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The gendered crisis: livelihoods and mental well-being in India during COVID-19

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Abstract: This paper studies the impact of the COVID-19 crisis on the gendered dimensions of employment and mental health among urban informal-sector workers in India. First, we find that men's employment declined by 84 percentage points post-pandemic relative to pre-pandemic, while their monthly earnings fell by 89 per cent relative to the baseline mean. 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 pandemic-induced mental stress, with wives reporting greater stress than husbands. Third, this gendered pattern in pandemic-induced mental stress is partly explained by men's employment losses, which affected wives more than husbands. In contrast, staying employed during the pandemic is associated with worse mental health for women and their (unemployed) husbands. Fourth, pre-existing social networks are associated with higher mental stress for women relative to men, possibly due to the 'home-based' nature of women's networks.

Keywords: COVID-19, informal sector, employment, mental health, social networks, gender, India

JEL classification: J16, J22, J23, O14

Note: tables and figures at the end

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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 is facing significant policy challenges, both humanitarian and economic, in the wake of the COVID-19 crisis and the subsequent nationwide lockdown. Many of these workers have faced job and income losses and 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 as a result of the COVID-19 crisis and the nationwide lockdown due to the economic uncertainty and the social distancing measures put in place to control the spread of the epidemic, which have put pressure on the social fabric and feeling of community connectedness.

This paper aims to provide direct evidence on the impact of the COVID-19 crisis on some of the most 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 and mental health of urban, primarily informal-sector workers in India. We also focus on the gender differences in the impact of the COVID-19 crisis.

Our data come from two rounds of surveys: a pre-pandemic survey in May 2019 of over 1,600 women and their husbands living in households in urban clusters of Delhi, and a follow-up post-pandemic phone survey around the peak of the COVID-19 health crisis, in April and May 2020.

Our main findings are as follows. First, men's employment was significantly more impacted than women's employment by the COVID-19 shock. In particular, men's self-reported employment declined by 84 percentage points (pp) post pandemic. This is primarily driven by wage and casual labourers who experienced an almost 94 pp reduction in employment, followed by the self-employed and salaried workers. Men's monthly earnings also declined by 89 pp relative to pre-pandemic mean earnings. In contrast, women (wives) did not experience any significant impact on employment as a result of the pandemic, as reported by their husbands.

Second, we are the first to document very high levels of mental stress due to the pandemic among the urban poor in India, driven primarily by financial (93 per cent) and health (85 per cent) concerns. While this is true for both men and women, the latter report relatively greater mental stress. In particular, women report 0.23 standard deviation greater mental stress compared to men. The key aspects of women's stress appear to be anxiety and nervousness, followed by sleeplessness and health worries.

Third, part of this gendered pattern of pandemic-induced mental stress may be explained by the employment losses suffered by men during the pandemic, which appear to have affected wives more than husbands. Specifically, wives whose husbands lost their livelihood during the pandemic report 0.75 standard deviation greater mental stress, while these men themselves report a 0.68 standard deviation increase in mental stress. In contrast, women who continued to remain employed during the pandemic (but whose husbands were unemployed) report 0.22 standard deviation *higher* mental stress compared to their unemployed counterparts. This may be indicative of the internalization by women of the 'male breadwinner' gender norms which were severely disrupted by the pandemic-induced employment losses suffered by men. Husbands of employed women report 0.166 standard deviation greater mental stress, driven primarily by health worries. This could be picking up husbands' concerns about their wives' exposure to the virus when they went out to work. Further, we also find that wives' continued employment during the pandemic is

positively correlated with reported depression among (unemployed) men, consistent with internalization of 'male breadwinner' norms among these men.

Fourth, we analyse the mediating role of pre-existing social networks on mental health outcomes during the pandemic by exploiting rich data on pre-existing social networks. We find that the size of the pre-pandemic social networks, as measured by total number of (unique) friends, is associated with lower reported mental stress for men, but the opposite is true for women. In particular, we find that one additional social connection in men's networks reduces mental stress by 0.061 standard deviations. However, this pattern is reversed for women, such that one additional connection in their social network increases women's mental stress by 0.037 standard deviations. In other words, social networks appear to play a mitigating role for men's mental health but an exacerbating role for women's mental health, especially in times of crisis.

We also find that this positive association for women between pre-pandemic network size and post-pandemic mental stress appears to be entirely driven by the 'home-bound' nature of their networks. While for men, having an additional 'home-friend' is associated with 0.088 standard deviation lower mental stress, for women, it is associated with an additional 0.035 standard deviation *higher* reported mental stress. In addition, women who owned mobile phones and enjoyed greater phone interaction with their home-friends prior to the pandemic report higher post-pandemic mental stress, while the opposite holds for men. In contrast, having 'work-friends' is associated with lower reported levels of mental stress for *both* men and women, although neither is statistically significant.

Our preferred interpretation of these findings is that women, irrespective of their loss of connection with their social network due to social distancing, experienced greater levels of stress the larger the size of their home-bound networks. This result points to the 'stress-contagion' role rather than the 'stress-buffering' role of the home-bound social networks for women, but not men. 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 their '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, who may be spreading anxiety among each other.

The main contributions of our paper are as follows. We add to the emerging global literature on the devastating impact of the COVID-19 pandemic on economic well-being by providing evidence of its implications for the employment and earnings of poor, urban, informal-sector workers in India, with special attention to the gendered dimension of the crisis. More importantly, we provide one of the first analyses of the mental health consequences, and the gender differences therein, of the COVID-19 pandemic in the context of a developing country like India, with further focus on analysing the roles of post-pandemic employment losses and social networks in mediating these effects. Taken together, these findings contribute to our understanding of the processes needed for response, recovery, and building resilience against such a devastating and widespread shock among vulnerable groups more broadly.

The rest of the paper is organized as follows. Section 2 presents a summary of the literature. Section 3 describes the data, variables, and methodology. 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 (Gupta and Kudv 2020; Kesar et al. 2020), income, and consumption losses in India (Bertrand et al. 2020) due to the severe lockdown which began on 24 March 2020 but eased from June 2020 onwards. As a consequence of the lockdown, the impact on economic activity across the country was catastrophic and India entered a recession. India's gross domestic product (GDP) contracted by 23.9 per cent over April to June and by 7.5 per cent in the second quarter (July to September) of the 2020–21 fiscal year as opposed to 5 per cent growth in GDP in 2019–20 (The Economic Times 2020). Thus, the effects of the shutdown on the economy persist and are likely to have longer-term implications for the 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 (Afridi et al. 2021; Deshpande 2020; 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 et al. (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 of the 1990s in the Latin American countries, where a number of scholars document that women's employment among low-income households is counter-cyclical and rises during crises. They basically compensate 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, Alon et al. (2020) show that for the first time in a recession, in the USA, UK, Spain, and 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 the hospitality and service sectors, as well as their increased childcare responsibilities. In contrast, our study is focused on households where women were mostly involved in childcare even pre-COVID-19 and often 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 be aggravated by economic recession. Indeed, evidence suggests that casual jobs were lost disproportionately more in the early phase of the lockdown in India (April to May). However, formal sector employment witnessed a decline with the 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 to May) in India (Afridi et al. 2021). Similar to these papers, we also find differential impacts on different categories of labour.

Unanticipated large losses of income may also affect mental well-being. Using exogenous variation in the interview dates of the 2008 Health and Retirement Study of the USA, McInerney et al. (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 symptoms of depression—a loss of US$50,000 in non-housing wealth increases the likelihood of feeling depressed by 8 per cent. Indeed, early research on the psychological effects of the COVID-19 pandemic indicates significant increases in 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 USA.

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 USA 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 per cent. Etheridge and Spantig (2020) document similar gender differences in the UK and suggest that having a larger social network before the pandemic is a strong predictor of decline in well-being after the pandemic's onset. Interestingly, women reported having more close friends before and greater loneliness after the pandemic.

While, in the developing-country context, particularly India, 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 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 behavioural change, including improvement in savings choices and health-seeking behaviour. Baranov et al. (2020) show 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 also relates to studies of how social networks mediate aggregate shocks. Makridis and Wang (2020), for example, 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 (Kawachi and Berkman 2001) has documented gender differences in the effects of social networks on psychological well-being—social networks of women may paradoxically increase the psychological distress among women due to higher pressure to provide support to others. A gender gap during times of crisis in support provided between spouses, whereby women give more support, has also been shown to increase demoralization and depression. There can be 'stress contagion' through social networks when the participants are facing similar shocks. Women's networks, when composed of others similar to them in terms of having low levels of resources, do not help with upward mobility and can often exact emotional or physical penalties (Belle 1990).

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

3 Data, variables, and methodology

3.1 Data description

Pre-pandemic survey

With the aim of studying the factors driving low female labour force participation in urban India, we started with a survey of five districts of Delhi covering the period from May to July 2019.[1] Within these five districts, we chose ten assembly constituencies with a 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 it had at least one married couple in the 18–45-year age group.

The baseline (pre-pandemic) survey consisted of two surveys: a household survey and an individual survey. The household survey comprised 1,613 households and provided us with information about household composition, socioeconomic characteristics, and assets owned, etc. The questionnaire was supposed to be answered by the household head, but, when the head was unavailable, any knowledgeable adult was allowed to give the answers. Following the household survey, the youngest couple in the household[2] (between 18 and 45 years of age) was interviewed as part of the individual survey, enabling us to collect information for 97 per cent 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 of the household head's name from the pre-pandemic household survey with the husband's name from the pre-pandemic individual survey, we retained 1,034 pre-pandemic households in which the husband was the main respondent for both individual (male) and household surveys at baseline.[3]

Post-pandemic survey

The Indian government ordered a stringent 21-day national lockdown to deal with the COVID-19 pandemic from 24 March until 14 April 2020, which was later extended to 30 May 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 (3 April to 19 April 2020), which coincided with the initial stringent lockdown, 458 households were surveyed. In Phase 2 (20 April to 9 May 2020), when some of the restrictions had been lifted, an additional 966 households were surveyed. The survey date for our respondents was randomly selected. Hence, as Appendix Table A1 shows, those who were interviewed earlier (Phase 1) mostly

[1] For the baseline sample, we first drew a list of electoral board (EB) wards around planned industrial estates in Delhi, concentrated in five (North, North-West, West, North-East, and Shahdara) of Delhi's 11 districts. Dropping wards that comprised only planned, 'regularized' colonies (and hence are relatively economically better off compared to unauthorized settlements and slum dwellings), EB wards were mapped to census wards. These census wards were located within 10 assembly constituencies (ACs). In each AC, ten polling stations (PS) were randomly sampled and 15 households within each PS were sampled through systematic random sampling. Eight additional polling stations were randomly sampled to address interview refusals. Thus, our final sample consists of 108 polling stations and 1,613 households therein. The PSs form our PSUs.

[2] When there were multiple couples in this age group in the household.

[3] The remaining 579 households (1,613 - 1,034) were dropped because of a matching score of < 0.4.

have similar socioeconomic characteristics to those who were interviewed later (Phase 2). Therefore, we present the results using combined data from the two phases.

As most women in our sample do not own a personal phone, the main respondents to our phone survey for all questions, including employment and mental health, were the husbands. However, we also separately asked their wives questions about mental health by asking the husbands, after their interview was complete, to pass the phone to their wives..[4] 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 1,034 pre-pandemic households, where the same individual was interviewed in both surveys..[5] See Figure 2 for more details of the sample creation process.

Our sample data for the employment results comes from both pre-pandemic and post-pandemic surveys, and hence constitutes a panel dataset of 1,779 household observations, comprised of 1,034 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 1,266, of which 737 observations correspond to husbands and the remaining 529 to wives.

Table 1(a) presents the summary statistics for the household characteristics in our sample. The average household has 5.16 members, with an average of 2.3 children. Nearly all households live in *pucca* houses, with two-thirds owning the house they live in. Sixty-one per cent have ration cards, while 76 per cent belong to lower castes. Eighty-three per cent are Hindu and 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 four years older than his wife. They have an average of almost 8 years of formal schooling, compared to 6.7 years in case of their wives. The female employment rate in our sample is significantly low at 18 per cent, compared to 90 per cent for males..[6] Fifty-seven per cent of the males in our sample are daily wage earners in factories and construction or are self-employed in the informal sector (e.g. small retail shops). This demographic group is particularly vulnerable to economic and health shocks and is likely to need significant support through public transfers to tide over the loss of their livelihoods. They live in clusters of households, which include both *jhuggi-jhopri* or slum clusters and authorized residential colonies in which slum dwellers have been resettled by the Delhi government, with very high density, which makes social distancing particularly challenging. Furthermore, assessments by the Central Pollution Control Board point out that these clusters are critically polluted and do not meet air, water, or soil pollution safety parameters, all of which can make these residents particularly vulnerable to the virus (Wu et al. 2020).

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[4] It is possible that some husbands may have been present when their wives gave us their responses to the mental health questions, but even if so, this is likely to bias our findings on women's mental health downwards as women are likely to under-report their anxieties in front of their husbands (much like women under-reporting domestic abuse).

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

[6] According to the Periodic Labour Force Survey (PLFS) conducted by the Ministry of Statistics and Programme Implementation (MOSPI), Government of India, the urban female labour-force participation rate in India was 16.1 per cent in 2018–19.

Moreover, as Table 1(a) shows, although our respondents are not short-term or seasonal migrants but have been residing in Delhi for over 28 years on average, over 65 per cent of the respondents' original state of residence is outside Delhi, primarily Uttar Pradesh (over 40 per cent) and Bihar (9 per cent). Hence, the earnings and incomes of these families may have implications not just for their own welfare but also for their rural relatives through remittances.

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

3.2 Outcome variables

Our main outcome variables of interest are employment and mental health. As mentioned in Section 3.1, we collected self-reported employment data in both the pre-pandemic and post-pandemic surveys, but we collected mental health data only in the post-pandemic survey. Section 3.4 discusses the implications of this data structure for our estimation methods.

Employment

Our first outcome variable of interest is 'employment' or working status. In both the pre-pandemic (individual) and the post-pandemic surveys, the male respondents were asked to report their main occupation in the months prior to the date of interview..[7] In the pre-pandemic survey, if they reported their main occupation as working (labourers, self-employed, and salaried), they were then asked whether they were currently working. In the post-pandemic survey, the current working status of the respondents who were working pre-pandemic was determined after taking account of the number of days worked after lockdown, the income earned during that period, and the type of commute they used to go to work after lockdown..[8] Based on their responses in both surveys, the employment variable for males is constructed as a binary variable equal to 1 if the male respondent was currently employed during the relevant reference period, and 0 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.

Earnings

The second variable of interest is male earnings. In the pre-pandemic (individual) survey, male respondents were asked about their monthly earnings, if employed. In the post-pandemic survey, they were asked to report their total earnings from the first day of the lockdown (24 March 2020) until the date of the survey. In order to make this comparable with the pre-pandemic data, if the

[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 24 March in the post-pandemic survey.

[8] To elaborate further, in the post-pandemic survey an individual is considered to be working if the number of days worked after lockdown is not zero, the income earned is positive, or the respondent did not report 'don't go to work currently' in response to the commute question.

total number of days worked was less than 30, the income reported by the respondent was directly used in the analysis. However, if the number of days worked was more than 30, we calculated income per day and then multiplied it by 30 to derive monthly earnings in the follow-up survey.[9] As the main respondents to the post-pandemic survey were men, we do not have earnings data for women.

Mental health

The third 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 relating specifically to the COVID-19 pandemic. 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 my and my family's health';
Financial stress: 'I feel stressed about my and my family's financial situation';
Depressed: 'I am feeling down, depressed or hopeless';
Sleep disorder: 'I am having sleeping trouble (too much or too little).'

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 which equals 1 if the answer is either 1 or 2, and 0 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 index values, therefore, indicate worse mental health.

3.3 Other constructed variables

Social network variables

In addition to the impact of the pandemic on mental health, we also examined 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 each of eight hypothetical situations.[10] These situations (categories) are as follows:

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

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[9] If, in some cases, income reported during the follow-up survey was positive but the total number of days worked was reported to be zero, then we use the total days since the beginning of the lockdown to the date of the survey to first calculate income per day and then the average monthly earnings.

[10] These friends/dose relatives were not people residing in the same house as the respondent.

The response options were: '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 the answers to all these questions gave us the total number of *friends* for each individual, which ranged from 2 to 16.[11] To avoid any duplication, we performed fuzzy matching between names in pairs of two for all the names provided by the individual. If the matching score between any two names was equal to 1, we reported one observation to be missing for each pair. Then, adding up the answers for all the category questions gave us a total unique number of friends for each individual, ranging from 2 to 13 for females and 2 to 10 for males.

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

(i) 'home-friends' comprised of friends based around the home, including 'parent', 'uncle/aunt', 'cousin/siblings', 'in-laws', 'friends', 'neighbour/friend from nearby lane/block',[12] and 'others';[13] and
(ii) 'work-friends' comprised of friends in workplace i.e.'co-workers'.

We calculated the total number of each of 'home-friends' and 'work-friends' for inclusion in the regression analysis. As Table 1(b) shows, women reported having almost twice as large a social network (6.24 friends on average) than men (3.79 friends on average), but almost all women's friends were around their home. Men also reported having more home-based friends, but around 5 per cent of their friends were from their workplace.

3.4 Methodology

In order to study the impact of the COVID-19 pandemic on employment and earnings, we conducted a before-and-after analysis using the following ordinary least squares (OLS) regression specification:

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

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 0 if it refers to the pre-pandemic time period. The coefficient β captures the average impact of the COVID-19 pandemic. Z_i is a vector of pre-pandemic individual and household socioeconomic characteristics such as age, education, occupation, religion, years of residence, type of house, number of children, number of household members, caste, and native state, etc.

We further explore the differential impact of the pandemic 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):

[11] We use the term 'friends' throughout to denote both friends and dose relatives.

[12] Our results are qualitatively similar if we further disaggregate between home-friends and neighbourhood-friends (available upon request from the authors).

[13] The answers under 'others' were dassified as home-friends as most of the detailed answers induded in this category were related to home-friends.

$$y_{it} = \alpha + \beta PostCovid_t + \gamma Z_i + \delta_1 Wage_i X PostCovid_t + \delta_2 Selfemployed_i X PostCovid_t + \delta_3 Salaried_i X PostCovid_t + \varepsilon_{it} \quad (1a)$$

where the coefficient δ_1 captures the differential impact of the pandemic for casual workers/daily wage earners, δ_2 captures the same for the self-employed, and δ_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.

In order to analyse the gender difference in the mental health experience of the COVID-19 pandemic, we conduct a cross-sectional analysis using the following OLS regression specification:

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

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 0 if male partner. The coefficient δ captures the differential impact of the COVID-19 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, religion, years of residence, type of house, number of children, number of household members, caste, and native state, etc.

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

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

where $Friends_i$ indicates the total number of friends/close relatives reported by individual i. The coefficient π on $Friends_i$ captures the impact of social network size on the mental stress reported by men, while the coefficient on the interaction term μ captures the differential impact of social networks on the mental health of women relative to men. We also explore an extension of equation 2(a) using the disaggregated $Friends$ variables by *type* of social network (as discussed in Section 3.3 above).

4 Impact on employment and earnings

4.1 Men's employment

We find that the COVID-19 pandemic and subsequent lockdown led to a massive shock to the livelihoods of our study participants (see Figure 3). As expected, the vast majority of the workers in these residential areas (approximately 84 per cent of the men) were completely unable to work, and, as suggested by the responses in Phase 2 of our survey, this situation did not improve over time, even after the easing of some restrictions (see Appendix Figure A1).

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 wage earners not attached to one specific sector) were by far the most adversely affected in terms of loss of livelihoods, followed by the self-employed in the informal sector and salaried workers. 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 (see Appendix Figure A2). 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.

These descriptive patterns are also borne out in our regression analysis. We find that men's self-reported employment (working) status declined by 88 pp post pandemic relative to pre-pandemic (see Table 3, column 1). Consistent with our descriptive evidence, we find that wage and casual labourers experienced an almost 5 pp greater employment loss post-pandemic (significant at the 10 per cent level) compared to the omitted group of salaried workers (see Table 3, column 3). However, we cannot reject the equality of coefficients for male wage labourers with that of self-employed men (p-value=0.51)..[14] Whether these reported own job losses were permanent or temporary is something we hope to decipher in subsequent survey rounds.

Many of the respondents surveyed reported relying on friends and family to help them over temporary setbacks. We asked about job losses among their social networks as this would presumably lead to higher levels of stress than otherwise. Seventy-six per cent reported job losses within their family and over 73 per cent within their network of friends and relatives (see Appendix Figure A3). More respondents reported job losses within their social network (family, relatives, and friends) in Phase 2 (77 per cent) compared to Phase 1 (67 per cent). A majority of respondents initially perceived the job losses as temporary (see Appendix Figure A4), but over time there was an increase in the proportion who perceived the job losses in their social network as permanent—from 12 per cent in Phase 1 to 20 per cent 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.

4.2 Men's earnings

Consistent with the pandemic's negative impact on men's employment, we also find that approximately 83 per cent of the respondents reported that they did not earn *any* income from their main occupation during the period of study (see Appendix Figure A1). Moreover, for those who were gainfully employed pre-pandemic, their monthly earnings declined from an average of approximately Rs12,300 pre-pandemic to Rs1,259 during the pandemic, a drop of 89 per cent (see Figure 5). The biggest impact was on casual and wage workers, who experienced a reduction of 98 per cent, followed by self-employed (93 per cent) and salaried workers (82 per cent) (see Figure 6.)

These descriptive patterns are also borne out in our regression analysis. Men's reported (unconditional) monthly incomes declined on average by Rs10,689 during this period, which is approximately 96 per cent of reported baseline incomes (see Table 4, column 1). Men across all occupation types were affected by the negative income shock (Table 4, column 3). We cannot reject the equality of the coefficients for male wage labourers with that of self-employed men (p=0.57)..[15] Hence, irrespective of whether the loss of work was temporary or permanent, households experienced immediate and massive income shocks due to the crisis.

4.3 Women's employment

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

[14] These results remain qualitatively similar if we use the balanced panel, as reported in Appendix Table A2.

[15] These results remain qualitatively similar if we use the balanced panel, as reported in Appendix Table A3.

men's employment, we do not find any significant change in reported women's employment post pandemic (see Table 5, 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 5, column 3) but not statistically significantly different from the omitted group of salaried workers. We cannot reject the equality of the coefficients for female wage labourers with that of self-employed women (p-value=0.59).[16] We did not collect information on women's earnings postcrisis.

5 Impact on mental health

Emerging evidence points to significant increases in mental and emotional stress across the world as a result of the COVID-19 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 the UK, USA, and European nations (Banks and Xu 2020; Etheridge and Spantig2020; Kuan-Yu et al. 2020; McGinty et al. 2020; Pierce et al. 2020; Proto and Quintana-Domeque 2021), we know little about the impact of the pandemic on the mental health of 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 per cent) and health concerns (85 per cent). Consistent with emerging evidence (Banks and Xu 2020; Etheridge and Spantig 2020; Proto and Quintana-Domeque 2021), women appear to be suffering from greater mental stress than men (see Figure 7). For example, nearly 90 per cent of women reported feeling worried about the physical health of their families compared to 85 per cent of men. Sixty-six per cent of men and 70 per cent of women reported feeling depressed about their situation. 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 per cent of women felt anxious or nervous about the current situation compared to 64 per cent of men, while 50 per cent of women and 43 per cent of men reported having trouble getting adequate sleep.

The overall descriptive patterns are also borne out in our regression analysis which attempts to systematically examine the gender difference in the mental health experience of the COVID-19 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 7. Women report 0.234 standard deviation greater mental stress compared to men (Table 6, column 1). The key aspects of women's stress appear to be anxiety and nervousness, followed by sleeplessness and health worries (see columns 2–6). Women also appear to suffer more health stress compared to men, but not more financial stress.

5.1 Role of pandemic-induced loss of employment

As the COVID-19 pandemic has led to a massive loss of livelihoods, we examine whether such post-pandemic employment losses are directly correlated with worse mental health outcomes during the pandemic and differ by gender. We find that, for men, remaining employed during the pandemic is negatively correlated with their mental stress (see Table 7, column 1), primarily through the lowering of financial stress (Table 7, column 2). Employed men reported 0.68 standard

[16] These results remain qualitatively similar if we use the balanced panel, as reported in Appendix Table A4.

deviation lower mental stress, and a 0.25 lower likelihood of experiencing financial stress. In contrast, women who continued to work during the pandemic (but whose husbands were unemployed) reported 0.22 standard deviation higher mental stress post-pandemic compared to their unemployed counterparts, both overall and across all stress types. This may be indicative of the internalization by *women* of the 'male breadwinner' gender norms, which were severely disrupted by the pandemic-induced employment losses suffered by men.

Given the pre-existing gendered nature of employment in our sample, and the widespread employment losses, we also examine the implications of spousal employment on individual mental well-being post pandemic. We find that spousal (wife's) employment is positively correlated with men's reported mental stress, driven primarily by health worries likely caused by husbands' concerns about their wives' exposure to the virus when they went out to work. Men whose wives remained employed during the pandemic reported 0.166 standard deviation increase in overall mental stress, and a 0.09 greater likelihood of experiencing health worries. Further, we also find that spousal employment during the pandemic is positively correlated with reported depression among men and could again be reflecting internalized gender attitudes relating to the traditional 'male breadwinner' model among *men*, which was severely disrupted by the pandemic-induced employment losses that men suffered.

In contrast, spousal employment is negatively correlated with women's mental stress. In other words, the negative economic impact of the pandemic on men's employment and earnings played a key role in heightening mental stress among their wives. Wives whose husbands lost their livelihood during the pandemic reported 0.75 standard deviation greater mental stress, while these men themselves reported a smaller increase of 0.68 standard deviations in their mental stress.[17]

5.2 Role of social 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. They highlight the 'stress-buffering' role of networks for individuals in crisis through the provision of economic and psychological support. On the other hand, Kawachi and Berkman (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 role played by social networks in mental stress during the pandemic. For this purpose, we exploit rich social network data that we collected in our pre-pandemic survey, as described in Section 3.3. We find that the size of the pre-pandemic social network, as measured by the total number of (unique) friends, is associated with lower post-pandemic mental stress for men.[18] Men with larger social networks reported 0.086 standard deviation lower mental stress during COVID-19 compared to those without (Table 8, column 2). However, this pattern is reversed for women, such that women with larger pre-pandemic social networks reported, on average, 0.035 standard deviation *higher* mental stress than those without. In other words, social networks appear to play a mitigating role for

[17] The results are robust to the indusion of relevant baseline control variables and their respective interactions with gender (see Appendix Table A6).

[18] Our results remain robust if we use total number of friends (induding duplication) instead of total 'unique' friends (see Appendix Table A5).

men's mental health but an exacerbating role for women's mental health, especially in times of crisis. One interpretation of this difference could be that women, with larger pre-pandemic social connections and who are hence more reliant on social networks, suffered a bigger mental health impact from the pandemic-induced lockdown, which curtailed interactions with friends and extended family, relative to men.

To investigate further, we disaggregate the network effect by *type* of social network, in terms of 'home-friends' and 'work-friends'. We find that the positive association between pre-pandemic network size and post-pandemic mental stress for women appears to be entirely driven by what we call the 'home-bound' nature of women's networks, in particular 'home-friends' (Table 8, column 3). While, for men, having an additional 'home-friend' is associated with 0.088 standard deviation lower reported mental stress, for women, this is associated with an additional 0.035 standard deviation *higher* reported mental stress. In contrast, having more 'work-friends' is associated with lower reported mental stress for *both* men and women, although neither is statistically significant.

Next, we attempt to unpack the competing mechanisms that can explain the observed relationship between type of network and mental health. The gender-disaggregated analysis of how pre-pandemic networks are utilized in our sample shows that women are more dependent on their home-bound networks for social and recreational support (e.g., going for walks to the park, to the market, and social events), relative to men (see Table 9). It therefore appears that social distancing may have resulted in greater stress among women due to the loss of home-bound friends' support during the crisis, linked to the 'stress-buffering' role of social ties.

However, if this mechanism holds, then women who own mobile phones should experience lower levels of mental stress because they would have been able to continue to remain connected to their home-based networks through their phones. To examine this in greater detail, we analyse the implications for mental well-being in our sample by pre-pandemic 'type of network' and pre-pandemic 'mobile ownership', differentiated by gender. Contrary to expectations, we find that women who own mobile phones reported higher post-pandemic mental stress in the case of their home-bound friends (see Table 8, column 4), while the opposite holds for men. To obtain a deeper understanding of the underlying mechanism, we further analyse the role of the frequency of our participants' reported interactions with friends by phone, conditional on phone ownership, for a subset of their four closest friends for whom this data was collected. Although no longer statistically significant, the positive coefficient on the triple interaction term 'wife*home-friend*phone interactions' suggests that women who enjoyed greater phone interaction with their home-friends before the pandemic report higher post-pandemic mental stress (see Table 8, column 5). In contrast, the opposite is true for men. We can reject the equality of these coefficients vis-à-vis home-friends at the 10 per cent significance level ($p=0.08$), but not for work-friends ($p=0.75$). Note that mobile ownership is less likely to be subject to measurement error as compared to frequency of interactions. While we cannot ascribe causal interpretations to this analysis, it is interesting nevertheless to understand the correlates of the observed gender differences in post-pandemic mental well-being.

Hence, we tentatively conclude that women, irrespective of their loss of connection with their social network due to social distancing, experienced greater stress the larger the size of their home-bound networks. This result points to the 'stress-contagion' role rather than the 'stress-buffering' role of the home-bound social networks for women, but not men.

6 Conclusion

We use data from poor households and individuals in urban India for before (May to July 2019) and after (April to 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 panel 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 was mediated by the size and nature of social networks.

In line with the emerging evidence, we estimate a large negative shock to men's employment status immediately following the shutdown of economic activity due to the nationwide lockdown, relative to the pre-pandemic period. This was also accompanied by a drastic reduction in men's monthly earnings. In contrast, we do not find any significant impact on women's employment.

In contrast to the extensive documentation of the impact of the crisis on livelihoods, however, there is almost a complete absence of data on mental well-being in India and other developing countries. We fill this lacuna by documenting significant psychological impacts due to the financial and health-related concerns surrounding the pandemic (higher amongst women than men), which increased with the extension of the lockdown in our sample. Surprisingly, larger social networks are associated with a lower adverse emotional impact of the pandemic for men, but not for women. We provide suggestive evidence that this appears to be driven by the 'stress-contagion' role rather than the 'stress-buffering' role of home-bound social networks for women, but not men.

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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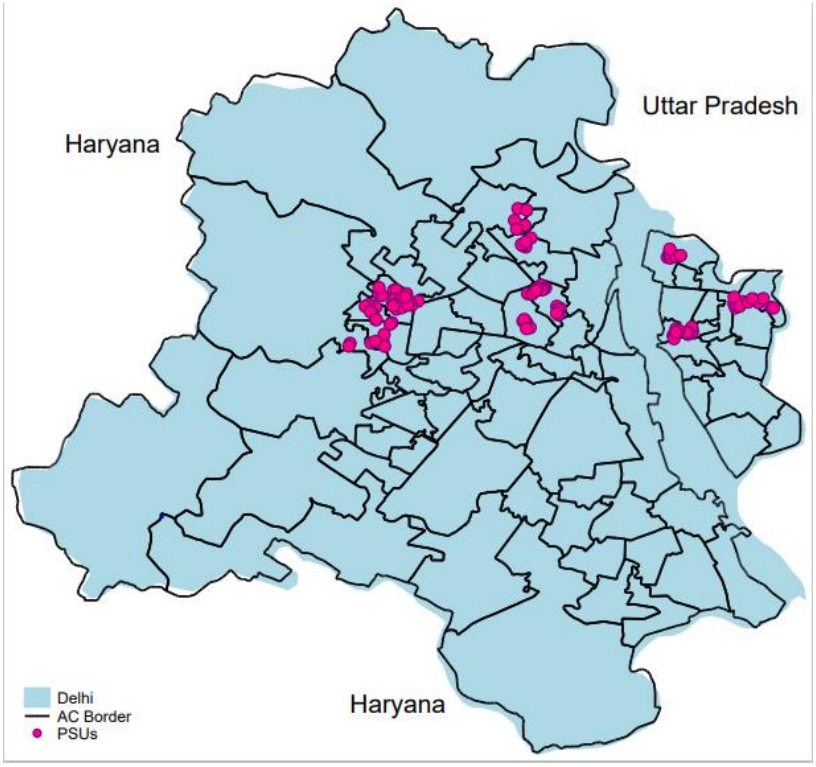
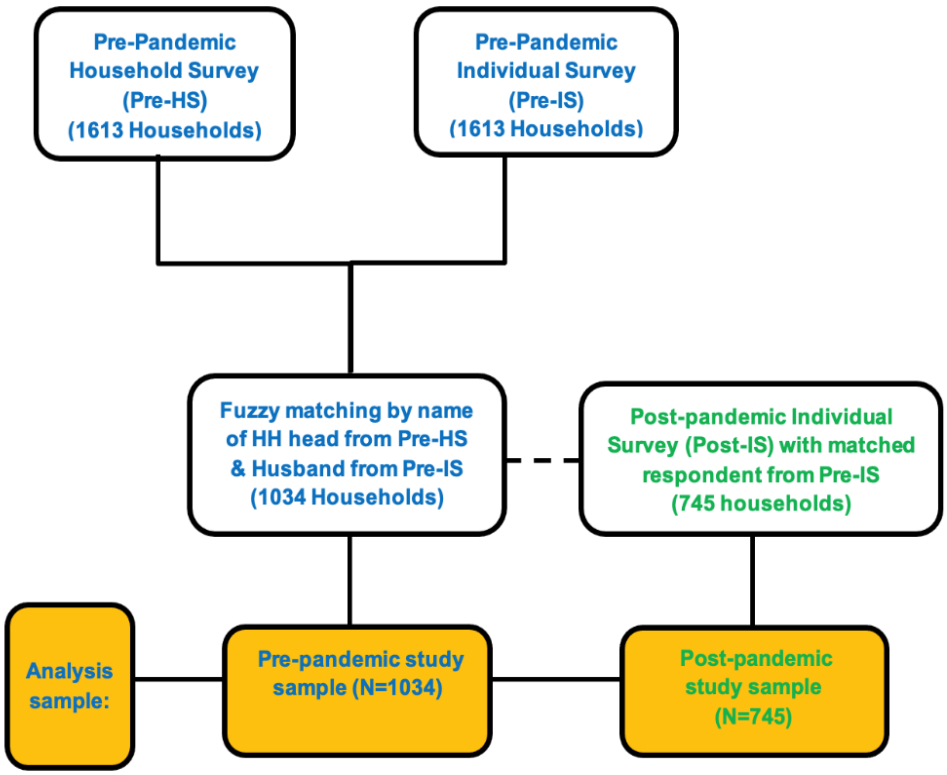
Figure 1: Sample selection—108 primary survey units



Note: this figure is a graphical representation of our sample area for this study. The area shaded in blue represents the entire Delhi region, and the pink dots denote the 108 primar ysurvey units (PSUs) 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.

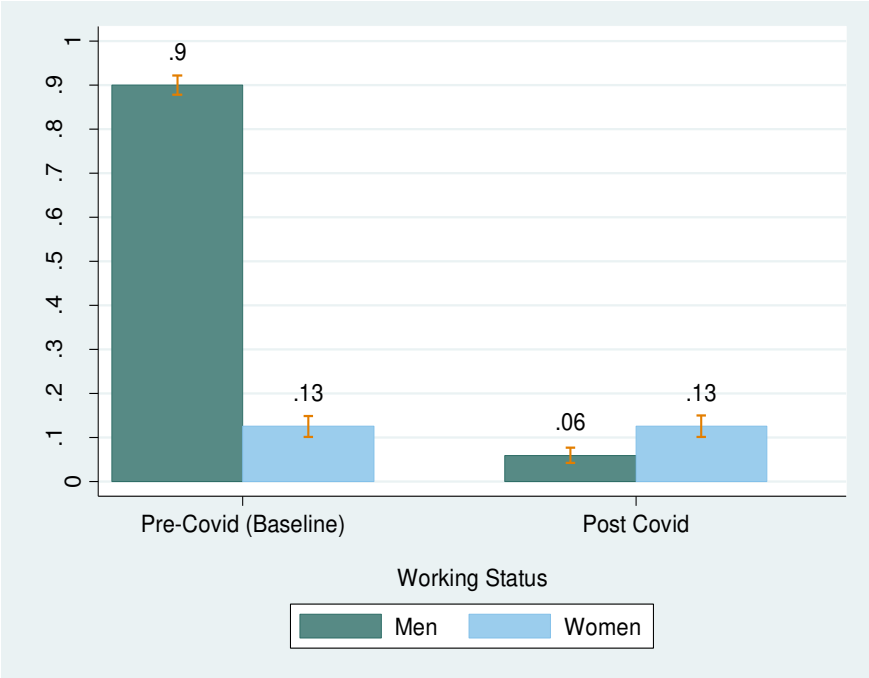
Source: authors' calculations based on Census 2001 (Government of India 2001) and pre-pandemic data.

Figure 2: Sample creation flowchart



Source: authors' calculations based on pre-pandemic and post-pandemic data.

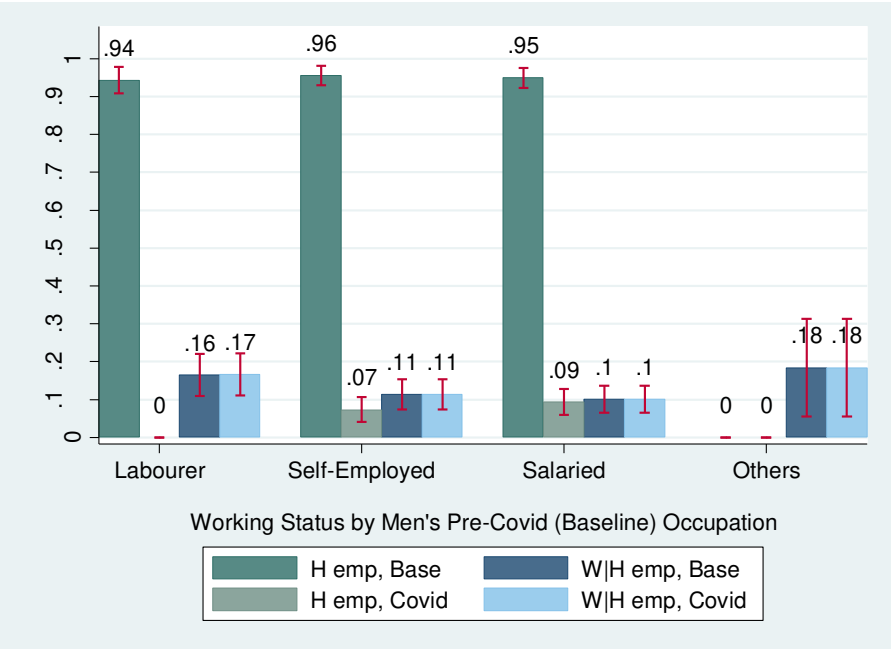
Figure 3: Employment status before and during COVID-19, by gender



Note: this figure illustrates the percentage of those employed (working) before and after theCOVID-19 pandemic, by gender. The sample size for pre-COVID (post-COVID) survey is 740 (744) and 743 (741) observations for husbands and wives respectively.

Source: authors' calculations based on pre-pandemic and post-pandemic data.

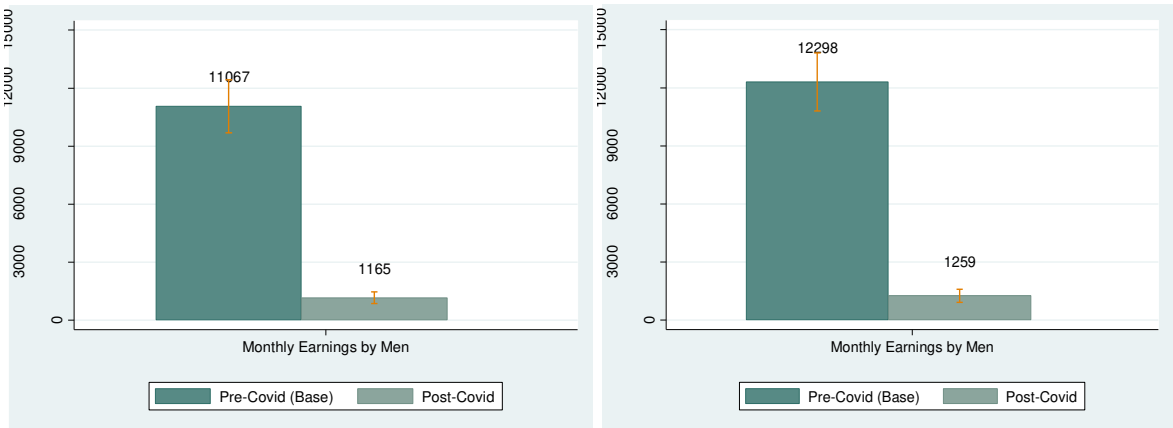
Figure 4: Employment status before and during COVID-19, by gender and pre-COVID-19 occupation



Note: this figure illustrates the percentage of those employed (working) before and during the COVID-19 pandemic, by gender and pre-pandemic (baseline) occupation. The sample size for the pre-COVID (post-COVID) survey is 740 (744) and 743 (741) observations for husbands and wives respectively.

Source: authors' calculations based on pre-pandemic and post-pandemic data.

Figure 5: Monthly earnings by men, before and during COVID-19

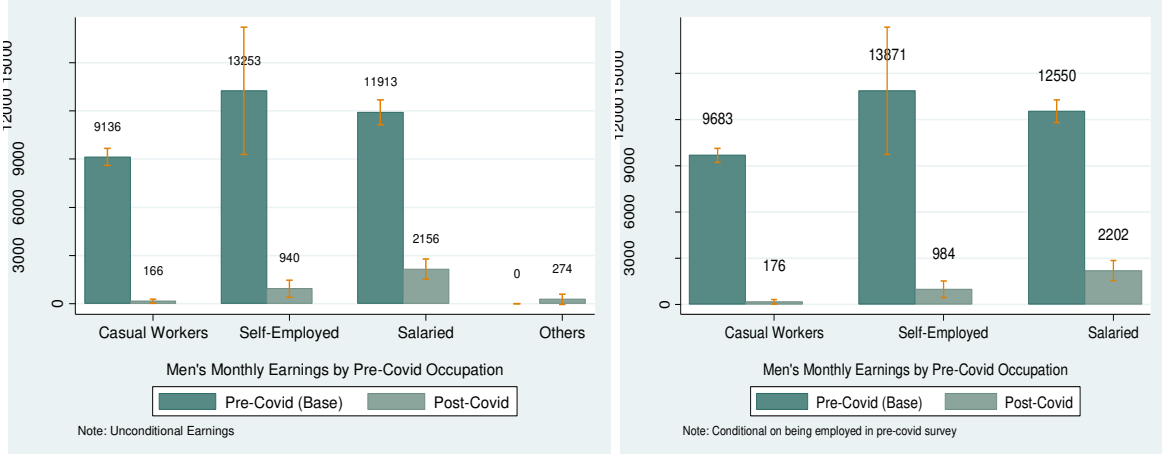


A. Unconditional **B. Conditional on baseline employed**

Note: this figure illustrates the average monthly earnings before and after theCOVID-19 pandemic for men. Figure 5A denotes unconditional earnings, which takes the value 0 if the respondent is unemployed. Figure 5B denotes earnings conditional on respondents being employed during the pre-pandemic (baseline) survey. The sample size for the unconditional earnings (conditional earnings) survey is 739 (665) and 739 (661) observations for the pre- and post-pandemic surveys respectively.

Source: authors' calculations based on pre-pandemic and post-pandemic data.

Figure 6: Monthly earnings by men, before and during COVID-19, by baseline occupation

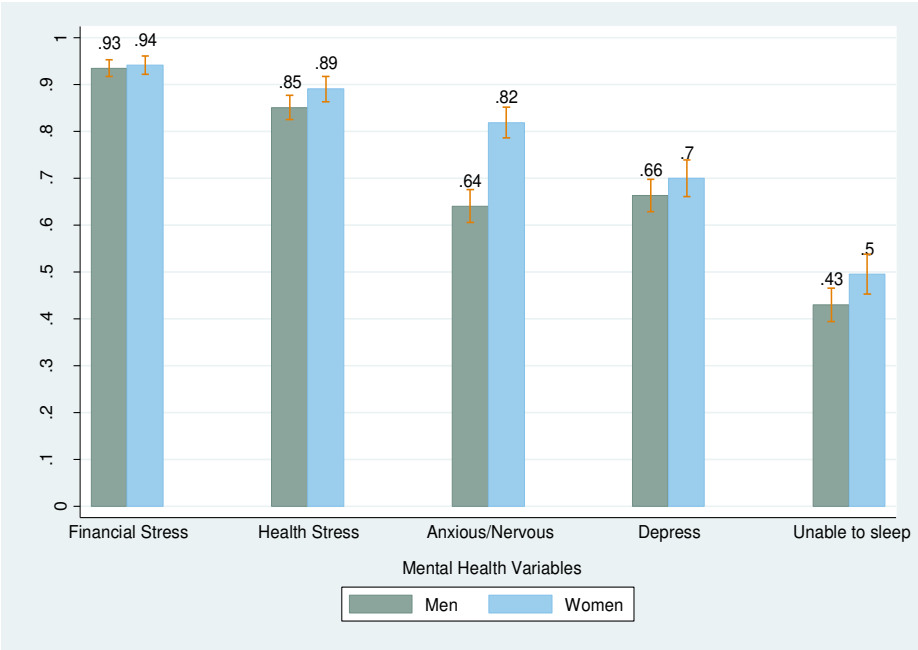


A. Unconditional **B. Conditional on baseline employed**

Note: this figure illustrates the average monthly earning sbefore and after the COVID-19 pandemic for men, by their pre-pandemic (baseline) occupation status. Figure 6A denotes unconditional earnings, which takes the value 0 if the respondent is unemployed. Figure 6B denotes earnings conditional on respondents being employed during pre-pandemic (baseline) survey. The sample size for the unconditional earnings (conditional earnings) survey is 739 (665) and 739 (661) observations for the pre- and post-pandemic surveys.

Source: authors' calculations based on pre-pandemic and post-pandemic data.

Figure 7: Mental health outcomes, by gender



Note: this figure shows the female and male participants' responses to the different mental health questions during the COVID-19 pandemic, as discussed in Section 3.2. The overall sample covers the period from 3 April to 9 May. Thesample sizes for women and men are 529 and 741 respectively. The reference period for all respondents was from 25 March until the date of survey.

Source: authors' calculations based on post-pandemic data.

Table 1(a): Pre-COVID-19 household characteristics

	N	Mean	SE
No. of householdmembers	745	5.16	0.06
No. of years in currentlocation	745	28.29	0.5
No. of children	722	2.26	0.05
Has*pucca*house (0/1)	745	0.96	0.01
Ownshouse (0/1)	745	0.66	0.02
Hasrationcard (0/1)	744	0.61	0.02
Caste	738		
Scheduledcaste		0.41	0.02
Scheduledtribe		0.02	0.01
Otherbackwardcaste		0.33	0.02
General		0.24	0.02
Hindu (0/1)	745	0.83	0.01
Meanassetindex	745	1.81	0.02
Meanassetindex of bottom 25th percentile	745	0.91	0.02
Meanassetindex of top 25th percentile	745	2.59	0.02
Householdheadfrom Delhi (0/1)	745	0.35	0.02

Note: this table presents the pre-COVID-19 pandemic household characteristics of the 745 households that are common in the pre-pandemic and post-pandemic surveys. 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 1,034 households. Of these 1,034 households, the same individual was interviewed in 745 households during the post-pandemic survey. The asset 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, air conditioning, computer, mobile, and sewing machine. Further, using this continuous asset index, we constructed a categorical variable which divides the population into four cohorts:below the 25th percentile, below 50th percentile, between 50th and 75th percentile, and below 75th percentile.

Source: authors' calculations based on pre-pandemic data.

Table 1(b): Pre-COVID-19 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
Employed (0/1)	723	0.18	0.01	740	0.90	0.01
Monthlyincome, unconditional (in Rs)	723	758	83	739	11,067	698
Monthlyincome, ifemployed (in Rs)	129	4,240	324	665	12,298	761
Total friends	723	6.24	0.10	740	3.79	0.06
Total uniquefriends	723	5.51	0.07	740	3.54	0.05
Unique home-friends	723	5.48	0.07	740	3.35	0.05
Uniquew ork-friends	723	0.03	0.01	740	0.19	0.02

Note: this table presents the pre-COVID-19 pandemic individual characteristics of the 745 households common in the pre-pandemic and post-pandemic surveys. Fuzzy matching using household head's name from the pre-pandemic household survey and husband's name from the pre-pandemic individual survey created the pre-pandemic sample of 1,034 households. Of these 1,034 households, the same individual w as interview ed in 745 households during the post-pandemic survey. The 'employed' variable show s the percentage of people currently in employment/w orking from the total sample at baseline. The construction of the 'total friends' and 'total unique friends' variables, as w ell as the'home-friends' and 'w ork-friends' variables is discussed in Section 3.3. of the paper.

Source: authors' calculations based on pre-pandemic data.

Table 2: Attrition checks by baseline characteristics between pre- and post-covid-19 surveys

	Pre-COVID-19			Post-COVID-19			Difference	
	N	mean	SE	N	mean	SE	Mean	SE
Household characteristics								
No. of household members	1,034	5.2	0.05	745	5.16	0.06	-0.04	0.03
No. of years in current location	1,034	28.56	0.43	745	28.29	0.5	-0.25	0.28
No. of children	1,005	2.26	0.04	722	2.26	0.04	0.00	0.03
Has *pucca* house (0/1)	1,034	0.96	0.01	745	0.96	0.01	0.00	0.00
Owns house (0/1)	1,034	0.65	0.02	745	0.66	0.02	0.01	0.01
Has ration card (0/1)	1,034	0.62	0.02	745	0.61	0.02	-0.01	0.01
Caste	1,022			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)	1,034	0.82	0.01	745	0.83	0.01	0.01*	0.01
Mean asset index	1,034	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)	1,032	0.35	0.02	743	0.35	0.02	0.00	0.01
Individual characteristics								
Wife's age (years)	1,006	30.97	0.19	723	31.1	0.22	0.11	0.13
Husband's age (years)	1,028	35	0.19	740	35	0.22	0.00	0.14
Wife's education (years)	1,006	6.69	0.14	723	6.69	0.16	0.00	0.01
Husband's education (years)	1,028	7.54	0.12	740	7.88	0.14	0.34***	0.01
Wife's occupation	1,006			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	1,028			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 is employed (0/1)	1,006	0.20	0.01	723	0.18	0.01	-0.02*	0.01
Husband is employed (0/1)	1,028	0.90	0.01	740	0.90	0.01	0.00	0.01
Wife's monthly earning (Rs)	1,006	894	83	723	759	322	-135	64.29
Husband's monthly earnings (Rs)	1,025	11,080	628	739	11,067	698	-13	450

Note: 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%. The 'employed' variable shows the percentage of people currently in employment from total sample at the baseline and 'monthly income' is the average unconditional monthly earnings.

Source: authors' calculations based on pre-pandemic and post-pandemic data.

Table 3: Impact on male employment, by occupation

	Men's self-reported employment		
	(1)	(2)	(3)
Post-COVID-19	-0.883***	-0.883***	-1.073***
	(0.014)	(0.014)	(0.120)
Husband is labourer at baseline		-0.048***	-0.029
		(0.014)	(0.022)
Husband is self-employed at baseline		-0.008	0.004
		(0.011)	(0.015)
Wife is labourer at baseline		-0.063*	-0.075**
		(0.033)	(0.033)
Wife is self-employed at baseline		-0.059*	-0.070***
		(0.034)	(0.027)
Wife is housewife at baseline		-0.060**	-0.056***
		(0.027)	(0.013)
Post-Covid19*Husband is labourer at baseline			-0.047*
			(0.027)
Post-Covid19*Husband is self-employed at baseline			-0.030
			(0.027)
Post-Covid19*Wife is labourer at baseline			0.035
			(0.084)
Post-Covid19*Wife is self-employed at baseline			0.032
			(0.078)
Post-Covid19*Wife is housewife at baseline			-0.007
			(0.065)
Constant	0.922***	1.027***	1.104***
	(0.047)	(0.053)	(0.060)
Adj. R-sq.	0.78	0.78	0.78
Controls	Yes	Yes	Yes
Post-COVID-19*Controls	No	No	Yes
N	1,561	1,561	1,561

Note: the dependent variable denotes the self-reported employment status of men before and after the COVID-19 pandemic. It is a binary variable, where 1 represents employed, and 0 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. For this table, we use respondents who reported their pre-COVID-19 main occupation as working (labourers, self-employed, and salaried), resulting in 953 pre-pandemic and 688 post-pandemic observations, amounting to a total sample size of 1,643 observations. Owing to missing values in independent variables, as shown in this table, the sample size further reduced to 1,563. Here, the reference category for own and spouse's occupation is salaried. The baseline controls include low caste dummy, Hindu (religion) dummy, house type, household head native state dummy, number of years living in a location, owns a ration card dummy, own flat dummy, number of household members, asset index, age and education of the respondents. Standard errors clustered at PSU are reported in parentheses. Significant at $*$10%, $**$5%, and $***$1%.

Source: authors' calculations based on pre-pandemic and post-pandemic data.

Table 4: Impact on male earnings, by occupation

	(1)	(2)	(3)
		Men's monthly earnings	
Post-COVID-19	-10689.608***	-10694.158***	3599.419
	(759.086)	(764.964)	(6487.470)
Husband is labourer at baseline		-1468.898*	-1267.037
		(816.051)	(1434.242)
Husband is self-employed at baseline		-644.161	-301.330
		(1144.876)	(2011.356)
Wife is labourer at baseline		-890.800	-757.919
		(794.660)	(1243.627)
Wife is self-employed at baseline		-1512.931*	-1412.023
		(798.879)	(1109.104)
Wife is housewife at baseline		-355.599	550.717
		(766.873)	(1340.105)
Post-COVID-19*Husband is labourer at baseline			-434.926
			(1464.357)
Post-COVID-19*Husband is self-employed at baseline			-853.601
			(2061.048)
Post-COVID-19*Wife is labourer at baseline			-675.581
			(1834.091)
Post-COVID-19*Wife is self-employed at baseline			-3.385
			(1607.141)
Post-COVID-19*Wife is housewife at baseline			-2095.598
			(1919.078)
Constant	4133.721	5823.755*	129.315
	(2975.223)	(3471.273)	(6209.891)
Adj. R-sq.	0.11	0.11	0.11
Controls	Yes	Yes	Yes
Post-COVID-19*Controls	No	No	Yes
N	1,554	1,554	1,554

Note: the dependent variable denotes the unconditional average monthly earnings of men before and after the COVID-19 pandemic. The variable is continuous and takes value 0 if the respondent is not employed. This regression analysis is performed on a dataset where each observation has two separate rows: one for the pre-pandemic value and the other for the post-pandemic value. For this table, we use respondents who reported their pre-COVID-19 main occupation as working (labourers, self-employed, and salaried), resulting in 950 pre-pandemic and 685 post-pandemic observations, amounting to a total sample size of 1,635 observations. Owing to missing values in independent variables, as shown in this table, the sample size further reduced to 1,554. Here, the reference category for own and spouse's occupation is salaried. The baseline controls include low caste dummy, Hindu (religion) dummy, house type, household head native state dummy, number of years living in a location, owns a ration card dummy, own flat dummy, number of household members, asset index, age and education of the respondents. Standard errors clustered at PSU are reported in parentheses. Significant at *10%, **5%, and ***1%.

Source: authors' calculations based on pre-pandemic and post-pandemic data.

Table 5: Impact on female employment, by occupation

	(1)	(2)	(3)
	Women's employment as reported by husband		
Post-COVID-19	-0.004	-0.000	-0.005
	(0.008)	(0.005)	(0.070)
Husband is labourer at baseline		-0.003	0.000
		(0.024)	(0.023)
Husband is self-employed at baseline		-0.006	-0.006
		(0.019)	(0.020)
Wife is labourer at baseline		-0.091	-0.070
		(0.073)	(0.070)
Wife is self-employed at baseline		-0.339***	-0.330***
		(0.080)	(0.081)
Wife is housewife at baseline		-0.704***	-0.698***
		(0.058)	(0.055)
Post-COVID-19*Husband is labourer at baseline			-0.008
			(0.016)
Post-COVID-19*Husband is self-employed at baseline		-0.000	
			(0.013)
Post-COVID-19*Wife is labourer at baseline			-0.053
			(0.054)
Post-COVID-19*Wife is self-employed at baseline			-0.023
			(0.064)
Post-COVID-19*Wife is housewife at baseline			-0.014
			(0.042)
Constant	0.085	0.775***	0.779***
	(0.106)	(0.105)	(0.104)
Adj. R-sq.	0.05	0.47	0.46
Controls	Yes	Yes	Yes
Post-COVID-19*Controls	No	No	Yes
N	1,558	1,558	1,558

Note: the dependent variable denotes the employment status of women as reported by their husbands before and after the COVID-19 pandemic. It is a binary variable, where 1 represents employed, and 0 otherwise. This regression analysis is performed on a dataset where each observation has two separate rows: one for the pre-pandemic value and the other for the post-pandemic value. For this table, we use respondents who reported their pre-COVID-19 main occupation as working (labourers, self-employed, and salaried), resulting in 958 pre-pandemic and 688 post-pandemic observations, amounting to a total sample size of 1,646 observations. Owing to missing values in independent variables, as shown in this table, the sample size further reduced to 1,558. Here, the reference category for own and spouse's occupation is salaried. The baseline controls include low caste dummy, Hindu (religion) dummy, house type, 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 the respondents. Standard errors clustered at PSU are reported in parentheses. Significant at *10%, **5%, and ***1%.

Source: authors' calculations based on pre-pandemic and post-pandemic data.

Table 6: Impact on mental health, by gender

	(1)	(2)	(3)	(4)	(5)	(6)
	Mental stress	Financial stress	Health stress	Nervous/ anxiety	Depressed	Sleep disorder
Wife	0.234***	0.007	0.040**	0.178***	0.036	0.066***
	(0.036)	(0.011)	(0.017)	(0.022)	(0.024)	(0.023)
Constant	-0.117*	0.935***	0.851***	0.640***	0.663***	0.429***
	(0.062)	(0.010)	(0.018)	(0.024)	(0.024)	(0.031)
Adj. R-sq.	0.01	0.00	0.00	0.04	0.00	0.00
N	1,266	1,266	1,266	1,266	1,265	1,265

Note: the dependent variable in column 1 is a standardized mental health variable as described in Section 3.2 of the paper, where higher values indicate worse mental health. The remaining dependent variables in columns 2–6 are the components of the standardized variable, as described in Section 3.2. There are 737 observations for men and 529 for women, giving a total of 1,266 observations. Standard errors clustered at PSU are reported in parentheses. Significant at ∗10%, ∗∗5%, and ∗∗∗1%.

Source: authors' calculations based on post-pandemic data.

Table 7: Impact on mental health, by gender: role of post-COVID-19employment loss

	(1)	(2)	(3)	(4)	(5)	(6)
	Mental stress	Financial stress	Health stress	Nervous/ anxiety	Depressed	Sleep disorder
Wife	0.209***	-0.007	0.045**	0.182***	0.019	0.053**
	(0.040)	(0.011)	(0.019)	(0.026)	(0.025)	(0.023)
Employed Post-COVID-19	-0.683***	-0.252***	-0.095	-0.143*	-0.288***	-0.181**
	(0.169)	(0.061)	(0.064)	(0.076)	(0.075)	(0.075)
Wife*Employed Post-covid-19	0.906***	0.311***	0.154**	0.183**	0.394***	0.229**
	(0.196)	(0.063)	(0.073)	(0.084)	(0.093)	(0.097)
SpouseEmployed Post-COVID-19	0.166*	-0.000	0.090***	0.074	0.068*	0.000
	(0.087)	(0.026)	(0.031)	(0.047)	(0.040)	(0.056)
Wife*SpouseEmployed Post-COVID-19	-0.917***	-0.270***	-0.307***	-0.324***	-0.253**	-0.132
	(0.287)	(0.095)	(0.097)	(0.103)	(0.114)	(0.114)
Constant	-0.103	0.949***	0.844***	0.639***	0.669***	0.437***
	(0.067)	(0.011)	(0.020)	(0.027)	(0.026)	(0.033)
Adj. R-sq.	0.04	0.05	0.01	0.04	0.02	0.01
N	1,259	1,259	1,259	1,259	1,258	1,258

Note: the dependent variable in column 1 is a standardized mental health variable as described in Section 3.2 of the paper, where higher values indicate worse mental health. The remaining dependent variables in columns 2–6 are the components of the standardized variable, as described in Section 3.2. There are 737 observations for men and 529 for women, giving a total of 1,266 observations. Owing to missing values in pre-COVID-19 employment data, the sample size has truncated to 1,259 observations. Standard errors clustered at PSU are reported in parentheses. Significant at ∗10%, ∗∗5%, and ∗∗∗1%.

Source: authors' calculations based on post-pandemic data.

Table 8: Impact on mental health, by gender: role of social networks

	(1)	(2)	(3)	(4)	(5)
			Mental stress		
Wife	0.234***	-0.796**	-0.796**	-0.201	-0.161
	(0.036)	(0.337)	(0.335)	(0.429)	(0.522)
Total friends		-0.086**			
		(0.029)			
Wife*Total friends		0.121***			
		(0.037)			
Home-friends			-0.088**	0.116**	-0.061
			(0.029)	(0.045)	(0.084)
Wife*Home-friends			0.123***	-0.086	0.015
			(0.037)	(0.057)	(0.134)
Work-friends			-0.052	-0.183	-0.121
			(0.071)	(0.277)	(0.199)
Wife*Work-friends			-0.075	0.248	-0.195
			(0.137)	(0.735)	(0.634)
Owns mobile				0.520***	
				(0.249)	
Wife*Owns mobile				-0.519	
				(0.361)	
Owns mobile*Home-friends				-0.223***	
				(0.052)	
Wife*Owns mobile*Home-friends				0.234***	
				(0.067)	
Owns mobile*Work-friends				0.138	
				(0.286)	
Wife*Owns mobile*Work-friends				-0.347	
				(0.751)	
Phone interactions					0.611
					(0.380)
Wife*phone interactions					-1.021
					(0.704)
Home-friend*phone interactions					-0.209
					(0.136)
Wife*Home-friend*phone interactions					0.314
					(0.207)
Work-friend*phone interactions					0.042
					(0.268)
Wife*Work-friend*phone interactions					-0.297
					(0.957)
Constant	-0.117*	0.501*	0.503	-0.066	0.420
	(0.062)	(0.301)	(0.303)	(0.379)	(0.385)
Adj. R-sq	0.01	0.06	0.06	0.06	0.06
Controls	No	Yes	Yes	Yes	Yes
Wife*Controls	No	Yes	Yes	Yes	Yes
N	1,266	1,225	1,225	1,225	1,175

Note: the dependent variable is a standardized mental health variable as described in Section 3.2 of the paper, where higher values indicate worse mental health. There are 737 observations for men and 529 for women, giving a total of 1,266 observations, as shown in column 1. Total friends are total number of uniquefriends for each individual as described in Section 3.3 of the paper. 'Home-friends' comprise unique friends based around home, including 'parent', 'uncle/aunt', 'cousin/siblings', 'in-laws', 'friends', 'neighbour/friend from nearby lane/block', and

'others, while 'work-friends' comprise unique co-workers. In column 5, the' phone interactions 'variable equals 1 if frequency of pre-pandemic phone interactions between respondent and their friend is weekly or more, and 0 otherwise. This information is available for their four closest friends, as ranked by them. 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, asset index, age and education of the respondents, and employment status post-COVID-19 of the respondents. Post-pandemic employment statuses of men and women are also included as controls. Standard errors clustered at PSU are reported in parentheses. Significant at ∗10%, ∗∗5%, and ∗∗∗1%.

Source: authors'calculations based on pre-pandemic (friends variable) and post-pandemic data.

Table 9: Nature of dependencies in social networks, by gender

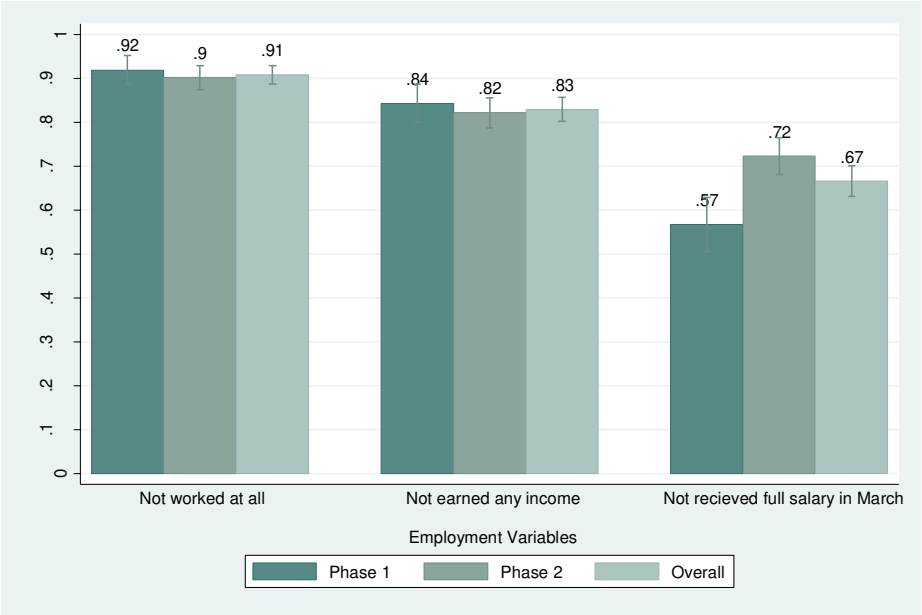
Proportion of friendsused to:	Men	Women
Borrow money	0.98	0.96
Medicalemergency	0.87	0.88
Food emergency	0.31	0.60
Going to park	0.30	0.87
Going to market	0.07	0.40
Going to festivals/religiousevents	0.09	0.38
Going for lunch at work	0.14	0.15
Travel to work	0.04	0.02

Note: this table denotes the proportion of respondents with friends in each category. The respondents were asked to report a maximum of two names for each category. The eight category questions asked were as follows: i) who would they borrow Rs400–500 from for a day in case of emergency; ii) who would theycontact if needed to rush to the hospital/doctor; iii) who would they contact to borrow food items like cooking oil, sugar, etc. Immediately from the neighbourhood; iv) who would they like to go for a walk or chat with in free time; v) who would they go with for shopping orto local market to buy groceries etc; vi) who would they approach for attending social functions or religious events like going to temple/mosque etc. together; vii) who would they have lunch with or spend free time with at work; viii) and who are their preferred friends to travel to work with.

Source: authors' calculations based on pre-pandemic data.

Appendix

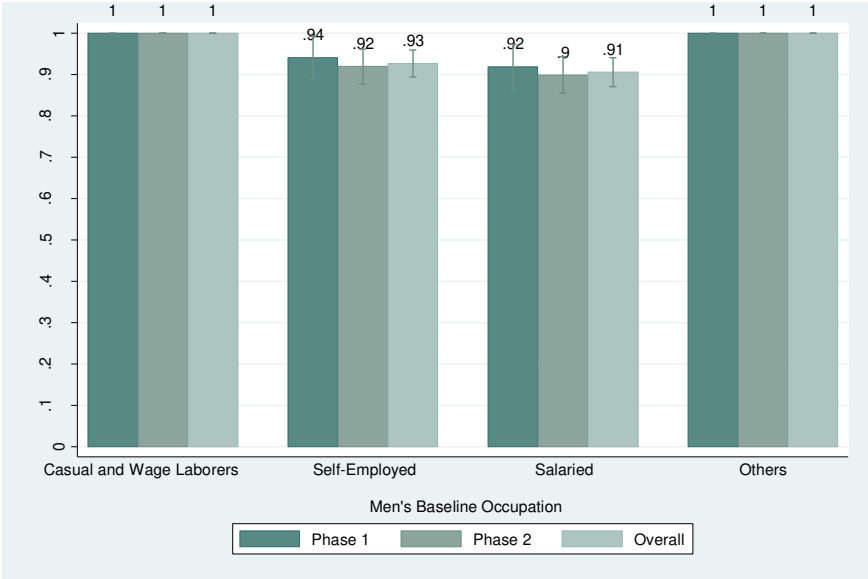
Figure A1: Men's employment status during COVID-19



Note: this figure depicts the employment status of men during the lockdown based on three issues:did not work at all; did not earn any income during lockdown from 24 March 2020); and did not receive full salary in the month of March. The overall sample covers the period from 3 April to 9 May. Phase 1 refers to respondents surveyed between 3 April and 19 April, and Phase 2 refers to respondents surveyed between 20 April and 9 May. Phase 1 consists of 268 data points, and Phase 2 consists of 477 data points. The reference period for all respondents was from 25 March until the date of survey.

Source: authors' calculations based on post-pandemic data.

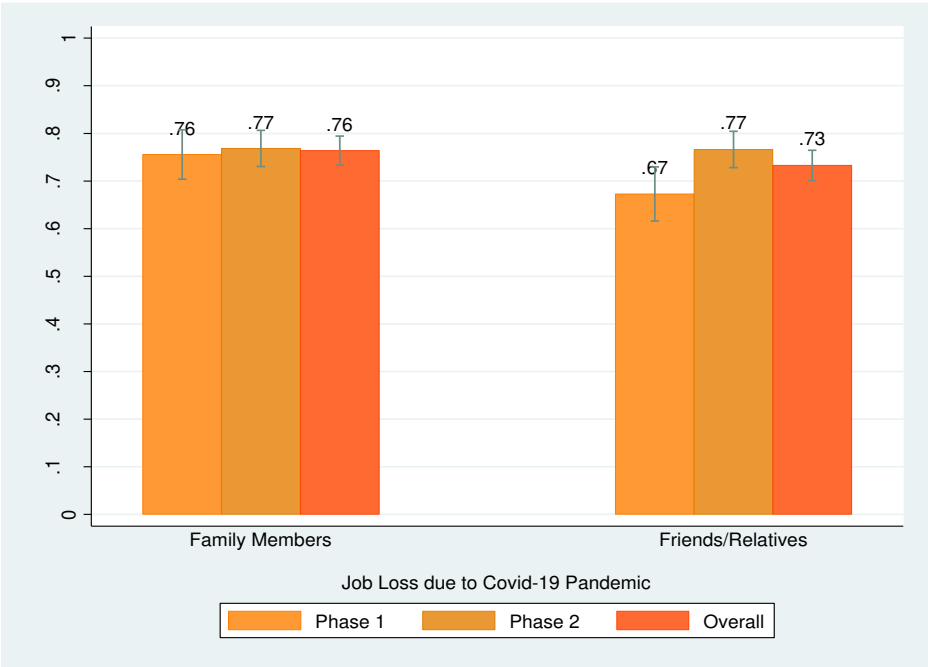
Figure A2: Men's unemployment status during COVID-19, by pre-COVID-19 occupation



Note: this figure illustrates the percentage of men unemployed during the lockdown by their pre-pandemic (baseline) occupational categories. The overall sample covers the period from 3 April to 9 May. Phase 1 refers to respondents surveyed between 3 April and 19 April, and Phase 2 refers to respondents surveyed between 20 April 20 and 9 May. Phase 1 consists of 268 data points, and Phase 2 consists of 477 data points. The reference period for all respondents was from 25 March until the date of survey.

Source: authors' calculations based on pre-pandemic and post-pandemic data.

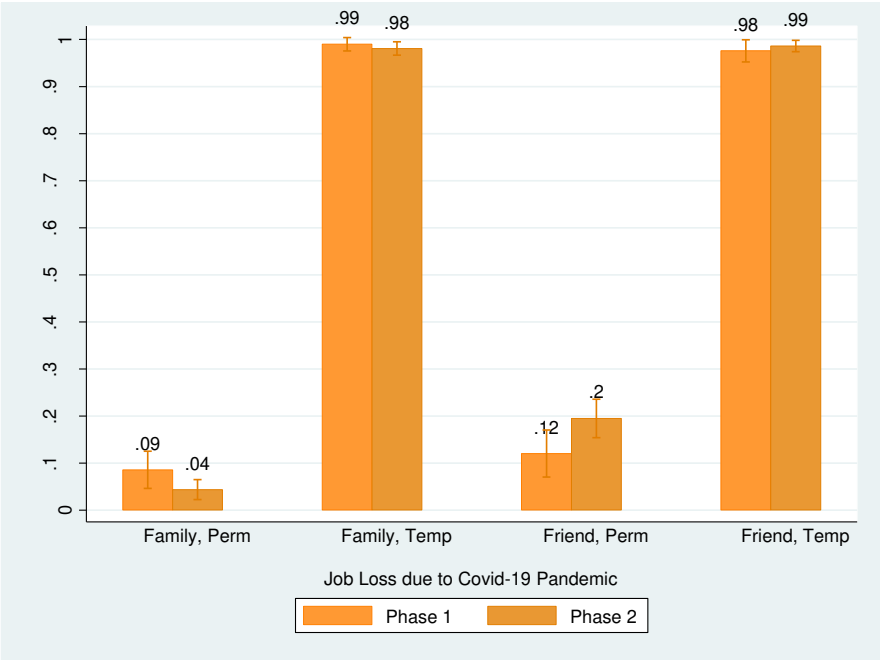
Figure A3: Family and friends job losses during COVID-19, by phase



Note: this figure indicates the percentage of friends and relatives of the respondents who lost their job due to lockdown, by phase. The overall sample covers the periodf rom 3 April to 9 May. Phase 1 refers to respondents surveyed between 3 April and 19 April, and Phase 2 refers to respondents surveyed between 20 April and 9 May. Phase 1 consists of 268 observations, and Phase 2 consists of 477 observations for males.The reference period for all respondents was from 25 March until the date of survey.

Source: authors' calculations based on post-pandemic data.

Figure A4: Family and friends job losses during COVID-19, by phase and type



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

Source: authors' calculations based on post-pandemic data.

Table A1: Pre-pandemic household and individual characteristics, by phase

	Phase 1			Phase 2		
	N	Mean	SE	N	Mean	SE
Householdcharacteristics						
No. of householdmembers	268	5.2	0.01	477	5.14	0.07
No. of years in currentlocation	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
Ownshouse (0/1)	268	0.68	0.03	477	0.64	0.02
Hasrationcard (0/1)	268	0.57	0.03	476	0.64	0.02
Caste	265			473		
Scheduledcaste		0.37	0.03		0.44	0.02
Scheduledtribe		0.02	0.01		0.02	0.01
Otherbackwardcaste		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
Meanassetindex	268	1.74	0.04	477	1.84	0.03
Meanassetindex of bottom 25thpercentile	68	0.91	0.03	103	0.90	0.03
Meanassetindex of top 25thpercentile	53	2.56	0.03	127	02.61	0.02
Householdheadfrom Delhi (0/1)	268	0.31	0.03	477	0.37	0.02
Individualcharacteristics						
Wife'sage (years)	262	31.11	0.36	461	31.1	0.28
Husband'sage (years)	268	35.09	0.37	472	34.94	0.29
Wife'seducation (years)	261	6.13	0.28	461	7	0.2
Husband'seducation (years)	268	7.54	0.24	471	8.1	0.17
Wife'soccupation	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'soccupation	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
Wife is employed (0/1)	262	0.20	0.03	461	0.17	0.02
Husband is employed (0/1)	268	0.90	0.02	472	0.90	0.01
Wives'monthlyearnings (in Rs)	52	3,823	340	78	4,477	427
Husbands'monthlyearnings (in Rs)	242	11,075	487	424	12,970	1.177

Source: authors' calculations based on pre-pandemic data.

Table A2: Male employment effects, by occupation—balanced panel

	(1)	(2)	(3)
	Men's self-reported employment		
Post-COVID-19	-0.888***	-0.888***	-1.074***
	(0.014)	(0.014)	(0.126)
Husband is labourer at baseline		-0.050***	-0.024
		(0.013)	(0.022)
Husband is self-employed at baseline		-0.011	0.005
		(0.012)	(0.016)
Wife is labourer at baseline		-0.039	-0.038
		(0.038)	(0.028)
Wife is self-employed at baseline		-0.061	-0.084**
		(0.042)	(0.036)
Wife is housewife at baseline		-0.055*	-0.047***
		(0.032)	(0.014)
Post-COVID-19*Husband is labourer at baseline			-0.052*
			(0.028)
Post-COVID-19*Husband is self-employed at baseline			-0.032
			(0.027)
Post-COVID-19*Wife is labourer at baseline			-0.001
			(0.079)
Post-COVID-19*Wife is self-employed at baseline			0.046
			(0.082)
Post-COVID-19*Wife is housewife at baseline			-0.017
			(0.066)
Constant	0.912***	1.012***	1.105***
	(0.051)	(0.059)	(0.068)
Adj. R-sq.	0.79	0.79	0.79
Controls	Yes	Yes	Yes
Post-COVID-19*Controls	No	No	Yes
N	1305	1305	1305

Note: the dependent variable denotes the self-reported employment status of men before and after the COVID-19 pandemic. It is a binary variable, where 1 represents employed, and 0 otherwise. This regression analysis is performed on a dataset where each observation has two separate rows: one for the pre-pandemic value and the other for the post-pandemic value. For this table, we use respondents who reported their pre-COVID-19 main occupation as working (labourers, self-employed, and salaried), resulting in 686 pre-pandemic and 690 post-pandemic observations, amounting to a total sample size of 1,376 observations. Owing to missing values in independent variables, as shown in this table, the sample size further reduced to 1,305. Here, the reference category for own and spouse's occupation is salaried. The baseline controls include low caste dummy, Hindu (religion) dummy, house type, household head native state dummy, number of years living in a location, owns a ration card dummy, own flat dummy, number of household members, asset index, age and education of the respondents. Standard errors clustered at PSU are reported in parentheses. Significant at *10%, **5%, and ***1%.

Source: authors' calculations based on pre-pandemic and post-pandemic data.

Table A3: Impact on male earnings, by occupation–balanced panel

	(1)	(2)	(3)
		Men's monthly earnings	
Post-COVID-19	-10520.898***	-10520.618***	2121.916
	(799.891)	(800.742)	(7958.081)
Husband is labourer at baseline		-945.468	-196.069
		(798.916)	(1583.752)
Husband is self-employed at baseline		196.927	1525.081
		(1138.199)	(2264.299)
Wife is labourer at baseline		-837.904	-248.079
		(942.051)	(1806.301)
Wife is self-employed at baseline		-2129.097**	-2844.105*
		(963.817)	(1443.665)
Wife is housewife at baseline		-654.813	222.980
		(808.803)	(1549.666)
Post-COVID-19*Husband is labourer at baseline			-1505.894
			(1637.844)
Post-COVID-19*Husband is self-employed at baseline			-2680.012
			(2353.637)
Post-COVID-19*Wife is labourer at baseline			-1185.421
			(2374.579)
Post-COVID-19*Wife is self-employed at baseline			1428.696
			(1740.955)
Post-COVID-19*Wife is housewife at baseline			-1767.861
			(2120.386)
Constant	6183.655**	7872.573**	1606.818
	(2422.640)	(3265.717)	(7393.596)
Adj. R-sq.	0.14	0.14	0.16
Controls	Yes	Yes	Yes
Post-COVID-19*Controls	No	No	Yes
N	1,300	1,300	1,300

Note: the dependent variable denotes the unconditional average monthly earnings of men before and after the COVID-19 pandemic. The variable is continuous and takes value 0 if the respondent is not employed. This regression analysis is performed on a dataset where eachobservation has two separate rows: one for the pre-pandemic value and the other for the post-pandemic value. For this table, we use respondents who reported their pre-COVID-19 main occupation as working (labourers, self-employed, and salaried), resulting in 685 pre-pandemic and 685 post-pandemic observations, amounting to a total sample size of 1,370 observations. Owing to missing values in independent variables, as shown in this table, the sample size further reduced to 1,300. Here, the reference category for own and spouse's occupation is salaried. The baseline controls include low caste dummy, Hindu (religion) dummy, house type, household head native state dummy, number of years living in a location, owns a ration card dummy, own flat dummy, number of household members, asset index, age and education of the respondents. Standard errors clustered at PSU are reported in parentheses. Significant at *10%, **5%, and ***1%.

Source: authors' calculations based on pre-pandemic and post-pandemic data.

Table A4: Female employment effects, by occupation—balanced panel

	(1)	(2)	(3)
	Wife's employment as reported by husband		
Post-COVID-19	0.001	0.001	-0.009
	(0.001)	(0.001)	(0.009)
Husband is labourer at baseline		-0.010	-0.011
		(0.027)	(0.027)
Husband is self-employed at baseline		-0.006	-0.005
		(0.021)	(0.022)
Wife is labourer at baseline		-0.122	-0.122
		(0.089)	(0.089)
Wife is self-employed at baseline		-0.357***	-0.362***
		(0.094)	(0.094)
Wife is housewife at baseline		-0.713***	-0.713***
		(0.070)	(0.071)
Post-COVID-19*Husband is labourer at baseline			0.004
			(0.003)
Post-COVID-19*Husband is self-employed at baseline			-0.001
			(0.001)
Post-COVID-19*Wife is labourer at baseline			-0.001
			(0.001)
Post-COVID-19*Wife is self-employed at baseline			0.008
			(0.008)
Post-COVID-19*Wife is housewife at baseline			0.001
			(0.001)
Constant	0.131	0.778***	0.782***
	(0.120)	(0.119)	(0.120)
Adj. R-sq.	0.06	0.47	0.46
Controls	Yes	Yes	Yes
Post-COVID-19*Controls	No	No	Yes
N	1,302	1,302	1,302

Note: the dependent variable denotes the employment status of women as reported by their husbands before and after the pandemic. It is a binary variable, where 1 represents employed, and 0 otherwise. This regression analysis is performed on a dataset where eachobservation has two separate rows: one for the pre-pandemic value and the other for the post-pandemic value. For this table, we use respondents who reported their pre-COVID-19 main occupation as working (labourers, self-employed, and salaried), resulting in 690 pre-pandemic and 688 post-pandemic observations, amounting to a total sample size of 1,378 observations. Owing to missing values in independent variables, as shown in this table, the sample size furtherreduced to 1,302. Here, the reference category for own and spouse's occupation is salaried. The baseline controls include low caste dummy, Hindu (religion) dummy, house type, household head native state dummy, number of years living in a location, owns a ration card dummy, own flat dummy, number of household members, asset index, age and education of the respondents. Standard errors clustered at PSU are reported in parentheses. Significant at *10%, **5%, and ***1%.

Source: authors' calculations based on pre-pandemic and post-pandemic data.

Table A5: Impact on mental health by gender: role of social networks for total number of friends

	(1)	(2)	(3)	(4)	(5)	(6)
			Mental stress			
Wife	0.234***	-0.654*	-0.726**	-0.722**	-0.310	-0.263
	(0.036)	(0.372)	(0.348)	(0.347)	(0.458)	(0.525)
Total friends		-0.061**	-0.064**			
		(0.025)	(0.025)			
Wife*Total friends		0.098***	0.096***			
		(0.029)	(0.029)			
Employed			-0.644***	-0.648***	-0.657***	-0.640***
			(0.172)	(0.171)	(0.171)	(0.180)
Wife employed			0.106	0.119	0.100	0.102
			(0.087)	(0.090)	(0.091)	(0.087)
Home-friends				-0.065**	0.084**	-0.087
				(0.026)	(0.039)	(0.086)
Wife*Home-friends				0.097***	-0.053	0.051
				(0.030)	(0.051)	(0.135)
Work-friends				-0.043	-0.214	-0.128
				(0.065)	(0.281)	(0.198)
Wife*Work-friends				-0.080	0.308	-0.185
				(0.134)	(0.726)	(0.631)
Owns mobile					0.352	
					(0.243)	
Wife*Owns mobile					-0.308	
					(0.374)	
Owns mobile*Home-friends					-0.162***	
					(0.044)	
Wife*Owns mobile* Home-friends					0.164***	
					(0.059)	
Owns mobile*Work-friends					0.181	
					(0.290)	
Wife*Owns mobile*Work-friends					-0.418	
					(0.742)	
Home-friend*phone interactions						-0.177
						(0.137)
Wife*Home-friend*phone interactions						0.255
						(0.208)
Work-friend*phone interactions						0.022
						(0.267)
Wife*Work-friend*phone interactions						-0.288
						(0.947)
Constant	-0.117*	0.375	0.411	0.411	0.004	0.495
	(0.062)	(0.311)	(0.299)	(0.300)	(0.374)	(0.384)
Adj. R-sq	0.01	0.04	0.06	0.06	0.06	0.06
Controls	No	Yes	Yes	Yes	Yes	Yes
Wife*Controls	No	Yes	Yes	Yes	Yes	Yes
N	1,266	1,233	1,225	1,225	1,225	1,175

Note: the dependent variable is a standardized mental health variable as described in Section 3.2 of the paper, where higher values indicate worse mental health. There are 737 observations for men and 529 for women, giving a total of 1,266 observations, as shown in column 1. 'Home-friend' comprises total number of friends (including duplication) based around home, including 'parent', 'uncle/aunt', 'cousin/siblings', 'in-laws', 'friends', 'neighbour/friendfromnearbylane/block', and 'others', while 'work-friends' comprise uniqueco-workers. In column 6, the 'phone interactions' variable equals 1 if frequency of pre-pandemic phoneinteractions between respondent and

their friend is weekly or more, and 0 otherwise. This information is available for their four closest friends, as ranked by them. 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, asset index, age and education of the respondents. The post-pandemic employment statuses of men and women are also included as controls. Standard errors clustered at PSU are reported in parentheses. Significant at ∗10%, ∗∗5%, and ∗∗∗1%.

Source: authors' calculations based on pre-pandemic (friends' variable, mobile ownership) and post-pandemic data.

Table A6: Impact on mental health, by gender: role of post-COVID-19 employment loss including controls

	(1)	(2)	(3)	(4)	(5)	(6)
	Mental stress	Financial stress	Health stress	Nervous/ anxiety	Depressed	Sleep disorder
Wife	-0.263	-0.078	-0.160	0.104	-0.018	-0.197
	(0.289)	(0.076)	(0.148)	(0.186)	(0.176)	(0.181)
Employed Post-COVID-19	-0.610***	-0.243***	-0.102	-0.129	-0.244***	-0.140*
	(0.173)	(0.062)	(0.066)	(0.078)	(0.075)	(0.080)
Wife*Employed Post-COVID-19	0.761***	0.287***	0.147*	0.165*	0.308***	0.163
	(0.202)	(0.067)	(0.079)	(0.086)	(0.092)	(0.099)
SpouseEmployed Post-COVID-19	0.058	-0.019	0.081**	0.052	0.023	-0.055
	(0.093)	(0.027)	(0.037)	(0.051)	(0.043)	(0.056)
Wife*SpouseEmployed Post-COVID-19	-0.772***	-0.253***	-0.321***	-0.273**	-0.173	-0.063
	(0.290)	(0.091)	(0.102)	(0.112)	(0.115)	(0.112)
Constant	0.152	1.007***	0.930***	0.674***	0.738***	0.525***
	(0.303)	(0.054)	(0.131)	(0.187)	(0.136)	(0.168)
Adj. R-sq	0.05	0.06	0.02	0.04	0.02	0.02
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Wife*Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	1,225	1,225	1,225	1,225	1,224	1,224

Note: the dependent variable in column 1 is a standardized mental health variable as described in Section 3.2 of the paper, where higher values indicate worse mental health. The remaining dependent variables in columns 2–6 are the components of the standardized variable, as described in Section 3.2. There are 737 observations for men and 529 for women, giving a total of 1,266 observations. Owing to missing values in pre-COVID-19 baseline controls, the sample size has truncated to 1,225 observations. 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, asset index, age and education of respondents. Standard errors clustered at PSU are reported in parentheses. Significant at ∗10%, ∗∗5%, and ∗∗∗1%.

Source: authors' calculations based on post-pandemic data.