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ABSTRACT

This article studies the impact of the COVID-19 pandemic on the gendered dimensions of employment and mental health among urban informal-sector workers in Delhi, India. First, the study finds that men's employment declined by 84 percentage points during the pandemic relative to pre-pandemic employment, while their monthly earnings fell by 89 percent relative to the baseline mean. In contrast, women did not experience any significant impact on employment during pandemic. Second, the study documents 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, women staying employed during the pandemic is associated with worse mental health for them and their (unemployed) husbands. Fourth, pre-existing social networks are associated with higher mental stress for women, possibly due to the "home-based" nature of women's networks.

KEYWORDS

COVID-19, wage employment, mental health, social networks, gender, India

JEL Codes: J16, J22, J23

HIGHLIGHTS

- In India, men suffered larger employment losses than women during the pandemic.
- Women reported greater mental stress than men, although both reported high stress.
- Men's employment losses affected their wives' mental health more than their own.

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- Having many peers is correlated with worse stress for women, but not men.

INTRODUCTION

While the COVID-19 pandemic has ravaged most countries across the world, India has been one of the worst affected. With its 1.3 billion population, of which vast numbers are self-employed, informal sector workers and daily wage earners lacking access to social security measures, India faces significant policy challenges, both humanitarian as well as economic, in the wake of the COVID-19 crisis. During the first wave of the pandemic, India imposed one of the strictest national lockdowns in the world on March 24, 2020 to contain the spread of the virus.[1] Countless informal sector workers faced job and income losses and food shortages, and required direct support in terms of cash and food. It has also become increasingly apparent that significant mental health concerns have arisen due to the COVID-19 crisis and subsequent lockdown, both due to economic uncertainty as well as social distancing measures imposed to control the spread of the pandemic, which has put pressure on the social fabric and feeling of community connectedness.

This article provides evidence on the impact of the first wave of the COVID-19 pandemic in India on the livelihoods and mental health of urban, primarily informal sector workers, who constitute some of the most vulnerable segments of the Indian population in its overcrowded, urban centers. In particular, we focus on the gender differences in these impacts of the COVID-19 crisis. To this end, we use two rounds of survey data: a pre-pandemic survey conducted in May 2019 for over 1,600 women and their husbands living in urban clusters of Delhi, and a follow-up phone survey during the pandemic around the peak of the COVID-19 national lockdown, in April and May 2020.

Our main findings are as follows. First, men's employment was significantly more impacted than women's employment due to the COVID-19 shock. In particular, men's self-reported employment declined by 84 percentage points (pp) during the pandemic. This was primarily driven by wage and casual laborers who experienced a nearly 94 pp reduction in employment, followed by self-employed and salaried workers. Men's monthly earnings also declined by 89 percent relative to pre-pandemic mean earnings. In contrast, women (wives) did not experience any significant impact in employment, as reported by their husbands, during the pandemic.[2]

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 percent) and health (85 percent) concerns. While this is true for both men and women, the latter report relatively greater mental stress.

In particular, women report 0.23 standard deviations 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 in pandemic-induced mental stress may be explained by 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 deviations greater mental stress, while the men themselves report 0.68 standard deviations higher mental stress. In contrast, women who continued to remain employed during the pandemic (but whose husbands were unemployed) report 0.22 *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. It could also be picking up incidence of spousal domestic violence due to male backlash (Macmillan and Gartner 1999; Luke and Munshi 2011; Dhanaraj and Mahambare 2022).[3] Husbands of employed women also report 0.166 standard deviation greater mental stress, driven primarily by health worries. This could be picking up husbands' concern about their wives' exposure to the virus when at 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 analyze the mediating role of social networks on mental health during the pandemic, by utilizing rich data on pre-pandemic social connections. We find that social network size, as measured by 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 network is associated with 0.061 standard deviations lower mental stress. But this pattern is reversed for women, such that one additional connection in their social network is associated with 0.037 standard deviations *higher* mental stress. 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, in times of crisis.

We also find that this positive association between pre-pandemic network size and reported mental stress for women during pandemic appears to be entirely driven by the *home-bound* nature of their networks. While for men, having an additional "home-friend"[4] is associated with 0.088 standard deviations lower mental stress, the same is associated with an additional 0.035 standard deviation *higher* reported mental stress for women. In addition, women who owned mobile phones, and enjoyed greater phone interaction with their home-friends before the pandemic, report higher mental stress during pandemic, while the opposite holds for men. In

contrast, "work-friends" are associated with lower reported mental stress for both men and women, although neither is statistically significant.

Our preferred interpretation of these findings is that, irrespective of the loss of connection with their social network due to pandemic-induced social distancing, women with larger home-bound networks experienced greater stress. This is consistent with the "stress-contagion" role rather than the "stress-buffering" role of social networks for women, but not men. The sociological literature suggests that this is likely due to increased pressures on women from their social networks (Kawachi and Berkman 2001). In our context, this could be driven by women's *home-bound* friends as opposed to *workplace* friends. One might expect the latter to provide some non-redundant information about jobs, while home-bound friends either cause contagion in stress levels or require more intensive caregiving by women, but not by men. It may also be due to the highly integrated nature of home-bound friends who may be spreading anxiety among each other. While we cannot ascribe causal interpretations to this analysis, it is interesting nevertheless to understand the correlates of the observed gender differences in mental well-being during the pandemic.

Our findings add to the emerging global literature on the devastating impact of the COVID-19 pandemic on economic well-being (Bertrand, Krishnan, and Schofield 2020; Deshpande 2020; Gupta and Kudva 2020; World Bank 2020; Afridi, Mahajan, and Sangwan 2021; Kesar et al. 2021) as well as to the feminist discourse on the gendered impact of the crisis (Kabeer, Razavi, and van der Meulen Rodgers 2021), including employment outcomes of vulnerable informal sector workers (Desai, Deshmukh, and Pramanik 2021; Ham 2021; Seck et al. 2021) and self-employed workers (Graeber, Kritikos, and Seebauer 2021; Kalenkoski and Pabilonia 2022).

We also 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,[5] complementing the findings of gender differentials in levels of stress, anxiety, and behavior relating to own health of doctors in Kazakhstan by Dana Bazarkulova and Compton (2021). We further contribute to the feminist discourse by analyzing the roles of pandemic-induced employment losses and social networks in mediating these differential effects by gender. In particular, our findings extend the literature on the role of internalized social norms about gender roles (Bertrand, Kamenica, and Pan 2015) by analyzing the implications of fewer pandemic-induced job losses for women compared to job losses for men on the home environment, specifically mental well-being of spouses (Gash and Plagnol 2021; Shang, Liu, and Yin 2018). Furthermore, our results on how the home-based nature of women's social networks shape their mental health during the pandemic differentially than men directly relates to the rich feminist literature on

the importance of mobility and physical autonomy on women's well-being (Jejeebhoy and Sathar 2001; Hanson 2010), and particularly how this has been affected during COVID-19 (Hamermesh 2020; Woskie and Wenham 2021).

While increasing attention is being paid to understand the overall psychological underpinnings of economic deprivation, with recent studies emphasizing the role of psychological empowerment in improving savings and health-seeking behaviour (Ghosal et al. 2022) and child investments (Baranov et al. 2020), there has been little focus so far on examining the pandemic's psychological impacts more specifically. To that extent, our article also relates to the emerging literature in developed countries on the overall psychological effects of the COVID-19 pandemic in Europe and the United States (Brodeur et al. 2020), as well as the gendered impact in the US (Adams-Prassl et al. 2020) and United Kingdom (Etheridge and Spantig 2020).

DATA, VARIABLES, AND ANALYSIS

Data description

Pre-pandemic survey

With the aim of studying factors driving women's low labor force participation in urban India, we started with a survey across five districts of Delhi in May–July 2019.[6] Within these five districts, we chose ten assembly constituencies with concentration of light industries, from which 108 primary sampling units PSUs were randomly selected (see Online Appendix Figure A1). From each PSU, fifteen eligible households were randomly chosen to participate in this study. A household was considered eligible if there was at least one married couple in the age group of 18–45 years.

The baseline (pre-pandemic) survey consisted of two surveys: a household survey and an individual survey. The household survey was comprised of 1,613 households and provided information regarding household composition, socioeconomic characteristics, assets owned, and so on. The questionnaire was supposed to be answered by the household head, but in case of unavailability, any knowledgeable adult was allowed to respond. Following the household survey, the youngest couple of the household (between 18–45 years of age) was interviewed as part of the individual survey,[7] where we were able to reach 97 percent of our target sample. The husband and wife were interviewed individually.[8]

Next, we created a combined pre-pandemic sample containing both household and individual characteristics. After fuzzy matching the household head's name from the pre-pandemic household survey with 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.[9]

Pandemic survey

The Indian government imposed a stringent twenty-one day national lockdown to deal with the pandemic on March 24, 2020 until April 14, which was later extended to May 30, 2020 with some easing of mobility restrictions thereafter. Hence, we were unable to conduct in-person follow-up surveys. Instead, we conducted a phone survey of 1,424 households during the pandemic, between April 3–19, 2020 that coincided with the initial, stringent lockdown.

Since most women in our sample do not own a personal phone, the main respondent of our phone survey was the husband. However, we also separately asked their wives questions on mental health, by requesting the husbands after their interview was complete, to pass the phone on to their wives.[10] This provided us with matched husband-wife data for mental health outcomes, giving a unique insight into the gendered experience of the crisis in this context. Our pandemic sample consists of 745 households out of the 1,034 pre-pandemic households, where the same individual was interviewed in both surveys.[11] See Online Appendix Figure A2 for more details on the sample creation process.

Our sample data for the employment results comes from both the pre-pandemic and pandemic surveys, and hence constitutes a panel dataset of 1,779 household observations, comprised of 1,034 pre-pandemic and 745 pandemic households. In contrast, our sample data for the mental health results is only obtained from the pandemic survey, and therefore constitutes a cross-sectional dataset of 745 households. The total number of individual observations in our mental health sample is 1,266, out of which 737 observations correspond to husbands and the remaining 529 to wives.

Table 1a presents the summary statistics of household characteristics of 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 percent possess ration cards, while 76 percent belong to lower castes. Eighty-three percent are Hindu. Two-thirds of the household heads have native homes outside Delhi.

Table 1b 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 almost eight years of formal schooling on average, compared to 6.7 years in case of their wives. The women's employment rate in our sample is significantly low at 18 percent, relative to 90 percent for men.[12] Fifty-seven percent of the men in our sample are daily wage earners in factories and construction, or self-employed in the informal sector (for example, small retail shops).

Table 1a Pre-COVID-19 household characteristics

	N	*mean*	*se*
No. of household members	745	5.16	0.06
No. of years in current location	745	28.29	0.5
No. of children	722	2.26	0.05
Has pucca house (0/1)	745	0.96	0.01
Owns house (0/1)	745	0.66	0.02
Has ration card (0/1)	744	0.61	0.02
Caste	738		
Scheduled caste		0.41	0.02
Scheduled tribe		0.02	0.01
Other backward caste		0.33	0.02
General		0.24	0.02
Hindu (0/1)	745	0.83	0.01
Mean asset index	745	1.81	0.02
Mean asset index of bottom 25th percentile	745	0.91	0.02
Mean asset index of top 25th percentile	745	2.59	0.02
Household head from Delhi (0/1)	745	0.35	0.02

Notes: This table presents the pre-COVID-19 pandemic household characteristics of the 745 households that are common in the pre-pandemic and post pandemic survey. The assets index was constructed using Principal Component Analysis. The variable considers fourteen assets: own flat/house, box tv, LCD/LED, fridge, clock, stove, cycle, bike, car, fan, cooler, AC, computer, mobile, and sewing machine.

This demographic group is particularly vulnerable to economic and health shocks and may be expected to need significant support through public transfers to tide over the loss of their livelihoods.

Online Appendix Table A2 shows little selective attrition between the pre-pandemic and pandemic samples, except for religion, assets, and husband's education.

Outcome variables

Employment

Our first outcome of interest is "employment" or working status. In both the pre-pandemic and the pandemic surveys, the men respondents were asked to report their main occupation in the months prior to the date of interview.[13] In the pre-pandemic survey, if they reported their main occupation as working (laborers, self-employed, and salaried), they were further asked whether they are currently working. In the pandemic survey, the current working status of the respondents who were working pre-pandemic was determined after taking into account the number of days

Table 1b 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 laborer		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
Monthly income, unconditional (in Rs)	723	758	83	739	11,067	698
Monthly income, if employed (in Rs)	129	4,240	324	665	12,298	761
Total friends	723	6.24	0.10	740	3.79	0.06
Total Unique friends	723	5.51	0.07	740	3.54	0.05
Unique home friends	723	5.48	0.07	740	3.35	0.05
Unique work friends	723	0.03	0.01	740	0.19	0.02

Notes: This table presents the pre-COVID-19 pandemic individual characteristics of the 745 households' common in pre-pandemic and post pandemic survey. The variable "employed" shows the percentage of people currently in employment/working from total sample at baseline. The construction of the variables "total friends" and "total unique friends," as well as "home-friends" and "work-friends" is discussed in the following section.

worked after lockdown, the income earned during the same period, and the type of commute used to go to work after lockdown.[14] Based on their responses in both the surveys, the employment variable for men is constructed as a binary variable that equals 1 if the male respondent was currently employed during the relevant reference period, and 0 otherwise.

In contrast, the employment variable for women 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 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 job loss in the pandemic survey. Similar to men, the employment variable for women is constructed as a binary variable that equals one if the woman was reported as employed during the relevant reference period, and 0 otherwise.

Earnings

In the pre-pandemic (individual) survey, male respondents were asked about their monthly earnings if employed. In the pandemic survey, they were asked to report their total earnings from the first day of the lockdown (March 24, 2020) until the date of the survey. In order to make this comparable with the pre-pandemic data, if total days worked were less than thirty, the income reported by the respondent is used directly in the analysis. However, if the number of days worked exceeded thirty, we calculated income per day and later multiplied it by thirty to derive monthly earnings in the follow-up survey.[15] Since the main respondents in the pandemic survey were men, we do not have earnings data for women.

Mental health

In contrast to employment data, we directly collected mental health data from both our men and women respondents, but only in the pandemic survey. Similar to Lukas Hensel et al. (2022), our respondents were asked questions about five different aspects of their mental health relating specifically to the COVID-19 pandemic: "To what extent do you agree or disagree with the following statements":

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

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

Similar standardized mental health indices have been used to study the impact of the COVID-19 pandemic on individuals' worries and depression across fifty-eight countries (Hensel et al. 2022); elderly mental health in Turkey (Altindag, Erten, and Keskin 2022), as well as the effect of education on mental health and violence in Turkey (Erten and Keskin 2020); the impact of cognitive behavioral therapy on mental health and

criminal behavior among Liberian youth (Blattman, Jamison, and Sheridan 2017); and the effect of psychological empowerment on self-image among marginalized groups in India (Ghosal et al. 2022). The advantages of using a mental health index are twofold. First, it gives us greater statistical power to identify effects for a family of variables that capture similar symptoms of mental well-being and move in the same direction (Erten and Keskin 2020). Second, it also helps us address potential multiple inference problems (Duflo, Glennerster, and Kremer 2007), since we are studying gender differences in the pandemic's impact on five mental health variables, raising concerns that these differences are simply being observed by chance among all the different outcome variables.

For robustness purposes, we present results with both the mental stress index, as well as the five binary variables relating to the individual mental health questions.

Other constructed variables

Social network variables

In the pre-pandemic individual survey, all the respondents were asked to name two friends/close relatives to whom they could reach out in case of each of eight hypothetical situations.[16] These situations (categories) are as follows:

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

The response options are: "parent," "uncle/aunt," "cousin/siblings," "in-laws," "friends," "co-workers." "neighbor/friend from nearby lane/block," "neighbor/friend from previous locality," "neighbor/friend from native home," and "others." Adding up answers for all these questions gives us the total number of *friends*[17] for each individual, which ranges from two

to sixteen.[18] Adding up answers for all the category questions gave us total number of unique friends for each individual, with values ranging from two to thirteen for women and two to ten for men.

To further analyze 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 home, including "parent," "uncle/aunt," "cousin/siblings," "in-laws," "friends," "neighbor/friend from nearby lane/block,"[19] and "others"[20];

(ii) *work-friends* comprised of friends in workplace, that is "co-workers." We calculated the total number of *home-friends* and that of *work-friends*. As Table 1b shows, women report nearly twice as large social networks (6.24 friends on average) as men (3.79 friends on average), but almost all of women's friends are around their home. Men too report more home-based friends, but around 5 percent of their friends are from their workplace.

Mobile ownership

The variable "owns mobile" equals 1 if individual reports owning a mobile phone in the pre-pandemic survey, and 0 otherwise.

Phone interactions

The variable "phone interactions" equals 1 if frequency of pre-pandemic phone interactions between respondent and their (index) friend is weekly or more, and 0 otherwise. This information is available for the participants' four closest friends, as ranked by them.

Empirical analysis

To study the impact of the COVID-19 pandemic on employment and earnings, we conduct a before-and-after analysis using the following regression specification estimates using OLS:

$$y_{it} = \alpha + \beta PostCOVID\text{-}19_t + \gamma Z_i + \varepsilon_{it} \quad (1)$$

where y_{it} indicates the dependent variable of interest for individual i in time t. $PostCOVID\text{-}19_t$ is a binary variable equal to 1 if the observation relates to the pandemic period, and 0 if it refers to the pre-pandemic period. The coefficient β captures the average impact of the COVID-19 pandemic. Z_i a vector of pre-pandemic individual and household socioeconomic characteristics including age, education, occupation type, religion, and

so on. We also explore the differential impact of the pandemic by pre-pandemic occupation type, including wage employment, self-employment, and salaried employment.

In order to analyze the gender difference in the mental health experience of the COVID-19 pandemic, we conduct a cross-sectional analysis using the following regression specification estimated using OLS:[21]

$$m_i = \alpha + \delta Wife_i + \rho Z_i + \varepsilon_i \tag{2}$$

where m_i indicates the standardized mental stress variable for 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 pre-pandemic individual and household characteristics as explained in equation (1). We also present robustness checks using an ordered probit model.

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

$$m_i = \alpha + \delta Wife_i + \pi Friends_i + \mu\ Wife_i\ X\ Friends_i + \rho Z_i + \varepsilon_i \tag{2a}$$

where $Friends_i$ indicates the total number of friends reported by an individual i. The coefficient π on captures the impact of social network size on mental stress reported by men, while the coefficient on the interaction term μ captures the differential impact of social networks on mental health of women relative to men.

IMPACT ON EMPLOYMENT AND EARNINGS

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 1). As expected, most workers in these residential areas (approximately 84 percent of the men) were completely unable to work, and this situation did not improve over time (Online Appendix Figure A3).

Examining the occupational distribution of this colossal employment shock in Figure 2, we find that wage laborers (for example, those employed in a specific sector such as manufacturing) and casual laborers (daily wagers not attached to one specific sector) were by far the most adversely affected, followed by the self-employed in informal sector and salaried workers, in terms of loss of livelihoods. We document a marginal decline in reported unemployment among the self-employed and salaried workers later in the lockdown, but not among wage and casual laborers (Online Appendix

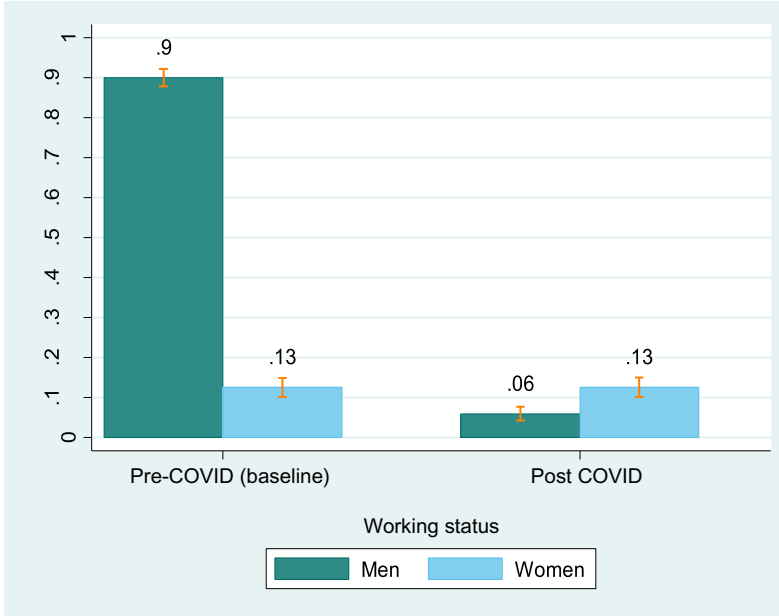


Figure 1 Employment status before and during COVID-19, by gender
Notes: The sample size for pre-COVID-19 (post-COVID-19) survey is 740 (744) and 743 (741) observations for husbands and wives, respectively.

Figure A4). 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 percentage points (pp) during pandemic relative to pre-pandemic (Column 1, Table 2). Consistent with our descriptive evidence, we find that wage and causal laborers experienced a nearly 5 pp greater employment loss during pandemic (significant at 10 percent level) compared to the omitted group of salaried workers (Column 3, Table 2). However, we cannot reject the equality of coefficients for male wage laborers with that of self-employed men (p-value = 0.51).[22] Whether these reported own job losses were permanent or temporary, we hope to decipher in subsequent survey rounds.

Many of the respondents surveyed reported relying on friends and family to tide over temporary setbacks. We asked about job losses among their social networks, as this would presumably lead to higher levels of stress than otherwise. Seventy-six percent reported loss of job in their family while

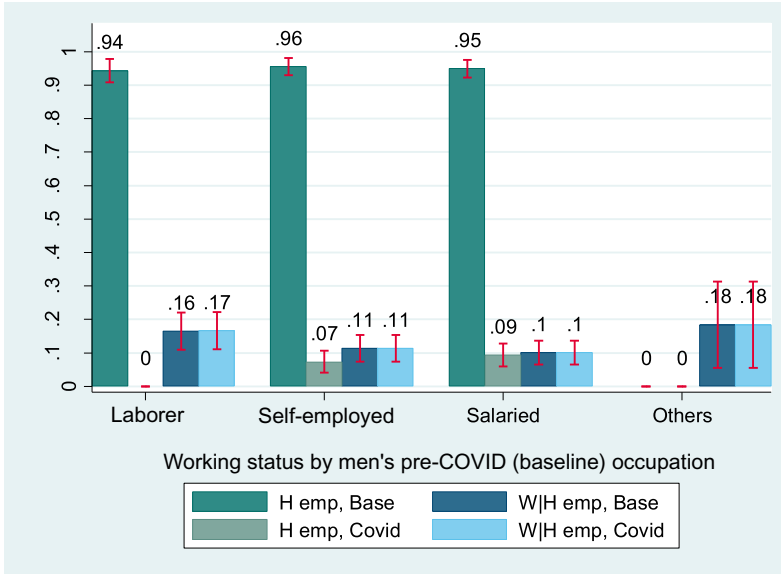


Figure 2 Employment status before and during COVID-19, by gender and pre-COVID-19 occupation
Notes: The sample size for pre-COVID-19 (post-COVID-19) survey is 740 (744) and 743 (741) observations for husbands and wives, respectively.

over 73 percent reported loss of job within their network of friends and relatives (Online Appendix Figure A5). More respondents reported loss of job within their social network (family, relative, and friends) later in the lockdown (77 percent) compared to earlier (67 percent). Most respondents initially perceived the job losses as temporary, but over time there was an increase in the proportion who perceived the job losses in their social network as permanent, suggesting that as the duration of the lockdown increased, more workers began to perceive their current unemployment status as a permanent job loss (Online Appendix Figure A6).

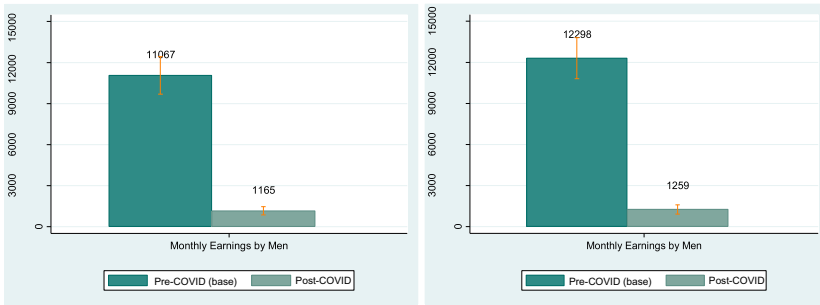
Men's earnings

Consistent with the pandemic's negative impact on men's employment, we also find that about 83 percent of the respondents report not earning *any* income during the period of study (Online Appendix Figure A3). Moreover, among those who were gainfully employed pre-pandemic, monthly earnings declined from an average of approximately Rs. 12,300 pre-pandemic to Rs. 1,259 during the pandemic, a drop of 89 percent (Figure 3). The biggest impact was borne by casual and wage laborers,

Table 2 Impact on men's employment, by occupation

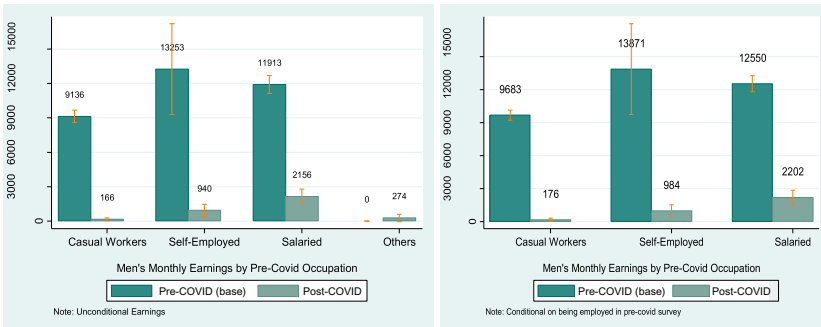
	(1)	*(2)*	*(3)*
	Men's self-reported employment		
Post-COVID-19	− 0.883***	− 0.883***	− 1.073***
	(0.014)	(0.014)	(0.120)
Husband is laborer at baseline		− 0.048***	− 0.029
		(0.014)	(0.022)
Husband is self-employed at baseline		− 0.008	0.004
		(0.011)	(0.015)
Wife is laborer at baseline		− 0.063*	− 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-COVID-19∗Husband is laborer at baseline			− 0.047*
			(0.027)
Post-COVID-19∗Husband is self-employed at baseline			− 0.030
			(0.027)
Post-COVID-19∗Wife is laborer at baseline			0.035
			(0.084)
Post-COVID-19∗Wife is self-employed at baseline			0.032
			(0.078)
Post-COVID-19∗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

Notes: The dependent variable denotes the self-reported employment status of men pre- and post-COVID-19 pandemic. It is a binary variable, where 1 represents employed and zero otherwise. For this table, we use respondents who reported their pre-COVID-19 main occupation as working (laborers, 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 table above, 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, assets index, and age and education of the respondents. Standard errors clustered at PSU are reported in parentheses. ***, **, * denote significance at the 1, 5, and 10 percent levels, respectively.



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

Figure 3 Monthly earnings by men, before and during COVID-19. A. Unconditional; B. Conditional on baseline employed
Notes: Figure 3A denotes unconditional earnings, which takes value zero if the respondent is unemployed. Figure 3B denotes earnings conditional on respondents being employed during pre-pandemic (baseline) survey. The sample size for unconditional earnings (conditional earnings) survey is 739 (665) and 739 (661) observations for pre- and post-pandemic surveys, respectively.



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

Figure 4 Monthly earnings by men, before and during COVID-19, by baseline occupation. A. Unconditional; B. Conditional on baseline employed
Notes: Figure 4A denotes unconditional earnings, which takes value zero if the respondent is unemployed. Figure 4B denotes earnings conditional on respondents being employed during pre-pandemic (baseline) survey. The sample size for unconditional earnings (conditional earnings) survey is 739 (665) and 739(661) observations for pre- and post-pandemic surveys.

who experienced a reduction of 98 percent, followed by self-employed (93 percent) and salaried workers (82 percent; Figure 4).

These descriptive patterns are also borne out in our regression analysis. Male reported (unconditional) monthly incomes declined on average

by Rs. 10,689 during this period, which is approximately 96 percent of reported baseline incomes (Column 1, Table 3). Men across all occupation types were affected by the negative income shock (Column 3, Table 3). We cannot reject the equality of the coefficients for male wage laborers with that of self-employed men ($p = 0.57$).[23] Hence, irrespective of whether the loss of work was temporary or permanent, households experienced immediate and massive income shocks due to the crisis.

Women's employment

Next, we study the impact of the pandemic on women's employment in order to examine the gendered dimension of the crisis. As discussed above, the husband reports wife's employment status in our pre-pandemic and pandemic surveys. In contrast to the large negative impact on men's employment, we do not find any significant change in reported women's employment during the pandemic (Column 1, Table 4). Comparing across occupations, we find that the estimated pandemic coefficients for women casual/wage workers and self-employed workers are negative (Column 3, Table 4), but not statistically significantly different from the omitted group of salaried workers. We cannot reject the equality of the coefficients for women wage laborers with that of self-employed women (p-value $= 0.59$).[24] We did not collect information on women's earnings during the pandemic.

IMPACT ON MENTAL HEALTH

Emerging evidence points to a significant increase in mental and emotional stress across the world due to 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, US, and European nations (Banks and Xu 2020; Etheridge and Spantig 2020; Kuan-Yu et al. 2020; McGinty et al. 2020; Pierce et al. 2020; Proto and Quintana-Domeque 2021), we know little about the pandemic's implications for mental health among people living in developing countries. In this section, we attempt to shed light on this important issue.

We document very high levels of mental stress due to the pandemic among men and women in our study sample, driven primarily by financial (90 percent) and health concerns (85 percent). Consistent with emerging evidence, women appear to be suffering from greater mental stress than men (Figure 5). For example, nearly 90 percent of women report feeling worried about the physical health of their families compared to 85 percent of men. 66 percent of men report feeling depressed about their situation, while 70 percent of women do. Strikingly, both men and women worry

Table 3 Impact on men's 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 laborer 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 laborer 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 laborer at baseline			− 434.926
			(1464.357)
Post-COVID-19∗Husband is self-employed at baseline			− 853.601
			(2061.048)
Post-COVID-19∗Wife is laborer 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

Notes: The dependent variable denotes the unconditional average monthly earnings of men pre- and post-COVID-19 pandemic. The variable is continuous and takes value zero if the respondent is not employed. For this table, we use respondents who reported their pre-COVID-19 main occupation as working (laborers, 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 table above, the sample size further reduced to 1,554. Here, the reference category for own and spouse's occupation is salaried. Baseline controls as described in Table 2. Standard errors clustered at PSU are reported in parentheses. ***, **, * denote significance at the 1, 5, and 10 percent levels, respectively.

Table 4 Impact on women's 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 laborer 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 laborer 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 laborer at baseline			− 0.008
			(0.016)
Post-COVID-19∗Husband is self-employed at baseline			− 0.000
			(0.013)
Post-COVID-19∗Wife is laborer 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

Notes: The dependent variable denotes the employment status of women as reported by their husbands pre- and post-COVID-19 pandemic. It is a binary variable, where 1 represents employed and zero otherwise. For this table, we use respondents who reported their pre-COVID-19 main occupation as working (laborers, 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 table above, the sample size further reduced to 1,558. Here, the reference category for own and spouse's occupation is salaried. Baseline controls as described in Table 2. Standard errors clustered at PSU are reported in parentheses. ***, **, * denote significance at the 1, 5, and 10 percent levels, respectively.

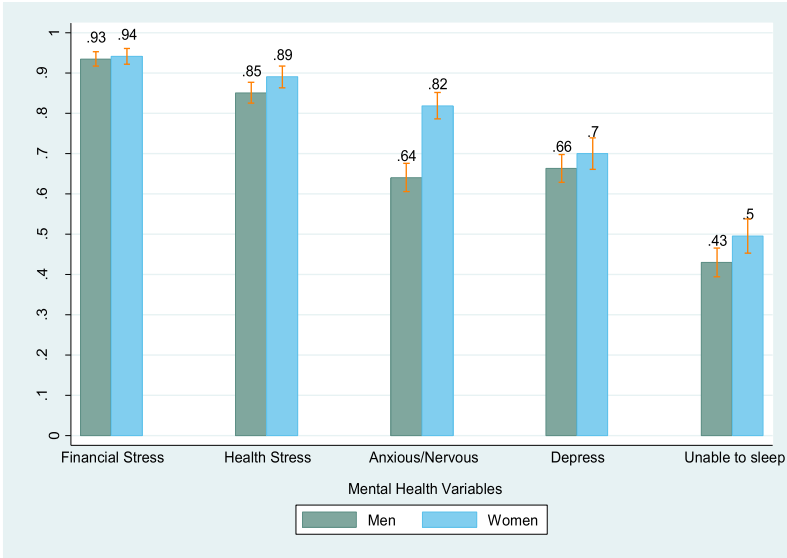


Figure 5 Mental health outcomes, by gender
Notes: The overall sample covers the period from April 3–May 9. The sample sizes for women and men are 529 and 741 respectively. The reference period for all respondents was from March 25 until the date of survey.

more about their family's financial adequacy than about their health, though the difference is not statistically significant. Almost 82 percent of women felt anxious or nervous about the current situation compared to 64 percent of men, while 50 percent of women and 43 percent of men report having trouble getting adequate sleep.

These overall descriptive patterns are also borne out in our regression analysis that systematically examines 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 5. Women report 0.234 standard deviations greater mental stress compared to men (Column 1, Table 5). The key aspects of women's stress appear to be anxiety and nervousness, followed by sleeplessness and health worries (Columns 2-6). Women also appear to suffer more health stress compared to men, but not more financial stress.[25]

Role of pandemic-induced employment losses

Since the pandemic led to massive loss of livelihoods, we examine whether such employment losses were directly correlated with worse

Table 5 Impact on mental health, by gender

	(1)	(2)	(3)	(4)	(5)	(6)
	Mental Stress	*Financial Stress*	*Health Stress*	*Nervous/Anxious*	*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

Notes: The dependent variable in column 1 is a standardized mental health variable as described earlier in the article, where higher values indicate worse mental health. The remaining dependent variables in columns 2–6 are the components of the standardized variable, as described earlier. 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. ***, **, * denote significance at the 1, 5, and 10 percent levels, respectively.

mental health outcomes during the pandemic, differentially by gender. We find that for men, remaining employed during the pandemic is negatively correlated with their mental stress (Column 1, Table 6), primarily through the lowering of financial stress (Column 2, Table 6). In particular, employed men report 0.68 standard deviations lower mental stress, and 0.25 lower likelihood of experiencing financial stress. In contrast, women who continued to work during the pandemic (but whose husbands were unemployed) report 0.22 standard deviations higher mental stress during pandemic compared to their unemployed counterparts. This holds qualitatively across all stress types. This may be indicative of the internalization by *women* of the "male breadwinner" gender norms that 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 during pandemic. We find that spousal (wife's) employment is positively correlated with men's reported mental stress, driven primarily by health worries that may be picking up husbands' concern about their wives' exposure to the virus when they went out to work. In particular, men whose wives remain employed during the pandemic report 0.166 standard deviations increase in overall mental stress (Column 1, Table 6), and 0.09 greater likelihood of experiencing health worries (Column 3, Table 6). Further, we also find that spousal employment during the pandemic is positively correlated

Table 6 Impact on mental health, by gender: Role of post-COVID-19 employment 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)
Spouse employed 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∗Spouse employed 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

Notes: The dependent variable in column 1 is a standardized mental health variable as described earlier, where higher values indicate worse mental health. The remaining dependent variables in columns 2–6 are the components of the standardized variable, as described earlier. 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. ***, **, * denote significance at the 1, 5, and 10 percent levels, respectively.

with reported depression among men and could again be reflecting internalized gender attitudes relating to the traditional "male breadwinner" model among men that were severely disrupted by the pandemic-induced employment losses men suffered.[26]

In contrast, spousal employment is negatively correlated with women's mental stress. Put differently, the negative economic impact of the pandemic on men's employment and earnings played a key role in heightening mental stress among their wives. In particular, wives whose husbands lost their livelihoods during the pandemic report 0.75 standard deviations greater mental stress, while these men themselves report a smaller increase of 0.68 standard deviations in their mental stress.[27]

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, Sheldon Cohen and Thomas Ashby Wills (1985) discuss the positive effects of social networks. In particular, they highlight the "stress-buffering" role of networks for individuals in crisis, through the provision of economic and psychological support. On the other hand, Ichiro Kawachi and Lisa F. Berkman (2001) analyze the potential negative impacts of social networks, arguing that they may paradoxically increase psychological distress owing to higher pressures to provide support to others ("stress-contagion"), especially when participants are facing similar shocks. 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 2019).

Given such theoretical ambiguity, we directly test for gender differences in the role played by social networks on mental stress during the pandemic. For this purpose, we utilize rich social network data that we collected in our pre-pandemic survey, as described earlier. We find that the size of the pre-pandemic social network, as measured by total number of (unique) friends, is associated with lower mental stress for men during pandemic.[28] In particular, men with larger social networks report 0.086 standard deviations lower mental stress during COVID-19 compared to those without (Column 2, Table 7). But this pattern is reversed for women, such that women with larger pre-pandemic social networks report on average 0.035 standard deviation *higher* mental stress than those without. 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 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 mental stress for women during pandemic appears to be entirely driven by what we label as the *home-bound*

Table 7 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

(*Continued*).

Table 7 Continued.

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
			Mental stress		
Controls	No	Yes	Yes	Yes	Yes
Wife∗Controls	No	Yes	Yes	Yes	Yes
N	1266	1,225	1,225	1,225	1,175

Notes: The dependent variable is a standardized mental health variable as described earlier, 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 unique friends for each individual as described earlier. In column 5, the variable "phone interactions" equals 1 if frequency of pre-pandemic phone interactions between respondent and their friend is weekly or more, and zero otherwise. This information is available for their four closest friends, as ranked by them. Baseline controls as described in Table 2, including post-pandemic employment status of men and women. Standard errors clustered at PSU are reported in parentheses. ***, **, * denote significance at the 1, 5, and 10 percent levels, respectively.

nature of women's networks, in particular "home friends" (Column 3, Table 7). While for men, having an additional "home-friend" is associated with 0.088 standard deviations lower reported mental stress, for women, the same 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 relationships between social networks and mental health. One interpretation of the gender difference in the role of social networks for mental health could be that women, with larger pre-pandemic social connections and hence more reliant on social networks, suffered a bigger mental health impact of the pandemic-induced lockdown that curtailed their interactions with friends and extended family, relative to men. Indeed, the gender-disaggregated analysis of how pre-pandemic networks are utilised in our sample shows that women are more dependent on their *home-bound* networks for social and recreational support (for example, going for walks to park, to the market, and social events), relative to men (Table 8). This is also consistent with pre-pandemic data from the Time Use Survey in India 2019. Among 15–59-year-old individuals in urban Delhi (closest age-range to our sample), a higher proportion of women (54 percent) report spending time in a day socializing with friends, compared to men (51 percent). Hence, it is possible that pandemic-induced social distancing may have resulted in greater stress among women due to the loss of *home-bound* friends' socializing and support during this crisis, linked to the "stress-buffering" role of social ties.

However, if this mechanism was to hold, 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 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 the positive correlation between *home-bound* friends' network size and reported mental stress during pandemic continues to hold for women owning mobile phones as well (Column 4, Table 7), while the opposite is observed for men. We also examined the frequency of our participants' reported interactions with these friends over 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 are those that report higher mental stress during pandemic (Column 5, Table 7). In contrast, the opposite is true for men. We can

Table 8 Nature of dependencies in social networks, by gender

Proportion of friends used to:	Men	Women
Borrow money	0.98	0.96
Medical emergency	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/religious events	0.09	0.38
Going for lunch at work	0.14	0.15
Travel to work	0.04	0.02

Notes: This table denotes proportion of respondents having friends in each category. The respondents were asked to report a maximum of two names for each category. The eight category questions are as described earlier.

reject the equality of these coefficients vis-à-vis home-friends at the 10 percent 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 mental well-being during the COVID-19 pandemic.

Hence, we conclude that, irrespective of their loss of connection with their social network due to social distancing, women with larger pre-existing *home-bound* networks experienced greater stress. The sociological literature suggests that this may likely be due to increased pressures on women from their social networks (Kawachi and Berkman 2001). In our context, *home-bound* friends may 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. Hence, we argue that 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.

CONCLUSION

We use data from poor households and individuals in urban India, before (May–July 2019) and after (April–May 2020) the COVID-19 pandemic struck to document the impacts on their employment and mental well-being. We assess how these impacts differ by gender by analyzing 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 is 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.

We document significant psychological impacts due to the financial and health related concerns surrounding the pandemic, but higher amongst women than men, which increased with the extension of the lockdown in our sample. Surprisingly, larger social networks are associated with lower adverse emotional impacts 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 "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 pandemic, particularly the gender differences therein, and their potential long-term implications for economic recovery and labor productivity in developing countries as they emerge from the devastation of the COVID-19 pandemic.

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NOTES

[1] India ranked among the highest on the COVID-19 Stringency Index by Oxford COVID-19 Government Response Tracker (OxCGRT; Hale et al. 2021).

[2] This result is in line with Sonalde Desai, Sonalde, Neerad Deshmukh, and Santanu Pramanik (2021) who find that women are less likely to experience a decline in employment overall, but conditional on for-wage occupations, women experienced larger declines in employment in India. In contrast, our study focuses on households where women were mostly involved in childcare even pre-COVID-19, and often working from home.

[3] We are unable to directly test for this channel since we did not collect data on domestic violence in our pandemic survey.

[4] As elaborated later, *home-friends* comprised of friends based around home, including relatives and neighbors.

[5] Onur Altindag, Bilge Erten, and Pinar Keskin (2022) examine the mental health impact of COVID-19 induced mobility restrictions for senior citizens in Turkey, but do not explore gender differences.

[6] For the baseline sample, we first drew a list of electoral board (EB) wards around planned industrial estates of Delhi, concentrated in five (North, North-West, West, North-East, and Shahdara) of the eleven districts of Delhi. Dropping wards that comprised of 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 contained within ten Assembly constituencies (AC). In each AC, ten polling stations (PS) were randomly sampled and fifteen households within each PS through systematic random sampling. Eight additional polling stations were randomly sampled to address interview refusals. Our final sample consists of 108 polling stations and 1,613 households. PS forms our primary sampling units.

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

[8] All personal information that would allow the identification of any person(s) described in the article has been removed.

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

[10] It is possible that some husbands were around when their wives gave us their responses on the mental health questions, but even if this were true, it is likely to bias our findings on women's mental health downwards, as women are likely to underreport their anxieties in front of their husbands (much like women underreporting domestic abuse).

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

[12] The urban women's labor force participation in India was 20.4 percent in 2017–18 (NSSO).

[13] In particular, we asked respondents to report their main occupation *over the last twelve months* in the pre-pandemic survey and *before lockdown was imposed on March 24th* in the pandemic survey.
[14] To elaborate further, in the 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 has not reported "don't go for work currently" in response to the commute question.
[15] 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.
[16] These friends/close relatives were not people residing in the same house as the respondent.
[17] We use the term "friends" throughout to denote both friends and close relatives.
[18] To avoid any duplication, we performed fuzzy matching between names, in pairs of two for all names provided by the individual. If the matching score between any two names was equal to 1, we reported one observation as missing for each pair.
[19] Our results remain qualitatively similar if we further disaggregate between home-friends and neighborhood-friends.
[20] The answers under "others" were classified into home-friends since most of the detailed answers included under this category were related to home friends.
[21] Using z-scores as a dependent variable in an regression model estimated using OLS is common in education economics, for example, using standardized test scores (Alan, Boneva, and Ertac 2019; Muralidharan, Singh, and Ganimian 2019) as well in research on poverty and mental health (Blattman, Jamison, and Sheridan 2017; Erten and Keskin 2020; Altindag, Erten, and Keskin 2022; Ghosal et al. 2022).
[22] These results remain qualitatively similar if we use the balanced panel (see Online Appendix Table A3).
[23] These results remain qualitatively similar if we use the balanced panel (see Online Appendix Table A4).
[24] These results remain qualitatively similar if we use the balanced panel (see Online Appendix Table A5).
[25] These results are robust to using ordered probit models, see Online Appendix Table A8.
[26] In a related vein, wives' employment may have heightened men's mental stress during the pandemic due to gender deviance or threats to their masculinity.
[27] The results are robust to inclusion of relevant baseline control variables and their respective interactions with gender (see Online Appendix Table A7), as well as ordered probit model (see Online Appendix Table A9).
[28] Our results remain robust if we use total number of friends (including duplication) instead of total "unique" friends (see Online Appendix Table A6).

SUPPLEMENTAL DATA

Supplemental data for this article can be accessed online at https://doi.org/10.1080/13545701.2023.2186461

REFERENCES

Adams-Prassl, Abi, Teodora Boneva, Marta Golin, and Christopher Rauh. 2020. "The Impact of the Coronavirus Lockdown on Mental Health: Evidence from the US."

HCEO Working Paper 2020-030. Human Capital and Economic Opportunity Global Working Group (HCEO), University of Chicago.
Afridi, Farzana, Kanika Mahajan, and Nikita Sangwan. 2021. "Employment Guaranteed? Social Protection During a Pandemic." IZA Discussion Paper 14099. Institute of Labor Economics.
Alan, Sule, Teodora Boneva, and Seda Ertac. 2019. "Ever Failed, Try Again, Succeed Better: Results from a Randomized Educational Intervention on Grit." *Quarterly Journal of Economics* 134(3): 1121–62.
Altindag, Onur, Bilge Erten, and Pinar Keskin. 2022. "Mental Health Costs of Lockdowns: Evidence from Age-Specific Curfews in Turkey." *American Economic Journal: Applied Economics* 14(2): 320–43.
Anderson, Michael L. 2008. "Multiple Inference and Gender Differences in the Effects of Early Intervention: A Reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects." *Journal of the American Statistical Association* 103(484): 1481–95.
Banks, James and Xiaowei Xu. 2020. "The Mental Health Effects of the First Two Months of Lockdown and Social Distancing During the Covid-19 Pandemic in the UK." IFS Working Paper W20/16. Institute for Fiscal Studies, London.
Baranov, Victoria, Sonia Bhalotra, Pietro Biroli, and Joanna Maselko. 2020. "Maternal Depression, Women's Empowerment, and Parental Investment: Evidence from a Randomized Controlled Trial." *American Economic Review* 110(3): 824–59.
Bazarkulova, Dana and Janice Compton. 2021. "Gender Differences in Self-Reported Stress and Health Behaviors of Doctors in Kazakhstan During COVID-19." *Feminist Economics* 27(1–2): 81–102.
Bertrand, Marianne, Kaushik Krishnan, and Heather Schofield. 2020. "How are Indian Households Coping Under the Covid-19 Lockdown? 8 Key Findings." University of Chicago Booth School of Business. https://www.chicagobooth.edu/research/rustandy/blog/2020/how-are-indian-households-coping-under-the-covid19-lockdown.
Bertrand, Marianne, Emir Kamenica, and Jessica Pan. 2015. "Gender Identity and Relative Income Within Households." *Quarterly Journal of Economics* 130(2): 571–614.
Blattman, Christopher, Julian C. Jamison, and Margaret Sheridan. 2017. "Reducing Crime and Violence: Experimental Evidence from Cognitive Behavioral Therapy in Liberia." *American Economic Review* 107(4): 1165–206.
Brodeur, Abel, Andrew E. Clark, Sarah Flèche, and Nattavudh Powdthavee. 2020. "COVID-19, Lockdowns and Well-Being:Evidence from Google Trends." IZA Discussion Paper 13204. Institute of Labor Economics.
Christov-Moore, Leonardo and Marco Iacoboni. 2019. "Sex Differences in Somatomotor Representations of Others' Pain: A Permutation-Based Analysis." *Brain Structure and Function* 224: 937–47.
Cohen, Sheldon and Thomas Ashby Wills. 1985. "Stress, Social Support, and the Buffering Hypothesis." *Psychological Bulletin* 98(2): 310–57.
Desai, Sonalde, Neerad Deshmukh, and Santanu Pramanik. 2021. "Precarity in a Time of Uncertainty: Gendered Employment Patterns During the COVID-19 Lockdown in India." *Feminist Economics* 27(1–2): 152–72.
Deshpande, Ashwini. 2020. "The COVID-19 Pandemic and Gendered Division of Paid and Unpaid Work:Evidence from India." IZA Discussion Paper 13815, Institute of Labor Economics.
Dhanaraj, Sowmya and Vidya Mahambare. 2022. "Male Backlash and Female Guilt: Women's Employment and Intimate Partner Violence in Urban India." *Feminist Economics* 28(1): 170–98.
Duflo, Esther, Rachel Glennerster, and Michael Kremer. 2007. "Using Randomization in Development Economics Research: A Toolkit." In *Handbook of Development Economics,*

Vol. 4, edited by T. Paul Schultz, and John A. Strauss, 3895–962. Amsterdam: Elsevier.

Erten, Bilge and Pinar Keskin. 2020. "Breaking the Cycle? Education and the Intergenerational Transmission of Violence." *Review of Economics and Statistics* 102(2): 252–68.

Etheridge, Ben and Lisa Spantig. 2020. "The Gender Gap in Mental Well-Being During the Covid-19 Outbreak: Evidence from the UK." ISER Working Paper Series 2020-08. Institute for Social and Economic Research, University of Essex.

Gash, Vanessa and Anke C. Plagnol. 2021. "The Partner Pay Gap: Associations Between Spouses' Relative Earnings and Life Satisfaction Among Couples in the UK." *Work, Employment and Society* 35(3): 566–83.

Ghosal, Sayantan, Smarajit Jana, Anandi Mani, Sandip Mitra, and Sanchari Roy. 2022. "Sex Workers, Stigma, and Self-Image: Evidence from Kolkata Brothels." *Review of Economics and Statistics* 104(3): 431–48.

Graeber, Daniel, Alexander S. Kritikos, and Johannes Seebauer. 2021. "COVID-19: A Crisis of the Female Self-Employed." *Journal of Population Economics* 34: 1141–87.

Gupta, Gaurav and Roopa Kudva. 2020. "Digitisation Makes Welfare Schemes Possible. It Can Be Discontinued When Pandemic Ends." *Indian Express*, July 13.

Hale, Thomas, Noam Angrist, Rafael Goldszmidt, Beatriz Kira, Anna Petherick, Toby Phillips, Samuel Webster, Emily Cameron-Blake, Laura Hallas, Saptarshi Majumdar, and Helen Tatlow. 2021. "A Global Panel Database of Pandemic Policies (Oxford COVID-19 Government Response Tracker)." *Nature Human Behaviour* 5: 529–38.

Ham, Sunyu. 2021. "Explaining Gender Gaps in the South Korean Labor Market During the COVID-19 Pandemic." *Feminist Economics* 27(1–2): 133–51.

Hamermesh, Daniel S. 2020. "Life Satisfaction, Loneliness and Togetherness, With an Application to Covid-19 Lockdowns." *Review of Economics of the Household* 18: 983–1000.

Hanson, Susan. 2010. "Gender and Mobility: New Approaches for Informing Sustainability." *Gender, Place & Culture* 17(1): 5–23.

Hensel, Lukas, Marc Witte, A. Stefano Cariac, Thiemo Fetzer, Stefano Fiorin, Friedrich M. Götz, Margarita Gomez, Johannes Haushofer, Andriy Ivchenko, Gordon Kraft-Toddi, Elena Reutskajaj, Christopher Roth, Erez Yoelil, and Jon M. Jachimowicz. 2022. "Global Behaviors, Perceptions, and the Emergence of Social Norms at the Onset of the COVID-19 Pandemic." *Journal of Economic Behavior & Organization* 193: 473–96.

Jejeebhoy, Shireen J. and Zeba A. Sathar. 2001. "Women's Autonomy in India and Pakistan: The Influence of Religion and Region." *Population and Development Review* 27(4): 687–712.

Kabeer, Naila, Shahra Razavi, and Yana van der Meulen Rodgers. 2021. "Feminist Economic Perspectives on the COVID-19 Pandemic." *Feminist Economics* 27(1–2): 1–29.

Kalenkoski, Charlene Marie and Sabrina Wulff Pabilonia. 2022. "Impacts of COVID-19 on the Self-Employed." *Small Business Economics* 58: 741–68.

Kawachi, Ichiro and Lisa F. Berkman. 2001. "Social Ties and Mental Health." *Journal of Urban Health: Bulletin of the New York Academy of Medicine* 78(3): 458–67.

Kesar, Surbhi, Rosa Abraham, Rahul Lahoti, Paaritosh Nath, and Amit Basole. 2021. "Pandemic, Informality, and Vulnerability: Impact of COVID-19 on Livelihoods in India." *Canadian Journal of Development Studies / Revue Canadienne D'études du Développement d'études du développement* 42(1): 145–64.

Kuan-Yu, Pan, Almar A. L. Kok, Merijn Eikelenboom, Melany Horsfall, Frederike Jörg, Rob A. Luteijn, Didi Rhebergen, Patricia van Oppen, Erik J. Giltay, and Brenda W. J. H. Penninx. 2020. "The Mental Health Impact of the COVID-19 Pandemic on People With and Without Depressive, Anxiety, or Obsessive-Compulsive Disorders: A Longitudinal Study of Three Dutch Case-Control Cohorts." *Lancet. Psychiatry* 8(2): P121–9.

Luke, Nancy and Kaivan Munshi. 2011. "Women as Agents of Change: Female Income and Mobility in India." *Journal of Development Economics* 94(1): 1–17.

Macmillan, Ross and Rosemary Gartner. 1999. "When She Brings Home the Bacon: Labor-Force Participation and the Risk of Spousal Violence Against Women." *Journal of Marriage and the Family* 61(4): 947–58.

McGinty, Emma E., Rachel Presskreischer, Hahrie Han, and Colleen L. Barry. 2020. "Psychological Distress and Loneliness Reported by US Adults in 2018 and April 2020." *JAMA* 324: 93–4.

Muralidharan, Karthik, Abhijeet Singh, and Alejandro J. Ganimian. 2019. "Disrupting Education? Experimental Evidence on Technology-Aided Instruction in India." *American Economic Review* 109(4): 1426–60.

Pierce, Matthias, Holly Hope, Tamsin Ford, Stephani Hatch, Matthew Hotopf, Ann John, Evangelos Kontopantelis, Roger Webb, Simon Wessely, Sally McManus, and Kathryn M. Abel 2020. "Mental Health Before and During the COVID-19 Pandemic: A Longitudinal Probability Sample Survey of the UK Population." *Lancet Psychiatry* 7: 883–92.

Proto, Eugenio and Climent Quintana-Domeque. 2021. "COVID-19 and Mental Health Deterioration by Ethnicity and Gender in the UK." *PLoS ONE* 16(1): e0244419.

Seck, Papa A., Jessamyn O. Encarnacion, Cecilia Tinonin, and Sara Duerto-Valero. 2021. "Gendered Impacts of COVID-19 in Asia and the Pacific: Early Evidence on Deepening Socioeconomic Inequalities in Paid and Unpaid Work." *Feminist Economics* 27(1–2): 117–32.

Shang, Qianqian, Wan-Hsin Liu, and Yongkun Yin. 2018. "The Impact of Within-Household Relative Income on Happiness: Does Gender Identity Matter?" *Journal of Research in Gender Studies* 8(2): 55–63.

World Bank. 2020. "In India, Women's Self-Help Groups Combat the COVID-19 (Coronavirus) Pandemic." https://www.worldbank.org/en/news/feature/2020/04/11/women-self-help-groups-combat-covid19-coronavirus-pandemic-india.

Woskie, Liana and Clare Wenham. 2021. "Do Men and Women "Lockdown" Differently? Examining Panama's Covid-19 Sex-Segregated Social Distancing Policy." *Feminist Economics* 27(1–2): 327–44.