at baseline		0.579***	0.928***
		(0.027)	(0.035)
Wife is labourer at baseline		0.015	-0.001
		(0.014)	(0.004)
Wife is self-employed at baseline		0.019	-0.001
		(0.013)	(0.003)
Wife is salaried at baseline		0.036	-0.003
		(0.022)	(0.004)
Wife is housewife at baseline		0.018**	0.006*
		(0.008)	(0.004)
Post Covid*Husband is labourer at baseline			-0.907***
			(0.036)
Post Covid*Husband is self-employed at baseline			-0.857***
			(0.037)
Post Covid*Husband is salaried at baseline			-0.833***
			(0.038)
Post Covid*Wife is labourer at baseline			0.072**
			(0.031)
Post Covid*Wife is self-employed at baseline			0.073**
			(0.033)
Post Covid*Wife is salaried at baseline			0.121**
			(0.060)
Post Covid*Wife is housewife at baseline			0.045**
			(0.022)
Constant	0.923***	0.343***	0.056*
	(0.042)	(0.042)	(0.032)
Adj. R-sq	0.79	0.86	0.90
Baseline Controls	Yes	Yes	Yes
Post*Baseline Controls	No	No	Yes
N	1742	1692	1692

Notes: The dependent variable denotes the self-reported employment status of men pre- and post-pandemic. It is a binary variable, where 1 represents employed and zero otherwise. This regression analysis is performed on a dataset where each observation has two separate rows: one for pre-pandemic value and other for post-pandemic value. We have 1034 pre-pandemic and 745 post-pandemic observations, which amount to a total sample size of 1779 observations. Owing to missing values of dependent variable, the sample size is reduced to 1742 observations in column 1. Here, the reference category for own and spouse's occupation is other jobs. The baseline controls include low caste dummy, hindu (religion) dummy, household head native state dummy, number of years living in a location, owns a ration card dummy, own flat dummy, number of household members, assets index,age and education of males.Standard errors clustered at PSU are reported in parentheses. Significant at ∗10%, ∗∗5%, and ∗∗∗1%

Table 4: Female employment effects, by occupation

	(1)	(2)	(3)
	Wife's employment as reported by husband		
Post Covid	-0.005	-0.002	-0.021
	(0.007)	(0.005)	(0.059)
Husband is labourer at baseline		-0.052	-0.056
		(0.046)	(0.043)
Husband is self-employed at baseline		-0.051	-0.059
		(0.042)	(0.040)
Husband is salaried at baseline		-0.045	-0.053
		(0.043)	(0.040)
Wife is labourer at baseline		0.630***	0.655***
		(0.054)	(0.050)
Wife is self-employed at baseline		0.372***	0.384***
		(0.064)	(0.063)
Wife is salaried at baseline		0.708***	0.716***
		(0.058)	(0.055)
Wife is housewife at baseline		0.013	0.020
		(0.014)	(0.013)
Post Covid*Husband is labourer at baseline			0.013
			(0.025)
Post Covid*Husband is self-employed at baseline			0.021
			(0.022)
Post Covid*Husband is salaried at baseline			0.019
			(0.022)
Post Covid*Wife is labourer at baseline			-0.065*
			(0.034)
Post Covid*Wife is self-employed at baseline			-0.032
			(0.046)
Post Covid*Wife is salaried at baseline			-0.023
			(0.041)
Post Covid*Wife is housewife at baseline			-0.022**
			(0.009)
Constant	0.054	0.092	0.102
	(0.098)	(0.089)	(0.090)
Adj. R-sq	0.05	0.46	0.46
Baseline Controls	Yes	Yes	Yes
Post*Baseline Controls	No	No	Yes
N	1687	1686	1686

Notes: The dependent variable denotes the employment status of women as reported by their husbands pre- and post-pandemic. It is a binary variable, where 1 represents employed and zero otherwise. This regression analysis is performed on a dataset where each observation has two separate rows: one for pre-pandemic value and other for post-pandemic value. We have 1034 pre-pandemic and 745 post-pandemic observations, which amount to a total sample size of 1779 observations. Owing to missing values of the dependent variable, the sample size is reduced to 1687 observations in column 1. Here, the reference category for own and spouse's occupation is other jobs. The baseline controls include low caste dummy, hindu (religion) dummy, household head native state dummy, number of years living in a location, owns a ration card dummy, own flat dummy, number of household members, assets index, age and education of males. Standard errors clustered at PSU are reported in parentheses. Significant at ∗10%, ∗∗5%, and ∗∗∗1%

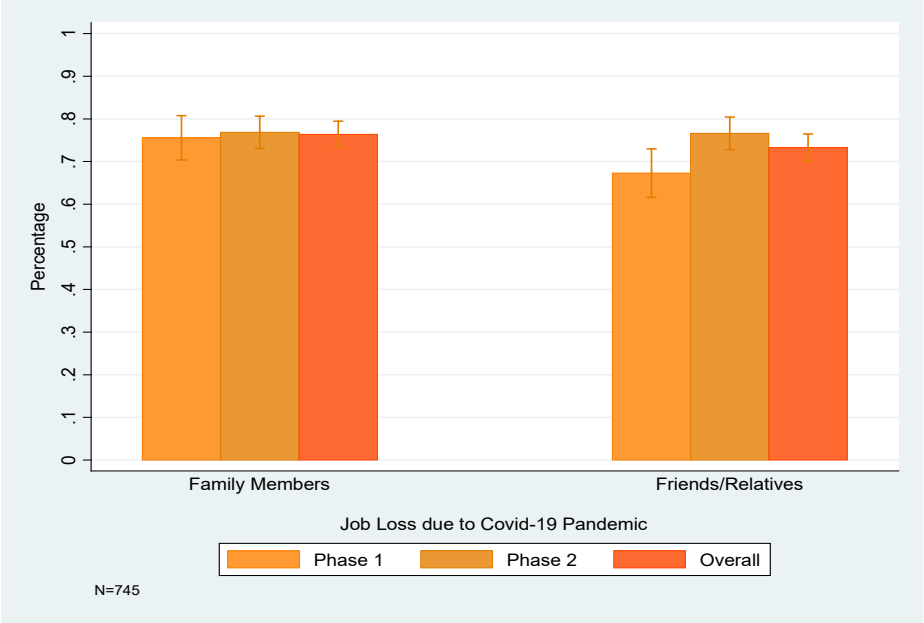
Table 5: Impact on Mental health by Gender: Role of Social networks

	(1)	(2)	(3)
		Mental stress	
Wife	0.043	-0.848**	-0.862*
	(0.037)	(0.378)	(0.388)
Friends		-0.059**	
		(0.024)	
Wife*Friends		0.098***	
		(0.029)	
Home-friends			-0.057**
			(0.025)
Wife*Home-friends			0.099***
			(0.033)
Work-friends			-0.044
			(0.063)
Wife*Work-friends			-0.014
			(0.135)
Neighborhood-friends			-0.071
			(0.043)
Wife*Neighborhood-friends			0.098**
			(0.040)
Constant	-0.023	0.455	0.448
	(0.060)	(0.302)	(0.305)
Baseline Controls	No	Yes	Yes
Baseline Interactions	No	Yes	Yes
Adj. R-sq	0.01	0.02	0.02
N	1266	1233	1233

Notes: The dependent variable is a standardized mental health variable as described in Section 3b of the paper, where higher values indicate worse mental health. There are 737 observations for men and 529 for women, giving a total of 1266 observations, as shown in Column 1.The baseline controls include low caste dummy, hindu (religion) dummy, household head native state dummy, number of years living in a location, owns a ration card dummy, own flat dummy, number of household members, type of house dummy, assets index, age and education of respondents. Standard errors clustered at PSU are reported in parentheses. Significant at ∗10%, ∗∗5%, and ∗∗∗1%

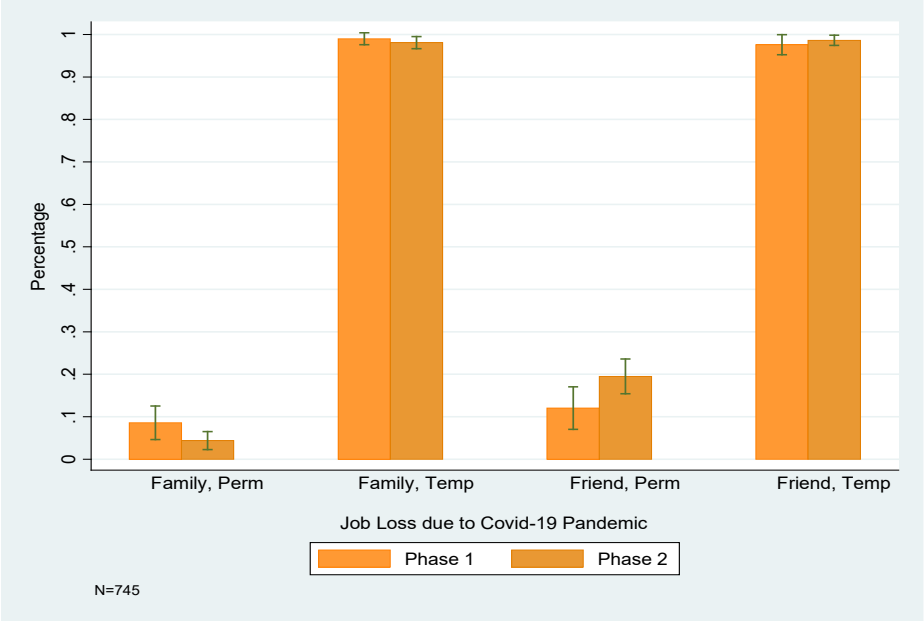
APPENDIX

FIGURE A1: Family and friends job loss during Covid-19 by phases



Notes: This figure indicates percentage of friends and relatives of the respondent who lost job due to lockdown, by phases. The overall sample covers the period from April 3rd-May 9th.Phase 1 refers to respondents surveyed between April 3rd- April 19th and Phase 2 refers to respondents surveyed between April 20th-May 9th. Phase 1 consists of 268 observations and Phase 2 consists of 477 observations for males. The reference period for all respondents was from March 25th until the date of survey.
Source: Authors' calculations based on post pandemic round of survey.

Figure A2: Family and friends job loss during Covid-19 by phases and type



Notes: This figure indicates percentage of friends and relatives of the respondent who lost job due to lockdown, by phases and types. Temp" here signifies the respondent's perception of job loss as temporary, where "Perm" here signifies their perception of job loss as permanent. The overall sample covers the period from April 3rd-May 9th.Phase 1 refers to respondents surveyed between April 3rd- April 19th and Phase 2 refers to respondents surveyed between April 20th-May 9th. Phase 1 consists of 268 observations and Phase 2 consists of 477 observations for males. The reference period for all respondents was from March 25th until the date of survey

Source: Authors' calculations based on post pandemic round of survey.

Table A1: Baseline Household and Individual Characteristics, by Phases

	PHASE 1			PHASE 2		
	N	mean	se	N	mean	se
Household characteristics						
No. of household members	268	5.2	0.01	477	5.14	0.07
No. of years in current location	268	26.52	0.84	477	29.28	0.62
No. of children	237	2.59	0.08	420	2.42	0.05
Has pucca house (0/1)	268	0.95	0.01	477	0.97	0.01
Owns house (0/1)	268	0.68	0.03	477	0.64	0.02
Has ration card (0/1)	268	0.57	0.03	476	0.64	0.02
Caste	265			473		
Scheduled caste		0.37	0.03		0.44	0.02
Scheduled tribe		0.02	0.01		0.02	0.01
Other backward caste		0.35	0.03		0.32	0.02
General		0.26	0.03		0.23	0.02
Hindu (0/1)	268	0.85	0.02	477	0.82	0.018
Mean assets index	268	1.74	0.04	477	1.84	0.03
Mean asset index of bottom 25th percentile	68	0.91	0.03	103	0.90	0.03
Mean asset index of top 25th percentile	53	2.56	0.03	127	02.61	0.02
Household head from Delhi (0/1)	268	0.31	0.03	477	0.37	0.02
Individual characteristics						
Wife's age (years)	262	31.11	0.36	461	31.1	0.28
Husband's age (years)	268	35.09	0.37	472	34.94	0.29
Wife's education (years)	261	6.13	0.28	461	7	0.2
Husband's education (years)	268	7.54	0.24	471	8.1	0.17
Wife's occupation	262			461		
Wage labourer		0.09	0.02		0.07	0.01
Self Employed		0.08	0.02		0.08	0.01
Salaried		0.03	0.01		0.05	0.01
Housewife		0.77	0.27		0.78	0.02
Other		0.03	0.01		0.02	0.01
Husband's occupation	268			472		
Wage labourer		0.26	0.03		0.22	0.02
Self Employed		0.32	0.03		0.34	0.02
Salaried		0.37	0.03		0.38	0.02
Other		0.05	0.01		0.06	0.01
Wives monthly earnings (in Rs)	52	3823	340	78	4477	427
Husbands monthly earnings (in Rs)	242	11075	487	424	12970	1177
Wife is employed (0/1)	53	0.98	0.02	94	0.83	0.05

Husband is employed (0/1)	255	0.95	0.01	446	0.95	0.01

Table A2: Impact on Mental health by Gender: Role of Social networks

	(1)	(2)	(3)
		Mental stress	
Wife	0.066***	-0.183*	-0.186*
	(0.010)	(0.104)	(0.107)
Friends		-0.017**	
		(0.007)	
Wife*Friends		0.028***	
		(0.008)	
Home-friends			-0.016**
			(0.007)
Wife*Home-friends			0.028***
			(0.009)
Work-friends			-0.013
			(0.018)
Wife*Work-friends			-0.003
			(0.037)
Neighborhood-friends			-0.020
			(0.012)
Wife*Neighborhood-friends			0.028**
			(0.011)
Constant	0.703***	0.841***	0.839***
	(0.017)	(0.087)	(0.089)
Baseline Controls	No	Yes	Yes
Baseline Interactions	No	Yes	Yes
Adj. R-sq	0.01	0.01	0.02
N	1266	1233	1233

Notes: The dependent variable is a mental stressindex constructed as described in Section 3b of the paper, where higher values indicate worse mental health. There are 737 observations for men and 529 for women, giving a total of 1266 observations, as shown in Column 1. The baseline controls include low caste dummy, hindu (religion) dummy, household head native state dummy, number of years living in a location, owns a ration card dummy, own flat dummy, number of household members, type of house dummy, assets index, age and education of respondents. Standard errors clustered at PSU are reported in parentheses. Significant at ∗10%, ∗∗5%, and ∗∗∗1%

Table A3(a): Impact on Financial Stress by Gender: Role of Social networks

	(1)	(2)	(3)
		Financial Stress	
Wife	0.007	-0.119	-0.120
	(0.011)	(0.081)	(0.082)
Friends		-0.008	
		(0.007)	
Wife*Friends		0.013*	
		(0.007)	
Home-friends			-0.008
			(0.007)
Wife*Home-friends			0.014*
			(0.008)
Work-friends			0.006
			(0.014)
Wife*Work-friends			-0.021
			(0.051)
Neighborhood-friends			-0.009
			(0.010)
Wife*Neighborhood-friends			0.014
			(0.011)
Constant	0.935***	1.026***	1.026***
	(0.010)	(0.060)	(0.060)
Baseline Controls	No	Yes	Yes
Post*Baseline Controls	No	Yes	Yes
Adj. R-sq	0	0.02	0.01
N	1266	1233	1233

Notes: The dependent variable is a binary (0/1) variable indicating whether or not the participant is suffering from financial stress. There are737 observations for men and 529for women, giving a total of 1266 observations, as shown in Column 1. Standard errors clustered at PSU are reported in parentheses. Significant at ∗10%, ∗∗5%, and ∗∗∗1%

Table A3(b): Impact on Health Stress by Gender: Role of Social networks

	(1)	(2)	(3)
		Health Stress	
Wife	0.040*	-0.181	-0.185
	(0.017)	(0.177)	(0.181)
Friends		-0.013	
		(0.008)	
Wife*Friends		0.021**	
		(0.010)	
Home-friends			-0.009
			(0.008)
Wife*Home-friends			0.019*
			(0.010)
Work-friends			-0.036
			(0.031)
Wife*Work-friends			0.054
			(0.060)
Neighborhood-friends			-0.021
			(0.013)
Wife*Neighborhood-friends			0.023
			(0.014)
Constant	0.851***	0.893***	0.885***
	(0.018)	(0.156)	(0.158)
Baseline Controls	No	Yes	Yes
Post*Baseline Controls	No	Yes	Yes
Adj. R-sq	0.00	0.00	0.00
N	1266	1233	1233

Notes: The dependent variable is a binary (0/1) variable indicating whether the participant is suffering from health worries. There are737 observations for men and 529for women, giving a total of 1266 observations, as shown in Column 1. Standard errors clustered at PSU are reported in parentheses. Significant at ∗10%, ∗∗5%, and ∗∗∗1%.

Table A3(c): Impact on Nervousness/Anxiety by Gender: Role of Social networks

	(1)	(2)	(3)
		Nervous/Anxious	
Wife	0.178*	-0.006	0.013
	(0.022)	(0.195)	(0.195)
Friends		-0.024**	
		(0.012)	
Wife*Friends		0.038***	
		(0.013)	
Home-friends			-0.024**
			(0.012)
Wife*Home-friends			0.036***
			(0.013)
Work-friends			-0.001
			(0.033)
Wife*Work-friends			0.022
			(0.076)
Neighborhood-friends			-0.031
			(0.022)
Wife*Neighborhood-friends			0.054**
			(0.022)
Constant	0.640***	0.703***	0.700***
	(0.024)	(0.179)	(0.184)
Baseline Controls	No	Yes	Yes
Post*Baseline Controls	No	Yes	Yes
Adj. R-sq	0.04	0.04	0.04
N	1265	1232	1232

Notes: The dependent variable is a binary (0/1) variable indicating whether or not the participant is suffering from nervousness or anxiety. There are737 observations for men and 529for women, giving a total of 1266 observations, as shown in Column 1. Standard errors clustered at PSU are reported in parentheses. Significant at ∗10%, ∗∗5%, and ∗∗∗1%

Table A3(d): Impact on Depression by Gender: Role of Social networks

	(1)	(2)	(3)
		Depressed	
Wife	0.036	-0.118	-0.146
	(0.024)	(0.214)	(0.218)
Friends		-0.016	
		(0.012)	
Wife*Friends		0.027*	
		(0.015)	
Home-friends			-0.019
			(0.012)
Wife*Home-friends			0.033**
			(0.016)
Work-friends			0.010
			(0.032)
Wife*Work-friends			-0.042
			(0.081)
Neighborhood-friends			-0.010
			(0.022)
Wife*Neighborhood-friends			0.009
			(0.020)
Constant	0.663***	0.739***	0.746***
	(0.024)	(0.140)	(0.142)
Baseline Controls	No	Yes	Yes
Post*Baseline Controls	No	Yes	Yes
Adj. R-sq	0.00	0.01	0.01
N	1265	1232	1232

Notes: The dependent variable is a binary variable indicating whether or not the participant is feeling depressed. There are736 observations for men and 529for women, giving a total of 1265 observations, as shown in Column 1. Standard errors clustered at PSU are reported in parentheses. Significant at ∗10%, ∗∗5%, and ∗∗∗1%

Table A3(e): Impact on Sleeplessness by Gender: Role of Social networks

	(1)	(2)	(3)
		Sleep disorder	
Wife	0.066***	-0.398**	-0.406*
	(0.023)	(0.193)	(0.200)
Friends		-0.022*	
		(0.013)	
Wife*Friends		0.041**	
		(0.017)	
Home-friends			-0.021
			(0.013)
Wife*Home-friends			0.042**
			(0.019)
Work-friends			-0.029
			(0.032)
Wife*Work-friends			-0.033
			(0.064)
Neighborhood-friends			-0.024
			(0.021)
Wife*Neighborhood-friends			0.037*
			(0.021)
Constant	0.429***	0.558***	0.556***
	(0.031)	(0.164)	(0.167)
Baseline Controls	No	Yes	Yes
Post*Baseline Controls	No	Yes	Yes
Adj. R-sq	0.00	0.02	0.01
N	1265	1232	1232

Notes: The dependent variable is a binary (0/1) variable indicating whether or not the participant is experiencing sleep disorders. There are736 observations for men and 529for women, giving a total of 1265 observations, as shown in Column 1. Standard errors clustered at PSU are reported in parentheses. Significant at ∗10%, ∗∗5%, and ∗∗∗1%

Table A4: Male employment effects, by occupation – Balanced Panel

	(1)	(2)	(3)
	Men's self-reported employment		
Post Covid	-0.887***	-0.887***	-0.179**
	(0.014)	(0.014)	(0.083)
Husband is labourer at baseline		0.485***	0.951***
		(0.018)	(0.034)
Husband is self-employed at baseline		0.509***	0.951***
		(0.020)	(0.034)
Husband is salaried at baseline		0.522***	0.951***
		(0.020)	(0.034)
Wife is labourer at baseline		0.035**	-0.003
		(0.016)	(0.004)
Wife is self-employed at baseline		0.037**	-0.001
		(0.018)	(0.003)
Wife is salaried at baseline		0.058*	-0.003
		(0.029)	(0.004)
Wife is housewife at baseline		0.029***	0.003
		(0.010)	(0.003)
Post Covid*Husband is labourer at baseline			-0.930***
			(0.036)
Post Covid*Husband is self-employed at baseline			-0.883***
			(0.038)
Post Covid*Husband is salaried at baseline			-0.858***
			(0.037)
Post Covid*Wife is labourer at baseline			0.075**
			(0.032)
Post Covid*Wife is self-employed at baseline			0.077**
			(0.034)
Post Covid*Wife is salaried at baseline			0.122**
			(0.059)
Post Covid*Wife is housewife at baseline			0.050**
			(0.021)
Constant	0.922***	0.388***	0.033
	(0.051)	(0.046)	(0.028)
Adj. R-sq	0.79	0.84	0.89
Baseline Controls	1415	1415	1415
Post*Baseline Controls	No	No	Yes
N	1459	1415	1415

Notes: The dependent variable denotes the self-reported employment status of men pre- and post-pandemic. It is a binary variable, where 1 represents employed and zero otherwise. This regression analysis is performed on a dataset where each observation has two separate rows: one for pre-pandemic value and other for post-pandemic value. We have 745 pre-pandemic and 745 post-pandemic observations, which amount to a total sample size of 1490 observations. Owing to missing values of dependent variable, the sample size is reduced to 1459 observations in column 1. Here, the reference category for own and spouse's occupation is other jobs. Standard errors clustered at PSU are reported in parentheses. Significant at ∗10%, ∗∗5%, and ∗∗∗1%

Table A5: Female employment effects, by occupation – Balanced Panel

	(1)	(2)	(3)
	Wife's employment as reported by husband		
Post Covid	0.076***	0.075***	-0.063
	(0.012)	(0.012)	(0.098)
Husband is labourer at baseline		-0.028	-0.044
		(0.027)	(0.053)
Husband is self-employed at baseline		-0.019	-0.036
		(0.023)	(0.047)
Husband is salaried at baseline		-0.018	-0.032
		(0.024)	(0.048)
Wife is labourer at baseline		0.796***	0.590***
		(0.032)	(0.064)
Wife is self-employed at baseline		0.662***	0.344***
		(0.040)	(0.075)
Wife is salaried at baseline		0.848***	0.693***
		(0.035)	(0.072)
Wife is housewife at baseline		-0.002	-0.002
		(0.008)	(0.015)
Post Covid*Husband is labourer at baseline			0.036
			(0.053)
Post Covid*Husband is self-employed at baseline			0.036
			(0.047)
Post Covid*Husband is salaried at baseline			0.030
			(0.048)
Post Covid*Wife is labourer at baseline			0.410***
			(0.064)
Post Covid*Wife is self-employed at baseline			0.637***
			(0.074)
Post Covid*Wife is salaried at baseline			0.307***
			(0.072)
Post Covid*Wife is housewife at baseline			0.001
			(0.016)
Constant	0.086	0.016	0.085
	(0.099)	(0.052)	(0.099)
Adj. R-sq	0.07	0.71	0.78
Baseline Controls	Yes	Yes	Yes
Post*Baseline Controls	No	No	Yes
N	1414	1414	1414

Notes: The dependent variable denotes the employment status of women as reported by their husbands pre- and post-pandemic. It is a binary variable, where 1 represents employed and zero otherwise. This regression analysis is performed on a dataset where each observation has two separate rows: one for pre-pandemic value and other for post-pandemic value. We have 745 pre-pandemic and 745 post-pandemic observations, which amount to a total sample size of 1490 observations. Owing to missing values of the dependent variable, the sample size is reduced to 1436 observations in column 1. Here, the reference category for own and spouse's occupation is other jobs. Standard errors clustered at PSU are reported in parentheses. Significant at ∗10%, ∗∗5%, and ∗∗∗1%

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