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COVID-19 pandemic intensity, migration status, and household financial vulnerability: Evidence from India (updated on 27/05/2024)

Sanket Mohapatra & Akshita Nigania

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COVID-19 pandemic intensity, migration status, and household financial vulnerability: Evidence from India*

Sanket Mohapatra[†‡] and Akshita Nigania[§]

Abstract

This paper employs COVID-19 as a quasi-natural experiment to conduct an analysis of the heterogeneous effects of the pandemic on households' financial vulnerability across districts in India and investigates the role of migration and gender of the household head in moderating financial vulnerability. Using Indian panel household surveys and a difference-in-differences approach with coarsened exact matching, we provide causal evidence of a larger increase in the financial vulnerability index (FVI) of households in Indian districts with a higher incidence of COVID-19 cases per capita. A similar effect is observed when considering satellite-based night-time lights, a proxy for economic activity. Furthermore, during the pandemic, households with an out-migrant family member experienced relatively lower FVI, with a more pronounced effect for female-headed households, likely due to the financial help given by migrants. However, households that had an out-migrant in the pre-pandemic period, but not during the pandemic, were more financially vulnerable. This study provides a novel contribution to the literature through a better understanding of the varied effects of the pandemic-induced health and economic shocks on households' financial vulnerability based on pandemic intensity, migration status, and gender.

Keywords: COVID-19 pandemic; household financial vulnerability; night-time lights; migration status; female-headed households

JEL Classification: G50; G51; J16; 015

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†Economics Area, Indian Institute of Management Ahmedabad, Gujarat, India. Email: sanketm@iima.ac.in

‡Corresponding author

§J-PAL South Asia. Email:akshita.nigania74@gmail.com

1. Introduction

The COVID-19 pandemic severely affected households across the world as many households lost their income either in part or entirely owing to the disruption to livelihoods and increased unemployment due to the pandemic (Martin, Markhvida, Hallegatte, & Walsh, 2020). Prior research has examined the impact of the COVID-19 pandemic on households in China (Chen, Qian, & Wen, 2021) and the US (Baker, Farrokhnia, Meyer, Pagel, & Yannelis, 2020). In recent studies on India, Gupta, Malani, and Woda (2021) and Beyer, Jain, and Sinha (2023) find an adverse impact of COVID-19 on the income and consumption of Indian households during the pandemic. The correlates of financial vulnerability of households have been studied, for instance, for Namibia (Leika & Marchettini, 2017) and India (Singh & Malik, 2022) for the pre-COVID period, and for the US during the COVID-19 crisis (Bruce et al., 2022).

Prior studies, however, have not paid sufficient attention to the impact of the geographical variation in the intensity of the COVID-19 pandemic on Indian households' financial vulnerability. Recent research has reported that COVID-19 impacted local economies, specifically Indian districts, to varying extents (Beyer, Franco-Bedoya, & Galdo, 2021; Beyer et al., 2023). We build on and complement earlier studies by examining the heterogeneous impact of COVID-19 on household financial vulnerability at the district level in India. For this purpose, we employ a newly-created household financial vulnerability index (FVI) based on nationally representative household-level panel surveys encompassing the pre-COVID and COVID-19 periods.

Furthermore, out-migration from Indian households and the remittances sent by migrants have been shown to positively influence their financial situation (Dey, 2015) and expenditure on human capital investments (Parida, Mohanty, & Raman, 2015). This is likely to have a moderating effect on the financial vulnerability of households. However, the COVID-19 pandemic-induced health and economic crisis led to many out-migrant workers returning to their homes, adversely impacting Indian households with out-migrants (Gupta, Zhu, Doan, Michuda, & Majumder, 2021; Rajan, Sivakumar, & Srinivasan, 2020) and likely exacerbating these households' financial vulnerability during the pandemic. Moreover, the gender of the household head has been shown to influence households' financial behavior (Guiso & Zaccaria, 2023), including in India (Ghosh & Vinod, 2017). These motivate us to examine whether migration, return migration (during the pandemic), and the gender of the household head influenced financial vulnerability of Indian households prior to and during the pandemic.

We create a new household financial vulnerability index (FVI) based on Indian households' observed financial behaviour (use of financial instruments, borrowing for consumption expenditure, and debt refinancing) and their perception of financial health. The measures of financial vulnerability considered in earlier studies including delayed payments (Duygan & Grant, 2006), net wealth of the households (Brown & Taylor, 2008), financial ratios (Michelangeli & Rampazzi, 2016), and subjective indicators (Anderloni, Bacchiocchi, & Vandone, 2012). Some studies have classified financially fragile households as those with high debt (see, for instance, Jappelli, Pagano, and Di Maggio (2013)). The FVI draws on the above studies and focuses on the financial well-being of households. It differs from other indices such as those based on households' income and probability of falling into poverty (for instance, see Gaiha and Imai (2008)).

We then attempt to understand how the relationship between household FVI and its correlates changed during COVID-19 compared to the pre-COVID period. A *difference-in-differences* (DID) approach and coarsened exact matching are used to compare the effect of COVID-19 on households' FVI in districts with a relatively higher number of COVID-19 cases per 100,000 population compared to households in other districts, which allows us to capture the heterogeneous impact of the intensity of the pandemic on households' financial vulnerability across regions. Additionally, as a robustness of our baseline estimations, we use night-time lights data, a measure of the district-level variation in economic activity in India (Beyer, Chhabra, Galdo, & Rama, 2018; Beyer et al., 2023), to capture the differential impact of COVID-19 intensity across Indian districts on households' financial vulnerability. In further analysis, the effects of out-migrant members in the household and gender of the household head on households' FVI during the COVID-19 period are studied.

First, we observe a significant variation in the financial vulnerability of households in India during the COVID-19 period (compared to the pre-COVID period) depending on their education, occupation, and income. We find that households with a better educated household head, higher levels of income, and white-collar employees experienced a relatively smaller increase in financial vulnerability during the COVID-19 period, while lower income households and households with daily wagers experienced a larger rise in financial vulnerability relative to the pre-COVID period. These findings suggest that improving education and employment opportunities can contribute to alleviating households' financial vulnerability.

Next, we employ the COVID-19 crisis as a quasi-natural experiment and exploit the geographical variation in pandemic intensity across Indian districts to better understand the differential impact of the pandemic on household FVI. We identify this effect using a *difference-in-differences* (DID) approach with coarsened exact matching. Our results provide causal evidence that the increase in household FVI was substantially larger for households in the top-third districts with the highest number of COVID-19 cases per 100,000 population compared to other districts. We find a similar impact for households in districts with the lowest night-time lights (a proxy for economic activity) during the COVID-19 period. These results suggest that measures to mitigate the financial vulnerability of households during a crisis are likely to be effective if these are based on the intensity of the crisis at the subnational (district) level.

Further, we find that households with at least one out-migrant member during the COVID-19 period, especially those with a female head, were less financially vulnerable during the pandemic, as compared to households with no out-migrant members. However, we observe that households with an out-migrant member in the pre-COVID period but not during the pandemic, were significantly more financially vulnerable during the pandemic compared to other households, with a larger adverse effect observed for female-headed households. The results suggest that migrants play an important role in mitigating financial vulnerability of migrant-sending households, while return migration during a crisis can exacerbate financial vulnerabilities.

The paper is structured as follows. The next section discusses the relevant literature on household FVI, migration during crisis, role of the gender in household finances and the COVID-19 pandemic, and the novel contributions of this paper to the extant literature. The data used for the estimations is discussed in Section 3. Section 4 discusses the FVI and its correlates prior to and during the COVID-19 pandemic. It also presents the empirical methodology and regression results for the differential impact of COVID-19 across districts based on COVID-19 cases, economic activity (proxied by night-time lights), migration status, and gender of the household head. Section 5 concludes with a summary of the findings and policy implications.

2. Literature review

The paper relates to the literature on correlates of household financial vulnerability, the effects of shocks faced by households due to the COVID-19 pandemic, and migration during crisis. The following sub-sections present a comprehensive summary of the related strands of literature, and the specific contributions of this study to the literature.

2.1. Household financial vulnerability across countries and in India

Previous literature has studied the correlates of financial vulnerability in developing and developed countries. For example, Daud, Marzuki, Ahmad, and Kefeli (2019) analyze financial vulnerability as the inability to meet household needs and the ability of households to deal with financial shocks and income uncertainty among the Malaysian households using survey data. Jappelli et al. (2013) link financial fragility to high debt based on cross-country data on household finances from UK, USA, and Germany. Some earlier studies have also established debt-to-income ratio and debt service-to-income ratio as key determinants of household financial vulnerability (Bańbuła, Kotuła, Przeworska, & Strzelecki, 2015; Dey, Djoudad, Terajima, et al., 2008). Other studies have also found a link between job insecurity and financial distress (Giannetti, Madia, & Moretti, 2014).

Recent research has also focused on creation of household financial vulnerability indices. Noerhidajati, Purwoko, Werdaningtyas, Kamil, and Dartanto (2021) use survey data from Indonesia to create a household financial vulnerability index using objective measures including household arrears, debt, budgeting ability, resilience to financial shocks and participation in basic social activities (see, Bialowolski and Weziak-Bialowolska (2014) for a similar index for Italian households). Ali, Khan, and Ahmad (2020) use survey data from approximately 17,000 households in Pakistan to investigate the relationship between the household head's education and an index of household financial vulnerability, which is based on income, consumption, physical wealth, savings, and employment status (see also Albacete et al. (2014) and Ampudia, Van Vlokhoven, and Żochowski (2016)).

Murphy and Scott (2014) create a household financial vulnerability index using subjective and objective indicators for households in rural Ireland and examine the effects of a housing crash and economic recession. Similarly, Anderloni et al. (2012) use survey data from Italian households to analyze household financial distress by developing an index using variables that indicate if the household had trouble making ends meet, if bank application was turned down, if the household had trouble paying bills and if the household had to go without healthcare.

Similarly, there has also been some studies on household financial vulnerability in the Indian context. A study by Singh and Malik (2022) creates a measure for household financial vulnerability using cross-sectional survey data for the pre-COVID period using three self-reported estimates: making ends meet, perception of income shock, and perception of expenditure shock to the determinants of household financial vulnerability. Kamble, Mehta, and Rani (2023) construct a financial well-being index at the household level based on four self-reported measures which capture financial satisfaction, financial capability, financial confidence, and financial anxiety of the household. Even though some studies in the Indian context do not create financial vulnerability indices directly, various comparable indicators of household welfare have been used. For instance, a study by Gaiha and Imai (2008) assesses household vulnerability as the probability of household consumption being below the poverty line in rural South India. Dhanaraj (2016) examines the economic vulnerability of households in Andhra Pradesh state in India in the event of a serious illness or the death of a household member using self-reported measures of health shocks and coping strategies.

2.2. *COVID-19 pandemic and households: International and Indian evidence*

The severity of the COVID-19 pandemic and the associated economic shocks affected households across countries. Some studies have discussed the pandemic's impact on overall income and consumption. For instance, while US households experienced an initial increase in spending followed by a decline (Baker et al., 2020), consumption of Chinese households fell during the pandemic (Chen et al., 2021). Several studies have focused specifically on financial vulnerability during the pandemic in countries other than India. Alhenawi and Yazdanparast (2022) use survey data from countries in North America, Europe, Africa, and Latin America and find that the pandemic created a state of financial vulnerability leading to a defensive decision making in spending, consumption, and investment. Using survey data from Netherlands, Van Ophem (2020) reports a significant increase in household financial vulnerability after the COVID-19 shock, particularly for households with uncertain incomes, inflexible budgets, lack of buffers, and persistent low income.

A study by Gupta, Malani, and Woda (2021) using household panel survey data from India finds a large decline in income and consumption of Indian households during the COVID-19 pandemic. Beyer et al. (2023) examine the differential impact of COVID-19 containment policies on economic activities at the district-level in India using night-time lights data, and find that districts with most severe restrictions observed significantly lower night-time lights intensity.[1] Using a survey of around 5,000 respondents across 12 states of India during the COVID-19 period, Kesar, Abraham, Lahoti, Nath, and Basole (2021) find that almost two-third of respondents reported losing employment during the lockdown, while those who continued to be employed witnessed a sharp decline in their earnings.

2.3. *Migration during crisis and role of gender in household finances*

Literature has documented evidence on the positive role of migrant family members for household during episodes of crisis. A study by Nguyen, Raabe, and Grote (2015) in Vietnam find

[1]The lockdown imposed in response to the COVID-19 by the Indian government was amongst the most stringent measures undertaken by any governments around the world (Hale, Petherick, Phillips, & Webster, 2020).

evidence that in households exposed to agricultural and economic shocks, migration for a employment is a livelihood support strategy, and has positive income growth effects. Mishra, Kondratjeva, and Shively (2022) provide evidence that remittances sent by migrants are an important source of food consumption and education expenditure for households in Nepal. Remittances from migrant family members also acts as insurance for relatives at home in events of negative income shocks (Yang & Choi, 2007) in the Philippines.

The COVID-19 pandemic led to many out-migrant workers returning to their homes (Guadagno, 2020). India also experienced large-scale return migration from urban regions to small towns and villages during the COVID-19 period (Rajan et al., 2020). A study by Gupta, Zhu, et al. (2021) conducted in a rural region of West Bengal in India, finds that in the month immediately after India's lockdown announcement to contain the pandemic, there was a 63% reduction in remittances sent by migrants to the household as compared to the pre-COVID period. Consequently, these households reported a substantial reduction in their meal portions' size and consumed fewer food items.

Studies have also examined the role of gender in household finances. In Italy, a study found that the gender of the household head can affect decisions on household finances (Guiso & Zaccaria, 2023). Ghosh and Vinod (2017) find that Indian households show a significant disparity in use and access to finance by gender. They report that female-headed households differ from their male counterparts in the use of formal and informal finance, with female-headed households favoring informal finance and being less likely to access formal finance compared to households headed by males.

2.4. *Novel contributions to literature*

This paper makes four novel contributions to the literature. Firstly, the literature on household financial vulnerability is mainly limited to its measure and correlates (O'Connor et al., 2019; Singh & Malik, 2022) and the relationship between financial vulnerability and factors such as household debt (for example, Jappelli et al. (2013) and Duygan and Grant (2006)) and education of the household head (Ali et al., 2020), without much focus on the impact of aggregate shocks such as the pandemic. In a cross-sectional study for the United States that is similar to ours, Bruce et al. (2022) find that US households that were ex-ante more financially vulnerable experienced greater financial strain during the pandemic. This paper contributes to the literature by analyzing the heterogeneous effects of the COVID-19 pandemic on household financial vulnerability based on variation in the intensity of the pandemic across districts in India.

Secondly, this paper provides novel evidence on the role of migrants and the the gender of the household head in mitigating the financial vulnerability of the household during the COVID-19 pandemic. Our study complements earlier studies that have found a positive impact of migration and remittances on households during times of uncertainty and natural disasters (Mishra et al., 2022; Yang & Choi, 2007). Furthermore, we contribute to a better understanding of the implications of large-scale return migration during the pandemic (Guadagno, 2020; Gupta, Zhu, et al., 2021; Rajan et al., 2020) by providing new evidence of a differential impact on financial vulnerability of Indian households that had a migrant in the pre-pandemic period but not during the pandemic. Alongside, our findings on the combined effects of out-migrant family members and the gender of the household head on financial vulnerability of the household add to the literature on the role of gender in household finances (Ghosh & Vinod, 2017; Guiso & Zaccaria, 2023).

Thirdly, this paper complements the recent research on household financial vulnerability across developed and developing countries. For example, Ampudia et al. (2016) analyze the financial fragility of households in the Euro area. Papers on household financial vulnerability in developing countries include studies from Pakistan (Ali et al., 2020), Malaysia (Daud et al., 2019), and Indonesia (Noerhidajati et al., 2021).

Finally, the paper uses a comprehensive panel household survey dataset, the Consumer Pyramids Household Survey (CPHS), to analyze the effect of COVID-19 on household financial vulnerability. Previous research in this context has usually relied on cross-sectional surveys owing to the limited availability of household panel data (Bruce et al., 2022; Midões & Seré, 2022). By utilising panel data instead of cross sectional data, this paper accounts for the time invariant household specific characteristics, helping in minimising the omitted variable bias that might arise due to unobserved household characteristics in a cross-sectional analysis (Yee & Niemeier, 1996).

3. Data

This section describes the data used for the analysis and creation of the household financial vulnerability index.

3.1. Indian household panel survey

The paper uses household level panel data from the Consumer Pyramids Household Survey (CPHS) conducted by the Centre for Monitoring the Indian Economy (CMIE) covering approximately 175,000 Indian households across 28 states and union territories.[2] Our analysis considers 9 CPHS waves from wave 13 through wave 21 covering the time period between January, 2018 to December, 2020. Each CPHS wave accounts for four months and the surveys are conducted thrice every year. Additionally, monthly income data from the CPHS Income Pyramids is aggregated to the wavely frequency and merged with the data on financial instruments, borrowings, and assets. Finally, the individual level dataset, that contains information about all the members of the households, is used to measure characteristics of the household head and migration behaviour.

3.2. Household financial vulnerability index (FVI) for Indian households

To determine the financial vulnerability of the Indian households, the paper creates a comprehensive indicator that combines both objective and subjective aspects to create the financial vulnerability index. Among the objective components of FVI, the first is an indicator for debt refinancing (borrowing for debt repayment), which is similar to Anderloni et al. (2012) who have used arrears in debt repayment to measure the households' ability to repay their debt. The second component is the number of instruments the household has saved in during the last 120

[2]The regions not covered by CPHS are Arunachal Pradesh, Nagaland, Manipur, Mizoram, Sikkim, Andaman & Nicobar Islands, Lakshadweep, Dadra & Nagar Haveli and Daman & Diu.

days (with the variable taking on value 2 if no savings at all, 1 if only one saving instrument, and 0 if more than one saving instrument), with higher values indicating greater vulnerability.[3] The third component is an indicator for borrowing by the household for consumption expenditure. This is in line with Giannetti et al. (2014) who define financial distress as an event where households report difficulty in keeping up with household expenses by the end of the month. The fourth and fifth components, which are subjective, are indicators for whether the household believes that its financial condition is worse than last year, and a household's unwillingness to purchase a consumer durable.[4] Previous literature has also used subjective measures to obtain a more comprehensive indicator of financial vulnerability (Anderloni et al., 2012; Noerhidajati et al., 2021).

Since all the variables included in the construction of the FVI in this paper are either binary or categorical, we employ multiple correspondence analysis (MCA) which is more appropriate for such variables. A number of studies have utilised MCA for creating health indicators (Kohn, 2012), asset indices (Booysen, Van Der Berg, Burger, Von Maltitz, & Du Rand, 2008), measurement of poverty (Ezzrari & Verme, 2013), and gender inequality (Ferrant, 2014). This paper follows Greenacre and Blasius (2006) to create the household financial vulnerability index. The first step is to create a matrix of binary or categorical variable used to measure the FVI for each household. MCA is then applied to the categorical matrix generating a set of category-weights for each variable. Finally, the FVI is created by combining the category-weights with the response to the variable. The following equation describes the construction of the FVI:

$$FVI_{i,t} = \sum_{t=1}^{t=T} \sum_{j=1}^{j=n} W_{i,j,t} * R_{i,j,t} \tag{1}$$

where, $R_{i,j,t}$ is response of household i to variable j at time period t and $W_{i,j,t}$ is the first dimension category-weight for household i and variable j at time period t calculated using MCA.

[3]Although household savings in amounts (usually calculated as the difference between disposable income and consumption) is arguably a better indicator than the discrete savings variable used in this paper, the former may have measurement problems owing to misreporting of income in household surveys (Deaton, 1997; Jha & Basole, 2022).

[4]This variable does not imply that the households are incapable of buying the goods, but are putting off such purchases for the near future.

$FVI_{i,t}$ is summation of the responses of all households to the aforementioned variables used in the construction of the FVI over all time periods. MCA weights for each variable are presented in Table A1.

3.3. *Independent variables*

The independent variables used in the empirical analysis are defined in Table 1. Prior studies have reported a correlation between household financial vulnerability and asset ownership (Ampudia et al., 2016), number of dependent members both children and seniors (Anderloni et al., 2012; Daud et al., 2019), and age and gender of the household head (Noerhidajati et al., 2021). Further, we also include the household head's occupation group as a determinant of FVI as it would reflect the type of job and earnings of the household, which, in turn, may be correlated with the FVI (Giannetti et al., 2014). Another commonly used determinant of household financial vulnerability is the overall income of the household which is directly related to the household's ability to absorb negative shocks. Previous studies concerning household financial vulnerability have found income to be a strong determinant (Ampudia et al., 2016; Leika & Marchettini, 2017). Research shows that education of the household head also influences the household income (Ali et al., 2020). Hence, we include level of education of the household head as a correlate of the household FVI.

The paper also examines the effect of migration status of household members on households' financial vulnerability. Households with out-migrants are those where at least one of the members has migrated out of the household for reasons related to employment including permanent or seasonal employment. Data for the migration status of households is obtained using the individual level dataset provided by the CPHS and then aggregated to the household level. We further examine the financial vulnerability of households where there were out-migrants prior to the COVID-19 period but no out-migrants during COVID-19.

3.4. *District-level COVID-19 cases*

Data on number of daily COVID-19 cases is obtained from Covid19India.org and SHRUG database by the Development Data Lab (Asher, Lunt, Matsuura, & Novosad, 2019). For the purposes of this paper, the daily frequency dataset is aggregated to a 'wavely' frequency by summing the number of cases over four months to match with the frequency of the household level data. The study uses the number of COVID-19 cases per 100,000 population for a relative comparison.

The COVID-19 indicator is a binary variable that takes on the value 1 for all the time periods from May, 2020 (CPHS wave 20) until December 2020, and 0 for the previous time periods from January, 2018. Wave 20 is considered since the previous wave 19 conducted from January to April 2020 includes two pre-COVID months. As a robustness check, we create an alternate indicator for the COVID-19 period which takes the value 1 for the period from CPHS wave 19 onward. Our baseline estimation sample based on availability of the dependent and explanatory variables includes 1,045,433 observations for 152,070 households across 469 Indian districts including both the pre-COVID and COVID-19 periods (see Table 2 for the summary statistics).

4. Empirical methodology and results

4.1. *Correlates of household FVI*

This section discusses the correlates of household FVI prior to and during the COVID-19 pandemic. The following equation is used to examine the relationship between FVI and its correlates across the pre-COVID and COVID-19 periods:

$$\begin{aligned} FVI_{i,t} = \alpha + \beta_0 Post_t + \beta_1 Post_t * \sum_{j=1}^{j=J} IncQuin_{i,t,j} + \beta_2 Post_t * \sum_{k=i}^{k=K} HohEdu_{i,t,k} \\ + \beta_3 Post_t * \sum_{l=1}^{l=L} HohOccup_{i,t,l} + \beta_4 CovidCases_{v,t} + \beta_5 \boldsymbol{X}_{i,t} + \mu_i + \theta_v + \tau_{st} + \gamma_t + \varepsilon_{i,t} \end{aligned} \quad (2)$$

The subscripts i, v, s and t represent household, district, state, and year, respectively. $Post_t$ is a COVID-19 indicator which takes on the value 1 for CPHS waves during the COVID-19 time period—waves 20 (May to August 2020) and 21 (September to December 2020)—and 0 otherwise.[5] $IncQuin_{i,t,j}$ indicates the households' income group where $j = 1, ..., 5$. The first income quintile in the pre-COVID period is considered as the reference category. $HohEdu_{i,t,k}$ categorises the education of the household head into four categories as given in Table 1. The reference category for this variable includes households with household heads that have a college or higher degree in the pre-COVID period. $HohOccup_{i,t,l}$ is the occupation group of the household head where $l = 1, ..., 8$. The occupations are divided into eight groups and are listed in Table 1. Households with household heads employed as white collar employees in the pre-COVID period are included in the reference category for this variable. $\boldsymbol{X}_{i,t}$ is a vector of household-level characteristics which includes $AssetIndex_{i,t}$, $Children_{i,t}$ (proportion of children younger than 10 years), $Seniors_{i,t}$ (proportion of senior members older than 64), $Femaleheaded_{i,t}$ (dummy for households with a female household head), and $HohAge_{i,t}$ (age of the household head).[6] The number of COVID-19 cases per 100,000 population in each district ($CovidCases_{v,t}$) is also included as an explanatory variable. The household and district fixed effects, μ_i and θ_v, account for unobserved household- and district-specific characteristics. The interactive state-year fixed effects, τ_{st}, account for time-varying factors across the different states. District-specific time trends, γ_t, capture longer-term trends in the dependent variable in the different districts. $\varepsilon_{i,t}$ is the error term. This estimation includes the pre-COVID and COVID-19 periods, from CPHS wave 13 through wave 21, i.e., from January, 2018 to December, 2020.

The results presented in Table 3 show the correlates of household FVI prior to and during the COVID-19 pandemic. The coefficients for income quintiles in column 1 for the pre-COVID and COVID-19 periods (reported in Figure 1) show that the financial vulnerability (FVI) for households in all five income groups was higher during the COVID-19 period as compared to the pre-COVID period. However, households in higher income quintiles were relatively less

[5]While the COVID-19 outbreak in India began in March, 2020, the number of cases began to rise after the nationwide lockdown imposed until May 2020 was relaxed.

[6]*AssetIndex* is calculated based on the ownership of houses, air conditioners, cars, two wheelers, computers, refrigerators, washing machines, televisions, tractors, and cattle using PCA.

vulnerable as compared to those in the lower quintiles. The coefficients of education levels during the COVID-19 period from column 2 (shown in Figure 2) suggest that as compared to households with household heads who had college or higher degree, all other households are more vulnerable during COVID-19. The coefficients for occupation groups during the COVID-19 period from column 3 (reported in Figure 3) show that the household FVI for all household heads' occupation groups was higher during the COVID-19 period as compared to the pre-COVID period, implying that all the occupation groups were more financially vulnerable during the pandemic. However, some groups such as small traders or home-based workers and daily wagers were relatively more affected.

4.2. Differential impact of COVID-19 on household FVI across Indian districts

In this section, we discuss the differential impact of COVID-19 on households' financial vulnerability based on variation in the intensity of the pandemic, as measured by COVID-19 cases per 100,000 population and satellite based night-time lights, across districts in India.

We use a difference-in-differences (DID) estimation to analyze the effect of the intensity of COVID-19 on the household FVI. To find the differential impact of the pandemic across districts, we compare households in the top one-third districts with the highest number of COVID-19 cases to similar households in the bottom two-third districts with the lowest number of COVID-19 cases. The number of cases is considered over two CPHS waves, wave 20 and 21 (May, 2020 to Dec, 2020) to indicate the intensity of spread of the pandemic in the districts. We employ the following DID estimation:

$$\begin{aligned} FVI_{i,t} = {} & \alpha + \beta_0 Post_t + \beta_1 HighCasesDist_v + \beta_2 Post_t * HighCasesDist_v \\ & + \beta_3 \sum_{j=1}^{j=J} IncQuin_{i,t,j} + \beta_4 \sum_{k=i}^{k=K} HohEdu_{i,t,k} + \beta_5 \sum_{l=1}^{l=L} HohOccup_{i,t,l} \\ & + \beta_6 CovidCases_{v,t} + \beta_7 \boldsymbol{X}_{i,t} + \mu_i + \theta_v + \tau_{st} + \gamma_t + \varepsilon_{i,t} \end{aligned} \quad (3)$$

In the above equation $FVI_{i,t}$ is the dependent variable which captures the financial vulnerability index of household *i* at time *t*. $Post_t$ is the COVID-19 indicator which takes on the value 1 for the CPHS waves during the COVID-19 time period, and 0 otherwise. CPHS waves 20 and 21 covering the time period between May, 2020 to December, 2020 are considered the COVID-19 time period. $HighCasesDist_v$ takes on value 1 for the top one-third districts with the highest number of COVID-19 cases per 100,000 population, and 0 for the bottom two-third districts. Therefore, the households in the top one-third districts with the highest number of cases are the 'treatment' group and the households in all the other districts are the 'control' group. β_2 is the *difference-in-differences* estimator and measures the effect of relatively higher intensity of COVID-19 on the household FVI. $\boldsymbol{X}_{i,t}$ are household level controls included in Equation 2. μ_i, θ_v, and τ_{st} are the household fixed effects, district fixed effects, and state-year fixed effects, respectively. We also include district-specific time trends, γ_t, for longer-term trends in the dependent variable at the district-level. $\varepsilon_{i,t}$ is the error term.

The sample for the analysis is created using coarsened exact matching (CEM) technique to account for the non-random assignment of the treatment, following Blackwell, Iacus, King, and Porro (2009). Here, we match the treated households (in high cases districts) and untreated households (in other districts) on the following characteristics: asset index, household income, education of the household head, and occupation group of the household head.[7] Figure 4 shows that households in high cases districts followed a fairly similar trend to the households in low cases districts before the pandemic with a lower average FVI for households in high cases districts, making it likely that the DID assumption of parallel trends holds.[8]

Table 4 presents the results for the heterogeneous impact of COVID-19 on FVI across districts using the number of COVID-19 cases per 100,000 population. The coefficient for the DID estimator term is positive implying that households in the top one-third districts with highest

[7]Since the data used for the analysis is a panel data and same households are surveyed each wave, we repeat the matching process for each wave individually to avoid a household being matched with another observation for the same household from a different time period. Further, to achieve covariate balance, we employ entropy balance technique on the matched sample as described in Hainmueller (2012).

[8]However, during the COVID-19 period, the average FVI for households in high cases districts increased exponentially, exceeding the average FVI for households in low cases districts.

number of cases per 100,000 population were more financially vulnerable during the COVID-19 period. The districts with higher number of cases were more affected by the health crisis and also likely had stricter and longer restrictions, making the households in such districts more vulnerable during this period.

A robustness check was performed for an alternate COVID-19 indicator with the full year defined as the COVID-19 period from January, 2020 to December, 2020 to account for the initial two months of COVID-19 outbreak and the nationwide lockdown in India. The regression results for this alternate definition of COVID-19 indicator are presented in Table 5 and are consistent with the earlier findings.

Next, we consider the differential impact of COVID-19 on household FVI across districts based on economic activity in the districts measured using night-time lights (NTL). Night-time lights has been used extensively to measure economic activities in the literature (Beyer et al., 2018, 2021). Here, the treatment group for the DID analysis consists of districts that have the lowest economic activity, which takes on the value 1 for the bottom one-third districts with lowest night-time lights value (with least economic activity) during the pandemic, and 0 otherwise for a matched sample of other districts. In this regression, we use the COVID-19 indicator with the full year defined as the COVID-19 period (January, 2020 to December, 2020) since economic activities were most affected during the complete lockdown period in March and April 2020. The results in column 1 of Table 6 show that households in the districts with largest disruption to economic activity (captured by bottom one-third districts with lowest NTL value) were more financially vulnerable during COVID-19, as compared to other districts. The results remain robust to controlling for different sets of household characteristics and are reported in the subsequent columns.

4.3. *Impact of COVID-19 on household FVI based on out-migration status and gender of the household head*

Migration out of the household for reasons related to work and employment can affect households' financial vulnerability. To understand the importance of out-migration on the households' FVI, we create an indicator for households with out-migrant members.[9] In order to account for possible return migration during the pandemic (Rajan et al., 2020), we create another variable that takes on the value 1 if the household had an out-migrant in the pre-COVID period but not during the pandemic, and 0 otherwise.[10] Here, the treatment period is taken as the entire year from January, 2020 to December, 2020 since most of the out-migration due to COVID-19 was observed in the initial months during the complete lockdown.

Columns 1 and 2 in Table 7 show that households that have at least one out-migrant member are less financially vulnerable in general and particularly during COVID-19, as compared to other households. This could be because of the contributions from out-migrant workers. Columns 3 and 4 report the impact on households that had an out-migrant in the pre-COVID waves but not during the COVID-19 period. Here, the positive coefficient suggests that financial vulnerability during COVID-19 is substantially higher for households that had an out-migrant in the period prior to the pandemic but not during the pandemic. This can be attributed to a loss of income due to the out-migrant members returning home, possibly owing to loss of jobs or restrictions to economic activities during the COVID-19 periods.

Table 8 presents the impact of COVID-19 on the household FVI based on both the gender of the household head and out-migration status. Usually, if there is a male out-migrant worker, the females in the household assume the position of the household head in their absence. We observe from columns 1 and 2 that household FVI is lower for households with an out-migrant household member during the COVID-19 period, with a relatively larger reduction for female-headed households possibly due to financial assistance provided by a migrant member during the health crisis. In the next two columns, we examine households where there was a migrant in the pre-COVID period but not during the pandemic. In such households, female-headed households were more adversely affected as compared to their counterparts signified by the

[9]Out-migration is measured as a binary variable that takes on the value 1 if a household has at least one out-migrant member living outside the household for reasons other than marriage, family split, and education, in the time period. We use the CEM matching technique paired with entropy balancing (as described in the previous sections) to create the sample based on migration status of the members of the household to compare households with and without out-migrant members.

[10]Here, to account for seasonality, we compare migration status of the members during COVID-19 to corresponding waves in the pre-COVID period.

larger positive coefficient of the interaction of the female-headed household indicator with the COVID-19 dummy. The potential loss of remittance income due to the pandemic-induced return of an out-migrant member, who is likely to be the main earning member for a female-headed household, possibly affects them to a larger degree.

5. Conclusion

This paper investigates the heterogeneous impact of COVID-19 on household financial vulnerability based on the geographical variation in the intensity of the pandemic across 469 Indian districts and households' migration status. Using a difference-in-differences approach, we find a higher increase in the financial vulnerability of households in the top-third districts with the highest number of COVID-19 cases per 100,000 population and the lowest night-time lights (a proxy for economic activity), suggesting that households in such districts were impacted more adversely than in other districts. Further, the study also considers the impact of having out-migrant members in households and the gender of household heads on FVI during the COVID-19 period. We find that households with at least one out-migrant member during this period, especially those with a female head, are less financially vulnerable during the pandemic. This is likely due to the financial contributions made by the out-migrant family members. However, households that had an out-migrant member in the pre-COVID period but not during the pandemic, possibly due to return migration, experience higher financial vulnerability during the pandemic, with a larger effect observed for female-headed households.

This paper contributes to the existing literature on household financial vulnerability by focusing on varied impact of the pandemic and households' migration status. The findings of the paper indicate that the COVID-19 pandemic had significant impact on households' financial well-being. This paper fills gaps in the extant literature by studying the differential impact of the intensity of the COVID-19 pandemic across Indian districts on households' FVI, and examining whether migration, return migration (during the pandemic), and the gender of the household head influenced household financial vulnerability prior to and during the pandemic.

Studying the correlates of financial vulnerability and the impact of COVID-19 has some broader policy implications since households' financial vulnerability can also affect their spending and consumption behaviour. An increase in financial distress of households may result in decreased overall consumption, adversely impacting aggregate demand and the growth of the economy. Further, possible loan defaults by households due to greater financial vulnerability can also impact banks and other financial institutions that have lent to these households, negatively affecting their balance sheets. Future research can examine the role of exogenous shocks and household financial vulnerability and their links to overall financial stability and economic growth.

References

Albacete, N., Eidenberger, J., Krenn, G., Lindner, P., Sigmund, M., et al. (2014). Risk-bearing capacity of households–linking micro-level data to the macroprudential toolkit. *Financial Stability Report*, *27*, 95–110.

Alhenawi, Y., & Yazdanparast, A. (2022). Households' intentions under financial vulnerability conditions: is it likely for the COVID-19 pandemic to leave a permanent scar? *International Journal of Bank Marketing*, *40*(3), 425–457.

Ali, L., Khan, M. K. N., & Ahmad, H. (2020). Education of the head and financial vulnerability of households: Evidence from a household's survey data in Pakistan. *Social Indicators Research*, *147*(2), 439–463.

Ampudia, M., Van Vlokhoven, H., & Żochowski, D. (2016). Financial fragility of Euro area households. *Journal of Financial Stability*, *27*, 250–262.

Anderloni, L., Bacchiocchi, E., & Vandone, D. (2012). Household financial vulnerability: An empirical analysis. *Research in Economics*, *66*(3), 284–296.

Asher, S., Lunt, T., Matsuura, R., & Novosad, P. (2019). The socioeconomic high-resolution rural-urban geographic dataset on India (SHRUG). *URL: https://doi.org/10.7910/DVN/DPESAK*.

Baker, S. R., Farrokhnia, R. A., Meyer, S., Pagel, M., & Yannelis, C. (2020). How does household spending respond to an epidemic? Consumption during the 2020 COVID-19 pandemic. *The Review of Asset Pricing Studies*, *10*(4), 834–862.

Bańbuła, P., Kotuła, A., Przeworska, J., & Strzelecki, P. (2015). Which households are really financially distressed: how MICRO-data could inform the MACRO-prudential policy. In *Irving Fisher Committee Workshop on "Combining Micro And Macro Statistical Data For Financial Stability Analysis. Experiences, Opportunities and Challenges," Warsaw, Poland* (pp. 14–15).

Beyer, R., Chhabra, E., Galdo, V., & Rama, M. (2018). Measuring districts' monthly economic activity from outer space. *World Bank Policy Research Working Paper No. 8523*.

Beyer, R., Franco-Bedoya, S., & Galdo, V. (2021). Examining the economic impact of COVID-

19 in India through daily electricity consumption and nighttime light intensity. *World Development*, *140*, 105287.

Beyer, R. C., Jain, T., & Sinha, S. (2023). Lights out? COVID-19 containment policies and economic activity. *Journal of Asian Economics*, *85*, 101589.

Bialowolski, P., & Weziak-Bialowolska, D. (2014). The index of household financial condition, combining subjective and objective indicators: An appraisal of Italian households. *Social Indicators Research*, *118*(1), 365–385.

Blackwell, M., Iacus, S., King, G., & Porro, G. (2009). CEM: Coarsened exact matching in Stata. *The Stata Journal*, *9*(4), 524–546.

Booysen, F., Van Der Berg, S., Burger, R., Von Maltitz, M., & Du Rand, G. (2008). Using an asset index to assess trends in poverty in seven Sub-Saharan African countries. *World Development*, *36*(6), 1113–1130.

Brown, S., & Taylor, K. (2008). Household debt and financial assets: evidence from Germany, Great Britain and the USA. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *171*(3), 615–643.

Bruce, C., Gearing, M. E., DeMatteis, J., Levin, K., Mulcahy, T., Newsome, J., & Wivagg, J. (2022). Financial vulnerability and the impact of COVID-19 on American households. *Plos One*, *17*(1), e0262301.

Chen, H., Qian, W., & Wen, Q. (2021). The impact of the COVID-19 pandemic on consumption: Learning from high-frequency transaction data. In *AEA Papers and Proceedings* (Vol. 111, pp. 307–311).

Daud, S. N. M., Marzuki, A., Ahmad, N., & Kefeli, Z. (2019). Financial vulnerability and its determinants: Survey evidence from Malaysian households. *Emerging Markets Finance and Trade*, *55*(9), 1991–2003.

Deaton, A. (1997). *The analysis of household surveys: a microeconometric approach to development policy*. World Bank Publications.

Dey, S. (2015). Impact of remittances on poverty at origin: A study on rural households in India using covariate balancing propensity score matching. *Migration and Development*, *4*(2), 185–199.

Dey, S., Djoudad, R., Terajima, Y., et al. (2008). A tool for assessing financial vulnerabilities in the household sector. *Bank of Canada Review*, *2008*(Summer), 47–56.

Dhanaraj, S. (2016). Economic vulnerability to health shocks and coping strategies: evidence from Andhra Pradesh, India. *Health Policy and Planning*, *31*(6), 749–758.

Duygan, B., & Grant, C. (2006). Household debt and arrears: What role do institutions play? In *Finance and Consumption Workshop, EUI.*

Ezzrari, A., & Verme, P. (2013). A multiple correspondence analysis approach to the measurement of multidimensional poverty in Morocco 2001–2007. In *Poverty and Social Exclusion around the Mediterranean Sea* (pp. 181–209). Springer.

Ferrant, G. (2014). The Multidimensional Gender Inequalities Index (MGII): A descriptive analysis of gender inequalities using MCA. *Social Indicators Research*, *115*(2), 653–690.

Gaiha, R., & Imai, K. (2008). Measuring vulnerability and poverty estimates for rural India. *WIDER Research Paper no. 2008/40*.

Ghosh, S., & Vinod, D. (2017). What constrains financial inclusion for women? Evidence from Indian micro data. *World Development*, *92*, 60–81.

Giannetti, C., Madia, M., & Moretti, L. (2014). Job insecurity and financial distress. *Applied Financial Economics*, *24*(4), 219–233.

Greenacre, M., & Blasius, J. (2006). *Multiple correspondence analysis and related methods*. Chapman and Hall/CRC.

Guadagno, L. (2020). Migrants and the COVID-19 pandemic: An initial analysis. *International Organization for Migration (IOM) Migration Research Series Working Paper No. 60*.

Guiso, L., & Zaccaria, L. (2023). From patriarchy to partnership: Gender equality and household finance. *Journal of Financial Economics*, *147*(3), 573–595.

Gupta, A., Malani, A., & Woda, B. (2021). *Explaining the income and consumption effects of COVID in India* (Tech. Rep.). National Bureau of Economic Research.

Gupta, A., Zhu, H., Doan, M. K., Michuda, A., & Majumder, B. (2021). Economic impacts of the COVID-19 lockdown in a remittance-dependent region. *American Journal of Agricultural Economics*, *103*(2), 466–485.

Hainmueller, J. (2012). Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. *Political Analysis*, *20*(1), 25–46.

Hale, T., Petherick, A., Phillips, T., & Webster, S. (2020). Variation in government responses to COVID-19. *Blavatnik School of Government Working Paper*, *No. 31*, 2020–11.

Jappelli, T., Pagano, M., & Di Maggio, M. (2013). Households' indebtedness and financial fragility. *Journal of Financial Management, Markets and Institutions*, *1*(1), 23–46.

Jha, M., & Basole, A. (2022). Labour Incomes in India: A Comparison of PLFS and CMIE-CPHS Data. *Centre for Sustainable Employment Working Paper No. 46, Azim Premji University, Bangalore*.

Kamble, P. A., Mehta, A., & Rani, N. (2023). Financial inclusion and digital financial literacy: Do they matter for financial well-being? *Social Indicators Research*, 1–31.

Kesar, S., Abraham, R., Lahoti, R., Nath, P., & Basole, A. (2021). Pandemic, informality, and vulnerability: Impact of COVID-19 on livelihoods in India. *Canadian Journal of Development Studies/Revue canadienne d'études du développement*, *42*(1-2), 145–164.

Kohn, J. L. (2012). What is health? A multiple correspondence health index. *Eastern Economic Journal*, *38*(2), 223–250.

Leika, M., & Marchettini, D. (2017). A generalized framework for the assessment of household financial vulnerability. *International Monetary Fund Working Paper No. 2017/228*.

Martin, A., Markhvida, M., Hallegatte, S., & Walsh, B. (2020). Socio-economic impacts of COVID-19 on household consumption and poverty. *Economics of Disasters and Climate Change*, *4*(3), 453–479.

Michelangeli, V., & Rampazzi, C. (2016). Indicators of financial vulnerability: A household level study. *Bank of Italy Occasional Paper No. 369*.

Midões, C., & Seré, M. (2022). Living with reduced income: an analysis of household financial vulnerability under COVID-19. *Social Indicators Research*, 1–25.

Mishra, K., Kondratjeva, O., & Shively, G. E. (2022). Do remittances reshape household expenditures? Evidence from Nepal. *World Development*, *157*, 105926.

Murphy, E., & Scott, M. (2014). Household vulnerability in rural areas: Results of an index applied during a housing crash, economic crisis and under austerity conditions. *Geoforum*, *51*, 75–86.

Nguyen, L. D., Raabe, K., & Grote, U. (2015). Rural–urban migration, household vulnerability, and welfare in Vietnam. *World Development*, *71*, 79–93.

Noerhidajati, S., Purwoko, A. B., Werdaningtyas, H., Kamil, A. I., & Dartanto, T. (2021). Household financial vulnerability in Indonesia: Measurement and determinants. *Economic Modelling*, *96*, 433–444.

O'Connor, G. E., Newmeyer, C. E., Wong, N. Y. C., Bayuk, J. B., Cook, L. A., Komarova, Y., ... Warmath, D. (2019). Conceptualizing the multiple dimensions of consumer financial vulnerability. *Journal of Business Research*, *100*, 421–430.

Parida, J. K., Mohanty, S. K., & Raman, K. R. (2015). Remittances, household expenditure and investment in rural India: Evidence from NSS data. *Indian Economic Review*, 79–104.

Rajan, I. S., Sivakumar, P., & Srinivasan, A. (2020). The COVID-19 pandemic and internal labour migration in India: A 'crisis of mobility'. *The Indian Journal of Labour Economics*, *63*(4), 1021–1039.

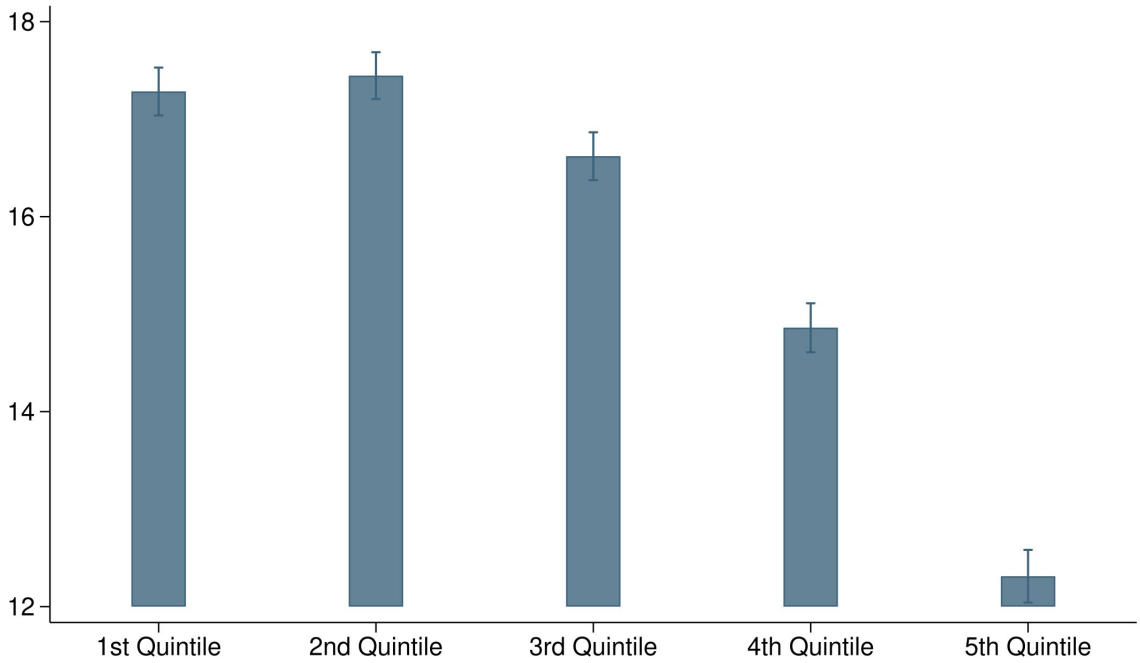
Singh, K. N., & Malik, S. (2022). An empirical analysis on household financial vulnerability in India: exploring the role of financial knowledge, impulsivity and money management skills. *Managerial Finance*, *48*(9/10), 1391–1412.

Van Ophem, J. (2020). COVID-19 and consumer financial vulnerability. *Central European Review of Economics and Management (CEREM)*, *4*(4), 115–132.

Yang, D., & Choi, H. (2007). Are remittances insurance? Evidence from rainfall shocks in the Philippines. *The World Bank Economic Review*, *21*(2), 219–248.

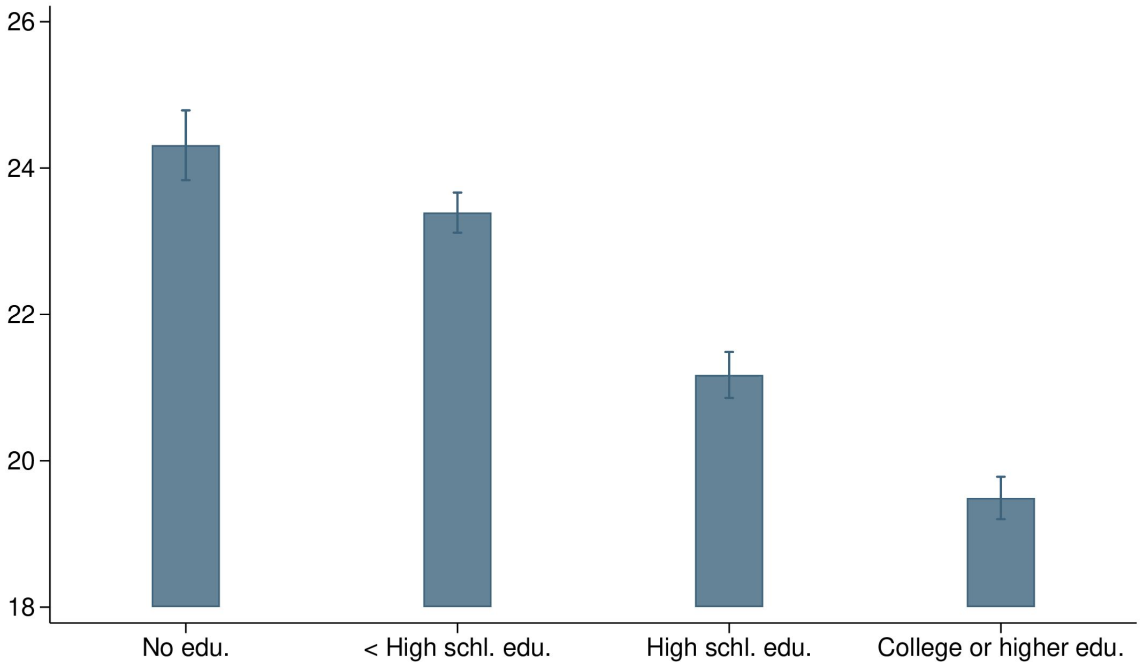
Yee, J. L., & Niemeier, D. (1996). Advantages and disadvantages: Longitudinal vs. repeated cross-section surveys. *United States Federal Highway Administration Research Paper*.

Figure 1: Correlates of household FVI during COVID-19: Income groups



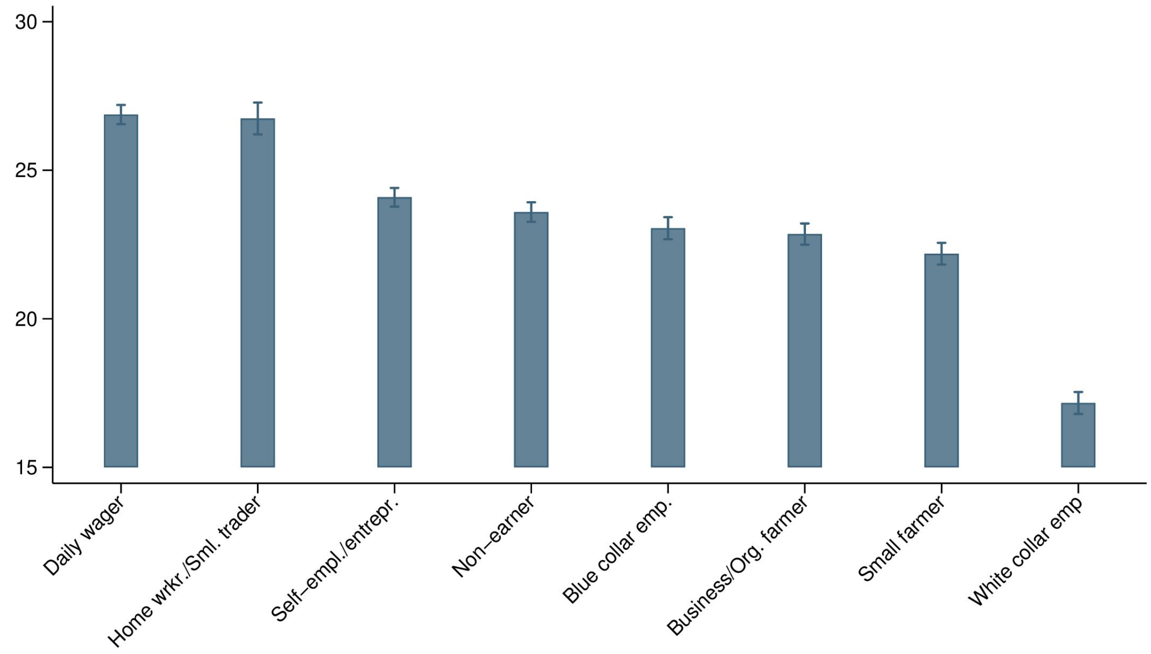
This figure presents the interaction coefficients between income quintiles and the COVID-19 indicator (see column 1 in Table 3). The 1st income quintile consists of households with the lowest income and the 5th quintile consists of households in the highest income group.

Figure 2: Correlates of household FVI during COVID-19: Education Groups



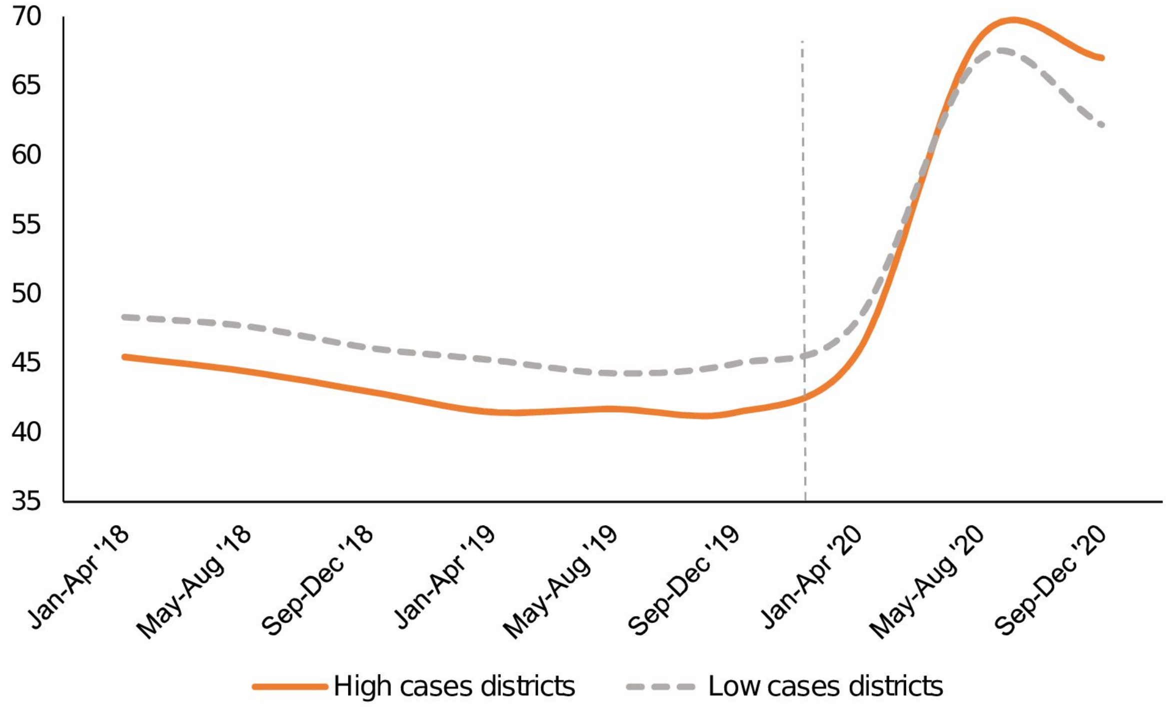
This figure presents the interaction coefficients between education levels and the COVID-19 indicator (see column 2 in Table 3).

Figure 3: Correlates of household FVI during COVID-19: Occupation Groups



This figure presents the interaction coefficients between occupation indicators and the COVID-19 indicator (see column 3 in Table 3).

Figure 4: Average household FVI pre- and post-COVID for high-cases and low-cases districts



This figure plots the average household FVI for high and low cases districts for CPHS waves 13 through 21 (Jan., 2018 to Dec., 2020). High cases districts include top-third districts with the highest number of average COVID-19 cases per 100,000 population in CPHS waves 20 and 21 (May to Dec., 2020). The vertical line separates the pre-pandemic and the COVID-19 periods in India.

Table 1: Description of variables

Variable	Description	Source
Financial Vulnerability Index (FVI)	An index measuring the households' financial vulnerability created using multiple correspondence analysis (MCA). The variables included in the index are: borrowing for consumption expenditure and debt repayment, use of financial instruments by the households, subjective measures such as perception of financial health and willingness to buy consumer goods.	Authors' calculation using CPHS
Borrowing for debt repayment	This variable is an indicator for households' borrowing for debt repayment. This variable takes on the value 1 if a household has borrowed for debt repayment, and 0 otherwise.	Authors' calculation using CPHS
Borrowing for consumption expenditure	This variable is an indicator for households' borrowing for consumption expenditure. It takes on the value 1 if a household has borrowed for consumption expenditure, and 0 otherwise. Consumption expenditure does not include expenditure on long-term consumer durable goods.	Authors' calculation using CPHS
Financial condition	This variable is a subjective variable that measures the perception of the households regarding their financial status compared to last year. It takes on the value 0 if a household perceives itself to be in a better financial condition, 1 if it perceives to be in the same financial condition as last year, and 2 if it perceives to be in a worse condition.	Authors' calculation using CPHS
Willingness to buy consumer goods	This variable is a subjective variable that measures the willingness of the households to buy consumer durable goods compared to last year. It takes on the value 0 if a household thinks it's a better time to buy durable goods than last year, 1 if the it thinks it is as good a time to buy durable goods as last year, and 2 if the it thinks its a worse time to buy durable goods compared to last year.	Authors' calculation using CPHS
Use of financial instruments	This variable measures the savings behaviour of the households. It includes saving in business, financial instruments, gold and real estate. Financial instruments include: chit funds, fixed deposits, Kisan Vikas Patra, life insurance, listed shares, mutual funds, NSC bonds, post office and provident fund. The variable takes on the value 0 if a household has saved in more than 1 instrument, 1 if it has savings in 1 instrument only, and 2 if it has no savings at all.	Authors' calculation using CPHS
COVID-19	This variable is an indicator for the COVID-19 time period and takes on a value 1 for the CPHS waves 20 (May to August, 2020) and 21 (Sept. to Dec., 2020) in the estimations (CPHS waves 19 to 21 from January to December, 2020 in some regression specifications), and 0 otherwise.	Authors' calculations
High cases dist.	This variable takes on a value 1 for the top-third districts with highest number of average COVID-19 cases per 100,000 population during waves 20 and 21, and 0 otherwise.	Authors' calculations based on COVID-19 cases data from Development Data Lab (SHRUG)

Table 1 – *Continued from previous page*

Variable	Description	Source
Low NTL dist.	This variable takes on a value 1 for the bottom one-third districts with lowest economic activities measures using data on satellite-based night-time lights (NTL).	Authors' calculations based on NTL data compiled by Robert Beyer and Daynan Crull
Household asset index	This is an index created using principal component analysis (PCA) that measures the asset ownership of the households.	Authors' calculation using CPHS
Share of members aged<10	This variable measures the proportion of dependent members in the households who are less than 10 years old.	CPHS
Share of members aged>64	This variable measures the proportion of dependent members in the households who are more than 64 years old.	CPHS
Age of household head	This variable measures the age of the head of the household.	CPHS
Female headed household	This variable takes on the value 1 if a household has a female household head, and 0 otherwise.	CPHS
Income quintiles	This variable divides the households into five income quintiles with the 1st income quintile consisting of the households with lowest income and the 5th quintile consists of households with the highest income.	Authors' calculation using CPHS
Educ.		
No educ.	This category includes household heads with no formal education or training. A member who has learnt to read and write on his own is included here.	CPHS
Less than high school educ.	Household heads who have some formal education but have not successfully passed high school i.e. grade 12 are classified as having less than high school education.	CPHS
High school educ.	Household heads whose highest level of education attained is high school i.e. people who have successfully passed the grade 12 are included in this category. These individuals do not have any further education.	CPHS
College or higher degree	This category includes all those household heads who have a successfully attained at least an undergraduate degree. Individuals with higher education than under graduation such as post-graduation or M.Phil/P.hD are also included in this category.	CPHS
Occup. group		
White collar empl.	This includes household heads who perform professional, desk, managerial, or administrative work.	CPHS
Non-earning	Non-earning members are categorised as all the household heads who are not employed or looking for employment. It includes members who are retired or aged and students studying at a formal educational institution, home makers and non-school children who are too small to attend school or have any occupation. Individuals working full-time as social workers/activists with no income gain are also classified under this category.	CPHS

Table 1 – *Continued from previous page*

Variable	Description	Source
Blue collar employee	This includes household heads who are support staff such as peons, janitors, lift-man, door keepers, watch-persons, drivers, gardeners, garbage collectors, cooks, housekeepers, delivery boys, and similar persons that provide support services. Industrial workers in the factory who are not daily wagers are also included in this group. Further this group includes non-industrial technical workers.	CPHS
Small farmer	Household heads that undertake farming to meet the consumption requirements of the household and manage survival only through tilling their land are classified as small farmers. They cultivate on a small scale and generate no or very little surplus to sell in the market.	CPHS
Small trader or home-based wkr.	This includes household heads that are occupied in a very small trading or business activity as an independent entrepreneurs and these activities are usually classified under the informal economy. These business owners do not have a fixed premise or office to run their business and are often home-based businesses. It includes occupations such as fruit and vegetable vendor, etc.	CPHS
Self-empl. profess. or entrepr.	This includes household heads who are self-employed entrepreneurs and qualified self-employed professionals that provide professional service by investing some amount of capital and by using expertise. Qualified self-employed professionals include people whose occupation is determined by a formal educational degree such as a doctor or a lawyer or by a specific skill such as a sportsman.	CPHS
Businessman or org. farmer	A household head who owns and runs a proprietorship concern or is a partner in a partnership concern is defined as a businessman. A businessman is expected to own and/or manage some fixed premises. Household heads who are organised farmers undertake farming as a regular business and generate surplus agricultural produce that can be sold in the markets.	CPHS
Daily wager	Household heads that seek employment for daily wages are included in this group. This includes industrial workers who work in factories or companies but are not employed on a regular basis.	CPHS

Table 2: Summary statistics

	(1) Obs.	(2) Mean	(3) Std. dev.	(4) Min.	(5) Max.
FVI	1,045,433	48.33	20.44	0.00	100.00
Components of FVI					
Borrowing for debt repayment	1,045,433	0.02	0.15	0.00	1.00
Borrowing for cons. exp.	1,045,433	0.26	0.44	0.00	1.00
Financial condition (compared to last year)					
Better	1,045,433	0.29	0.45	0.00	1.00
Same	1,045,433	0.52	0.50	0.00	1.00
Worse	1,045,433	0.19	0.39	0.00	1.00
Use of financial instruments					
Saved in>1 instrument	1,045,433	0.50	0.50	0.00	1.00
Saved in 1 instrument	1,045,433	0.25	0.43	0.00	1.00
No savings	1,045,433	0.26	0.44	0.00	1.00
Willingness to buy consumer good					
Better	1,045,433	0.24	0.42	0.00	1.00
Same	1,045,433	0.53	0.50	0.00	1.00
Worse	1,045,433	0.23	0.42	0.00	1.00
Explanatory variables					
COVID-19 Indicator	1,045,433	0.17	0.37	0.00	1.00
High cases dist.	1,045,433	0.45	0.50	0.00	1.00
Low NTL dist.	1,038,356	0.20	0.40	0.00	1.00
Household asset index	1,045,433	0.41	2.85	0.00	60.00
Share of members aged<10	1,045,433	0.06	0.13	0.00	1.00
Share of members aged>64	1,045,433	0.07	0.17	0.00	1.00
Log of income	1,045,433	11.11	0.76	2.89	14.68
Age of household head	1,045,433	50.98	11.53	10.00	110.00
Female-headed household	1,045,433	0.11	0.31	0.00	1.00
COVID-19 cases per 100,000 population (only COVID-19 period)	172,716	0.05	0.11	0.00	1.49
Income quintiles					
1st Quintile	1,045,433	0.19	0.39	0.00	1.00
2nd Quintile	1,045,433	0.20	0.40	0.00	1.00
3rd Quintile	1,045,433	0.20	0.40	0.00	1.00
4th Quintile	1,045,433	0.20	0.40	0.00	1.00
5th Quintile	1,045,433	0.20	0.40	0.00	1.00
Educ.					
No educ.	1,045,433	0.03	0.17	0.00	1.00
Less than high school educ.	1,045,433	0.72	0.45	0.00	1.00
High school educ.	1,045,433	0.10	0.30	0.00	1.00
College degree or higher	1,045,433	0.15	0.36	0.00	1.00
Occup. group					
White collar empl.	1,045,433	0.07	0.26	0.00	1.00
Daily wager	1,045,433	0.19	0.39	0.00	1.00
Blue collar employee	1,045,433	0.10	0.30	0.00	1.00
Small farmer	1,045,433	0.09	0.28	0.00	1.00
Small trader or home-based wkr.	1,045,433	0.03	0.18	0.00	1.00
Self-empl. profess. or entrepr.	1,045,433	0.14	0.35	0.00	1.00
Businessman or org. farmer	1,045,433	0.12	0.33	0.00	1.00
Non-earning	1,045,433	0.25	0.43	0.00	1.00

Table 3: Correlates of household financial vulnerability

The dependent variable in all estimations is the household financial vulnerability index (FVI). COVID-19 is an indicator for the COVID time-period which takes the value 1 for CPHS waves 20 (May to August, 2020) and 21 (Sept. to Dec., 2020). The baseline controls include those described in the text. The standard errors are clustered at the household level. ***, ** , * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)
Income quintiles (Ref.: 1st Quin. pre-COVID)			
1st Quintile*COVID-19	17.284***		
	(0.125)		
2nd Quintile	-2.612***		
	(0.067)		
2nd Quintile*COVID-19	17.446***		
	(0.123)		
3rd Quintile	-3.725***		
	(0.074)		
3rd Quintile*COVID-19	16.620***		
	(0.125)		
4th Quintile	-6.358***		
	(0.080)		
4th Quintile*COVID-19	14.861***		
	(0.128)		
5th Quintile	-9.000***		
	(0.093)		
5th Quintile*COVID-19	12.312***		
	(0.138)		
Educ. (Ref.: College or higher pre-COVID)			
College or higher*COVID-19		19.491***	
		(0.148)	
No educ.		6.686***	
		(0.198)	
No educ.*COVID-19		24.311***	
		(0.243)	
Less than high school educ.		3.375***	
		(0.123)	
Less than high school educ.*COVID-19		23.391***	
		(0.140)	
High school educ.		2.077***	
		(0.158)	
High school educ.*COVID-19		21.172***	
		(0.161)	
Occup. (Ref.: White collar empl. pre-COVID)			
White collar empl.*COVID-19			17.167***
			(0.188)
Daily wager			5.939***
			(0.132)
Daily wager*COVID-19			26.875***
			(0.165)
Blue collar employee			3.536***
			(0.132)
Blue collar employee*COVID-19			23.049***
			(0.190)
Small farmer			4.998***
			(0.146)
Small farmer*COVID-19			22.191***

Table 3 – *Continued from previous page*

	(1)	(2)	(3)
			(0.187)
Small trader or home-based wkr.			4.374***
			(0.167)
Small trader or home-based wkr.*COVID-19			26.743***
			(0.273)
Self-empl. profess. or entrepr.			3.240***
			(0.127)
Self-empl. profess. or entrepr.*COVID-19			24.091***
			(0.161)
Businessman or org. farmer			1.586***
			(0.135)
Businessman or org. farmer*COVID-19			22.851***
			(0.182)
Non-earning			4.509***
			(0.139)
Non-earning*COVID-19			23.592***
			(0.168)
Baseline Controls	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
District FE	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes
District specific time trends	Yes	Yes	Yes
Observations	1,045,433	1,045,433	1,045,433
Adjusted R-squared	0.444	0.438	0.440

Table 4: Heterogeneous impact of COVID-19 across districts using matched sample - Difference-in-differences analysis

The dependent variable in all estimations is the household financial vulnerability index (FVI). *High cases dist.* is defined as the top-third districts with the highest number of average COVID-19 cases per 100,000 population in CPHS waves 20 and 21 (May to Dec., 2020). COVID-19 is an indicator for the COVID time period which takes the value 1 for CPHS waves 20 (May to August, 2020) and 21 (Sept. to Dec., 2020). Baseline controls are the controls included in Table 3. The standard errors are clustered at the household level. ***, ** , * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
COVID-19	18.727***	18.626***	18.949***	18.663***	18.791***
	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)
High cases dist.*COVID-19	4.164***	4.173***	3.860***	4.133***	3.876***
	(0.151)	(0.150)	(0.150)	(0.150)	(0.150)
Educ. groups	No	Yes	No	No	Yes
Income quintiles	No	No	Yes	No	Yes
Occup. groups	No	No	No	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
District specific time trends	Yes	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes	Yes
Observations	1,045,433	1,045,433	1,045,433	1,045,433	1,045,433
Adjusted R-squared	0.438	0.439	0.445	0.441	0.446

Table 5: Heterogeneous impact of COVID-19 across districts using matched sample: Robustness to alternative COVID-19 period

The dependent variable in all estimations is the household financial vulnerability index (FVI). *High cases dist.* is defined as the top-third districts with the highest number of average COVID-19 cases per 100,000 population in CPHS waves 20 and 21 (May to Dec., 2020). In the estimations presented in the table, the COVID-19 indicator takes the value 1 for CPHS waves 19 to 21 (Jan. to Dec., 2020). The coefficient of *High cases dist.**COVID-*19* is presented, but the COVID-19 indicator is subsumed in the state-year fixed effects. Baseline controls are the controls included in Table 3. The standard errors are clustered at the household level. ***, ** , * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
High cases dist.*COVID-19	3.091***	3.077***	2.860***	3.094***	2.861***
	(0.201)	(0.200)	(0.199)	(0.200)	(0.198)
Educ. groups	No	Yes	No	No	Yes
Income quintiles	No	No	Yes	No	Yes
Occup. groups	No	No	No	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
District specific time trends	Yes	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes	Yes
Observations	1,045,433	1,045,433	1,045,433	1,045,433	1,045,433
Adjusted R-squared	0.388	0.389	0.394	0.391	0.397

Table 6: Heterogeneous impact of economic disruption due to COVID-19 on the FVI across districts

The dependent variable in all estimations is the household financial vulnerability index (FVI). *Low NTL dist.* is defined as the bottom one-third districts with the lowest night-time lights. In the estimations presented in the table, the COVID-19 indicator takes the value 1 for CPHS waves 19 to 21 (Jan. to Dec., 2020). The coefficient of *Low NTL dist.**COVID-*19* is presented, but the COVID-19 indicator is subsumed in the state-year fixed effects. Baseline controls are the controls included in Table 3. The standard errors are clustered at the household level. ***, ** , * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Low NTL dist.*COVID-19	2.909***	2.888***	2.765***	3.008***	2.809***
	(0.232)	(0.232)	(0.229)	(0.232)	(0.229)
Educ. groups	No	Yes	No	No	Yes
Income quintiles	No	No	Yes	No	Yes
Occup. groups	No	No	No	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
District specific time trends	Yes	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes	Yes
Observations	1,038,356	1,038,356	1,038,356	1,038,356	1,038,356
Adjusted R-squared	0.428	0.430	0.437	0.431	0.439

Table 7: Impact of COVID-19 based on out-migration status using matched sample

The dependent variable in all estimations is the household financial vulnerability index (FVI). Indicators for households with out-migrant take the value 1 for households that have an out-migrant in the current time period, and 0 otherwise. The time period considered for the analysis is from CPHS wave 16 to CPHS wave 21 (Jan, 2019 to Dec, 2020). Pre-COVID out-migrant households are defined as households that had out-migrants in the pre-COVID period but not during COVID-19. The COVID-19 indicator takes the value 1 for CPHS waves 19 to 21 (Jan. to Dec., 2020). Coefficients of the interaction terms are presented, but the COVID-19 indicator is subsumed in the state-year fixed effects. Baseline controls are the controls included in Table 3. The standard errors are clustered at the household level. ***, ** , * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Migrant household	-2.523***	-2.604***	-0.114	-0.365**
	(0.108)	(0.107)	(0.168)	(0.166)
Migrant household*COVID-19	-1.611***	-1.536***	-1.494***	-1.427***
	(0.109)	(0.107)	(0.109)	(0.107)
Pre-COVID mig. household *COVID-19			4.042***	3.757***
			(0.188)	(0.185)
Educ. groups	No	Yes	No	Yes
Income quintiles	No	Yes	No	Yes
Occup. groups	No	Yes	No	Yes
Baseline controls	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
District specific time trends	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes
Observations	653,342	653,342	653,342	653,342
Adjusted R-squared	0.438	0.448	0.439	0.449

Table 8: Impact of COVID-19 based on out-migration and gender of the household head

The dependent variable in all estimations is the household financial vulnerability index (FVI). Indicators for households with out-migrant take the value 1 for households that have an out-migrant in the current time period, and 0 otherwise. The time period considered for the analysis is from CPHS wave 16 to CPHS wave 21 (Jan, 2019 to Dec, 2020). Pre-COVID out-migrant households are defined as households that had out-migrants in the pre-COVID period but not during COVID-19. The COVID-19 indicator takes the value 1 for CPHS waves 19 to 21 (Jan. to Dec., 2020). Coefficients of the interaction terms are presented, but the COVID-19 indicator is subsumed in the time component of the state-year fixed effects. Baseline controls are the controls included in Table 3. The standard errors are clustered at the household level. ***, ** , * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Male-headed with mig.	-2.554***	-2.652***	-0.167	-0.420**
	(0.114)	(0.112)	(0.175)	(0.172)
Female-headed with mig.	-2.290***	-2.255***	0.275	0.048
	(0.256)	(0.253)	(0.332)	(0.329)
Male-headed with mig.*COVID-19	-1.497***	-1.409***	-1.370***	-1.293***
	(0.114)	(0.113)	(0.114)	(0.113)
Female-headed with mig.*COVID-19	-2.379***	-2.386***	-2.318***	-2.321***
	(0.258)	(0.254)	(0.259)	(0.255)
Male-headed with pre-COVID mig.*COVID-19			3.971***	3.719***
			(0.194)	(0.192)
Female-headed with pre-COVID mig.*COVID-19			4.560***	4.046***
			(0.411)	(0.406)
Educ. groups	No	Yes	No	Yes
Income quintiles	No	Yes	No	Yes
Occup. groups	No	Yes	No	Yes
Baseline controls	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
District specific time trends	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes
Observations	653,342	653,342	653,342	653,342
Adjusted R-squared	0.438	0.448	0.439	0.449

Appendices

Table A1: MCA weights for the FVI

The table provides the coordinates and contribution for each component of the FVI. The contribution suggests the weightage given to the variables in creation of the index.

	Coordinates	Contribution
Borrowing for debt repayment		
No borrowing for debt repayment	0.045	0.000
Borrowing for debt repayment	-1.925	0.017
Borrowing for cons. exp.		
No borrowing for cons. exp.	-0.169	0.005
Borrowing for cons. exp.	0.979	0.028
Financial condition (compared to last year)		
Better	-1.947	0.235
Same	0.431	0.021
Worse	2.924	0.210
Willingness to buy consumer goods		
Better	-2.018	0.223
Same	0.187	0.004
Worse	2.551	0.229
Use of financial instruments		
Saved in $>$ 1 instrument	-0.539	0.013
Saved in 1 instrument	-0.277	0.003
No savings	0.314	0.011