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

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

Abstract

The COVID-19 pandemic adversely impacted many households across the world. Recent studies on the pandemic have focused on its impact on income, consumption, and poverty of households, but not directly on their financial well-being. Building on the prior literature on measures of financial vulnerability, this paper analyses the heterogeneous effects of COVID-19 on household financial vulnerability based on the geographical variation in the intensity of the pandemic in India and households' migration status. Using a difference-in-differences approach and coarsened exact matching, we find a larger increase in household financial vulnerability in Indian districts that are more exposed to COVID-19 and those that experience a greater decline in night-time lights (a proxy for economic activity) compared to households in other districts. We also find that households with an out-migrant, particularly those with a female head, experience lower financial vulnerability during the pandemic, likely due to the financial contribution of migrants. However, financial vulnerability during COVID-19 is substantially higher for households that had an out-migrant in the prior period but not during the pandemic, with a larger effect observed for female-headed households. The findings of this paper contribute to a better understanding of the varied effects of the pandemic on households.

Keywords: COVID-19 pandemic; household financial vulnerability; night-time lights; migration status; female headed households
JEL Classification: G20; G21; E51

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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). Recent research has studied the impact of the COVID-19 pandemic on households across the world (Baker, Farrokhnia, Meyer, Pagel, and Yannelis (2020); Chen, Qian, and Wen (2020)) and in India (Beyer, Jain, and Sinha (2023); Gupta, Malani, and Woda (2021)). Several studies have considered the financial vulnerability of households during the pre-COVID period (Leika & Marchettini, 2017; O'Connor et al., 2019; Singh & Malik, 2022) and during the COVID-19 crisis (Bruce et al., 2022).[1] However, these studies have not analyzed the impact of the geographical variation in the intensity of the COVID-19 pandemic on household financial vulnerability. In this paper, we contribute to the literature by developing a measure of financial vulnerability using panel survey data for Indian households and analyzing the heterogeneous effects of the COVID-19 pandemic on households' financial vulnerability across more than 600 districts in India.

Previous studies have considered various indicators of financial vulnerability including delayed payments (Duygan & Grant, 2006), net wealth of the households (Brown & Taylor, 2008), financial ratios (Michelangeli & Rampazzi, 2016), and some 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)). Drawing on this literature, we create a household financial vulnerability index (FVI) based on Indian households' observed financial behaviour and their perceptions. The FVI captures use of financial instruments, borrowing for consumption expenditure, debt refinancing, and perceived financial health. This index focuses on the financial well-being of households and differs from other indices such as those based on households' income and probability of falling into poverty (for instance, see Gaiha and Imai (2008)).

[1]Previous research has also examined the effect of the global financial crisis in 2008-09 on households' financial distress (see, for instance, Albacete et al. (2014)).

In this study, we first attempt to understand how the relationsip between household FVI and its correlates changed during COVID-19 compared to the pre-COVID period. These correlates include occupation group of the household head, proportion of dependent members in the households, asset ownership, household head's level of education, household's income, and gender and age of the household head. We then use a *difference-in-differences* (DID) approach and coarsened exact matching to compare the effect of COVID-19 on households' FVI in districts with higher number of COVID-19 cases per 100,000 population relative to households in other comparable districts. This estimation, which exploits the regional heterogeneity in COVID-19 across districts in India, allows us to capture the impact of the pandemic on households' financial vulnerability. Additionally, the paper uses night-time lights data as a measure of economic activity in the districts and analyses its effects on households' financial vulnerability during the pandemic. Night-time lights data have been used extensively to measure economic activity (see, for example, Beyer, Chhabra, Galdo, and Rama (2018); Beyer et al. (2023); Keola, Andersson, and Hall (2015)). The night-time lights data is employed to capture the differential impact of COVID-19 on households' FVI based on district-level variation in economic activity during the pandemic.

In addition, the pandemic also led to many out-migrant workers returning to their homes (Bhagat et al., 2020; Guadagno, 2020). Households with out-migrants often face different shocks that affect their economic conditions and finances (Nguyen, Raabe, & Grote, 2015). Further, Zaccaria and Guiso (2020) show that the gender of the household head also affects decisions regarding household finances. Hence, in further analysis, the effects of out-migrant members in the household and gender of the household head on household's FVI during the COVID-19 period is studied. We first consider the differential impact of COVID-19 on FVI across households with out-migrant members and households with no out-migrant members. We then analyse the effect of COVID-19 on households' FVI for female-headed households with out-migrants relative to other households.

The results of this study suggest that, on average, there was a significant increase in financial vulnerability of households in India during the COVID-19 period compared to the pre-COVID period. We find that households with a higher level of education of the 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. We also find that the increase in household FVI was larger for households in the top-third districts with the highest number of COVID-19 cases per 100,000 population. 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. This suggests that households in districts that were impacted more severely by the pandemic experienced a greater increase in financial vulnerability as compared to households in other districts.

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. This is likely due to the financial contributions made by the out-migrant family 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 effect observed for female-headed households. This suggests that migration status and gender of the household head were relevant factors for household financial vulnerability during the COVID-19 crisis.

This paper makes several contributions to the literature. The literature on household financial vulnerability is mainly limited to its measure and correlates (see, for instance, O'Connor et al. (2019) and Singh and 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, Khan, & Ahmad, 2020a), without much focus on the impact of aggregate shocks such as the pandemic. In a 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. However, the authors don't consider the intensity or within-country geographical variation of the pandemic as we do. 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 and examining the implications of migration and gender on the impact of COVID-19 on financially vulnerable households.

Second, the paper uses a comprehensive panel household survey dataset, the Consumer Pyramids Household Survey (CPHS), to analyse 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 (see, for instance, Bruce et al. (2022); Midões and Seré (2022)). By utilising panel data instead of cross sectional data, this paper accounts for the time invariant household specific characteristics. This helps in minimising the omitted variable bias that might arise due to unobserved household characteristics in cross-sectional analysis (Yee & Niemeier, 1996).

Finally, this paper complements the recent research on household financial vulnerability across developed and developing countries by focusing on India, the second-largest emerging market economy, during the COVID-19 health crisis. For example, Ampudia, Van Vlokhoven, and Żochowski (2016) analyse the financial fragility of households in the euro area. Papers on developing countries include studies from Pakistan (Ali et al., 2020a; Ali, Khan, & Ahmad, 2020b), Malaysia (Daud, Marzuki, Ahmad, & Kefeli, 2019; Fei, Sabri, Mohamed, Wijekoon, & Majid, 2020), and Indonesia (Chaudhuri, Jalan, & Suryahadi, 2002; Noerhidajati, Purwoko, Werdaningtyas, Kamil, & Dartanto, 2021). Previous studies in India about financial vulnerability have focused mainly on the households' vulnerability to poverty (see Gaiha and Imai (2008)) and the determinants of financial vulnerability (Singh & Malik, 2022) in the pre-COVID period. This study extends the existing literature by using a panel household survey dataset and attempts to understand the impact of the pandemic on households' financial vulnerability.

The paper is structured as follows. The next section discusses the relevant literature on household FVI and the COVID-19 pandemic. The data used for the estimations is discussed in Section 3. Section 4 discusses the FVI and its correlates during the pre-COVID and COVID-19 periods. 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), and migration status. Section 5 concludes with a summary of the findings and policy implications.

2. Background and literature review

The paper relates to the literature on household financial vulnerability and the recent literature on the effects of the COVID-19 pandemic. The former refers to research on measurement and correlates of household financial vulnerability. The latter refers to the developing literature on effects of shocks faced by households due to the pandemic. The following sub-sections present a comprehensive summary of the related literature.

2.1. Household financial vulnerability indices

Research in this strand of literature has focused on measurement and creation of financial vulnerability indices for households using various indicators. Murphy and Scott (2014) create a household vulnerability index (HVI) using 21 subjective and objective indicators for households in rural Ireland and test the effects of housing crash and economic recession. They observe that there was a link between localities that experienced an increased supply of houses during the housing bubble and increase in household vulnerability.

Anderloni et al. (2012) use survey data from Italian households to analyse household financial distress by developing an index. They establish that households that have high levels of debt with an emphasis on unsecured consumer debt are more financially vulnerable. Further, the debt to income ratio is one of the main correlates of financial vulnerability. They use non-linear principal component analysis (NLPCA) to create the index using objective and subjective variables including if the household had trouble making ends meet, if bank credit application was turned down, if household had trouble paying bills and if the household had to go without health care. Jappelli et al. (2013) also link financial fragility to high debt. Using panel data for household lending, cross-country data on household finances from UK, USA, and Germany, they conclude that when hit by an income shock, highly indebted households are more likely to default on loans, making them more vulnerable to such shocks.

Some previous papers have also studied the correlates and measurement of financial vulnerability in developing countries. For example, Daud et al. (2019) analyze the prevalence of financial vulnerability amongst the Malaysian households using survey data from 902 respondents. They measure financial vulnerability as inability to meet household needs and the ability of households to deal with financial shocks and income uncertainty. They observe that the important correlates of financial vulnerability include income, marital status, age, and level of education. Some studies including Ali et al. (2020a) and Ali et al. (2020b) focus on household financial vulnerability in Pakistan. Ali et al. (2020a) investigate the relationship between the household head's education and household financial vulnerability using survey data from approximately 17,000 households. The authors first consider the financial margin which is defined as the income remaining after deducting taxes, debt payments, and basic living cost (other studies including Albacete et al. (2014); Ampudia et al. (2016); Bettocchi, Giarda, Moriconi, Orsini, and Romeo (2018) use similar measures). Further, they develop an index using the correlates of financial vulnerability such as income, consumption, physical wealth, savings, and employment.

Noerhidajati et al. (2021) assess the level of household financial vulnerability using survey data from Indonesia. They construct an index that ranges between 1-10 where a score of 1 indicates low vulnerability and 10 indicates very high vulnerability. They use an approach similar to Bialowolski and Weziak-Bialowolska (2014) to create the index using objective measures including debt ownership of households, household arrears, budgeting ability i.e the ratio of household expenditure to household income, resilience to financial shocks measured by the the time that the savings can cover the expenditure of the households in case of loss of the main source of income and participation in basic social activities.

Some earlier studies argue that the debt-to-income ratio and the debt service-to-income ratio determine the financial vulnerability of the households. For instance, Bańbuła, Kotuła, Przeworska, and Strzelecki (2015) and Dey, Djoudad, Terajima, et al. (2008) find that households with debt service-to-income ratio higher than 40% are more financially vulnerable due to excessive debt. Some studies have also found a link between different job categories and financial distress. For instance, Giannetti, Madia, and Moretti (2014) establish that greater job insecurity increases the risk of falling into financial distress. Their results also suggest that the effects of job insecurity on financial distress can be mitigated by high financial literacy.

In the context of India, Singh and Malik (2022) create a measure for household financial vulnerability using cross-sectional survey data for the pre-COVID period. They use three self-reported estimates: making ends meet, perception of income shock, and perception of expenditure shock to create an index and study the determinants of household financial vulnerability. Our research aims to complement the previous literature and study the changes in households' financial vulnerability during the COVID-19 period based on the variation in the intensity of the pandemic across the Indian districts.

2.2. *The COVID-19 pandemic*

COVID-19 has served as a massive shock to households everywhere in the world. In response to the pandemic, the Indian government announced a nationwide lockdown in late March, 2020. The lockdown was amongst the most stringent measures undertaken by governments around the world (Hale, Petherick, Phillips, & Webster, 2020). These measures along with the severity of the pandemic affected the financial behaviour of households making it necessary to understand the changes in household financial vulnerability due to COVID-19.

Several recent studies concerning the pandemic have considered the changes in consumption and expenditure behaviour of households using household surveys, administrative data, and transaction level data. For instance, a recent study by Gupta et al. (2021) using CPHS survey data finds a huge decline in income and consumption of Indian households during COVID-19. They also observe very large drops in the income of certain occupation groups such as salaried workers and daily wagers. Baker et al. (2020) use transaction-level data for the American household to find that as the severity of the COVID-19 pandemic increased, consumption of households initially increased especially in retail and credit cards purchases, which was followed by a sharp overall decrease in household spending. Chen et al. (2020) employ daily transaction data from 214 cities in China to observe a significant reduction in consumption following the pandemic. Beyer et al. (2023) examine the differential impact of COVID-19 relaxation policies on economic activities at the district-level in India using night-time light data. They find that districts with most severe restrictions observed significantly lower night-time lights intensity.

While there is a large literature on the impact of COVID-19 on income and consumption, some studies have discussed its impact on financial vulnerability in regions other than India. For example, Mogaji (2020) argues that COVID-19 has aggravated the financial vulnerability of individuals due to job loss, and highlight its impact on changes in financial behaviour. Alhenawi and Yazdanparast (2022) use survey data from countries in North America, Europe, Africa, and Latin America to study the implication of COVID-19 on households' financial behaviour. Their results indicate that the pandemic has instigated a state of financial vulnerability and stimulated instinctual defensive mechanisms among consumers. They also observe households' intentions to make defensive decisions in spending, consumption, planning, and investment.

Using data from two surveys in Netherlands, Van Ophem (2020) report a significant increase in household financial vulnerability after the COVID-19 shock. Their results suggest that households with uncertain incomes, inflexible budgets (with fixed and necessary expenses higher than disposable income), lack of buffers, and persistent low income, find it more difficult to deal with the financial risks and make ends meet. This paper complements the literature on the COVID-19 pandemic by analysing its impact on household financial vulnerability for Indian households. To the best of our knowledge, this is the first paper to study the impact of COVID-19 on FVI in India.

3. Data

This section describes the variables 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). CPHS surveys approximately 175,000 Indian households across 28 states and union territories.[2]. Recently, CPHS data has been widely used by various studies in different context such as unemployment (Gupta & Kishore, 2022) and poverty measurement (Sinha Roy & Van Der Weide, 2022). 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. CPHS's Aspirational India survey is used to measure the use of financial instruments and borrowing behaviour of households along with the information on their asset ownership. Data for household income and other characteristics is obtained from income and expenditure surveys. Income data for each household is collected on a monthly basis while the data on use of financial instruments, borrowings, and assets are available at the wavely frequency. The monthly income data is used to calculate the average income for each wave. Finally, the individual level dataset, that contains information about all the members of the households, is used to measure characteristics of the household heads and migration behaviour.

3.2. *Household financial vulnerability index (FVI)*

To determine the overall financial vulnerability of the Indian households, the paper proposes a comprehensive indicator that combines both objective and subjective aspects of household financial vulnerability to create the financial vulnerability index, based on existing literature on FVI for other countries. The objective measures include households' borrowing behaviour and use of financial instruments relating to the financial position of the households, including indicators for debt refinancing, number of instruments saved in by the households, and borrowing for consumption expenditure. We also consider the number of sources household has

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

borrowed from and the number of instruments they have saved in.[3] The subjective measures include perception of financial health and willingness to purchase consumer goods. Altogether, the subjective and objective measures underlying the FVI allows us to capture a rich set of financial behaviour of households.

Many studies focusing on creation of household financial vulnerability measures have used variables measuring ability of the households to repay their debt such as arrears on debt repayment (Anderloni et al., 2012). This paper uses debt refinancing, measured by borrowing for debt repayment, as a proxy for arrears on debt repayment. This is a good proxy as it is intuitive to assume that a household would further borrow to repay their debts only if they are unable to make the repayments in time. The debt refinancing variable takes on the value 1 if a household has borrowed for debt repayment, and 0 otherwise.

Previous literature has also documented that households with some form of savings usually indicate lower financial vulnerability. Measures such as households' ability to mitigate unexpected expenses (Anderloni et al., 2012) and amount of cash deposits or savings by households that can cover expenses in case of an income loss (Noerhidajati et al., 2021) have been used in the literature. On similar lines, this paper uses a measure for savings behaviour of households by considering the number of instruments the households have invested in during the last 120 days from the date of the survey, which could cover the expenses in case on income loss. The potential investment instruments include: fixed deposits, provident funds, mutual funds, listed shares, gold, post office savings, life insurance, NSC bonds (including both government bonds and PPF), Kisan Vikas Patra, chit funds, business, real estate, and other financial instruments. The categorical variable for household use of financial instruments is created such that no savings in any of the instruments suggests higher financial vulnerability. The variable takes the value 2 if a household has no savings at all, the value 1 if the household has saved in only one of the instruments, and 0 if they have saved in more than one instruments. Therefore, a higher

[3] Owing to data limitations, the FVI is based on categorical variables instead of amounts. For instance, the household savings in amounts is arguably a better measure than the discrete variable used in this paper. However, the amount of savings (usually calculated as the difference between disposable income and consumption) are subject to measurement problems owing to misreporting of income in household surveys (Deaton, 1997; Jha & Basole, 2022).

value of the variable suggests higher financial vulnerability.

Another variable frequently used for creating a financial vulnerability indicator is the ability of a household to 'make ends meet', which captures the inability of households to pay for basic necessities and keep up with regular expenses. Giannetti et al. (2014) define financial distress as an event where household heads report difficulty in keeping up with household expenses by the end of the month. In this paper, borrowing by households for consumption expenditure (such as food, beverages, clothing, rents & bills, and other basic necessities) is used to measure this variable. Borrowing for consumption expenditure is a binary variable which takes on the value 1 if a household has borrowed for consumption expenditure in the last 120 days, and 0 otherwise.

Some studies in the literature have used subjective measures for financial vulnerability to obtain a more comprehensive indicator (Anderloni et al., 2012; Noerhidajati et al., 2021). In this paper, answers to the following questions are used to measure households' perception of their financial health: a) if the household thinks that their current financial condition, as compared to a year ago, is same, better, or worse; and b) if they think it is an appropriate time to buy consumer goods. If the members of a household believe that their financial condition is worse than last year, we consider the household to be more financially vulnerable. Similarly, a household's unwillingness to purchase a consumer durable is likely to reflect a perception of financial vulnerability.[4]

Studies focusing on construction of the financial vulnerability index have typically used principal component analysis (PCA) or a generalization of PCA (Anderloni et al., 2012). However, PCA is usually applied to continuous variables as it assumes linear constraints on the distribution of the variables. 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 (Higuera-Mendieta, Cortés-Corrales, Quintero, & González-Uribe,

[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.

2016; 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).

The MCA methodology is very similar to PCA but imposes fewer assumptions and constraints on the data (Greenacre & Blasius, 2006). It reduces the dimensionality of the data by seeking a linear combination of the data that accounts for majority of the information. 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. $FVI_{i,t}$ 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. The correlates of financial vulnerability included in this paper are based on the previous literature. 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 the FVI because the household head usually has the highest income or is the sole earning member of the household. Therefore, their occupation group would reflect the type of job and earnings, which, in turn, may be correlated with the FVI (Giannetti et al., 2014). Another most commonly used determinant of household financial vulnerability is the overall income of the household. Household income will be 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 (see, for example, Leika and Marchettini (2017) and Ampudia et al. (2016)). Research shows that education of the household head along with influencing their own income also influences the education level of other household members, consequently affecting their incomes (Ali et al., 2020a). 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 classified as households where at least one of the members has migrated out of the household for purposes other than marriage, education, or in the event of a family splitting. The dummy variable representing the above households captures out-migration 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, likely due to the migrants returning home during the pandemic. A dummy variable for the above households calculated using the CPHS individual level dataset includes households that had out-migrants in the pre-COVID period but no out-migrants during the COVID-19 period.

3.4. District-level COVID-19 cases

Data on number of COVID-19 cases at the district-level is obtained from Covid19India.org and SHRUG database by the Development Data Lab which collates data reported by the central and state governments (Asher, Lunt, Matsuura, & Novosad, 2019).[5] The number of COVID-19 cases is available at a daily frequency. 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

[5] See http://www.devdatalab.org/covid

to match with the frequency of the household level data. The number of cases for the waves before COVID-19 is taken as 0. The study uses the number of COVID-19 cases per 100,000 population for a relative comparison.

The COVID-19 indicator represents the time periods after the start of the COVID-19 pandemic. It 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. Since wave 19 in CPHS was conducted from January, 2020 to April, 2020, it includes two COVID-19 months in India as the first measures against the pandemic were undertaken by the government in March, 2020. Therefore, we have created an alternate indicator for the COVID-19 period which takes the value 1 for the CPHS wave 19 onward, as a robustness check. This alternate indicator specifies the COVID-19 period in India as January, 2020 to April, 2021.

The COVID-19 indicator represents the time periods after the start of the COVID-19 pandemic. It 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.

4. Empirical methodology and results

This section discusses the empirical methodology used for the analysis. It first discusses the estimations to determine the correlates of household financial vulnerability index in the pre-COVID and during the COVID-19 time periods. Next, it presents the results for the differential impact of the pandemic on household FVI across districts based on the variation in COVID cases per 100,000 population and night-time lights, a proxy for economic activity. Further, the effect of out-migration and the gender of the household head on the households' financial vulnerability during the pandemic is studied.

4.1. *Correlates of the household financial vulnerability index*

The subsection discusses the estimation employed to determine the correlates of household FVI. It further evaluates the results of the analysis and assesses the changes in the correlation between household FVI and its correlates in the pre-COVID and the COVID-19 time periods

4.1.1. *Correlates of household FVI in the pre-*COVID *period*

The following equation is used to determine the relationship between the FVI and its correlates:

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

The subscripts i, s and t represent households, state, and year, respectively. $FVI_{i,t}$ is the household financial vulnerability index for household i in time period t. $IncQuin_{i,t,j}$ indicates the households' income group where $j = 1, ..., 5$. The first income quintile is considered as the reference category and higher income quintiles indicate higher income. $HohOccup_{i,t,l}$ is the occupation group of the household head where $l = 1, ..., 8$. The occupations are divided into eight groups: non-earning household heads, daily wagers, small farmer, small traders & home based workers, blue collar employees, self employed professionals & entrepreneurs, businessmen & organised farmers, and white collar employees. Here, households with household heads employed as white collar employees are included in the reference group. $HohEdu_{i,t,k}$ categorises the education of the household head into four categories: no education, less than high school education (someone who has not passed the grade 12), high school education, and college graduation or higher education. The reference category for this variable includes households with household heads that have a college or higher degree. $\boldsymbol{X}_{i,t}$ is a vector of household-level characteristics. These include $AssetIndex_{i,t}$ which is calculated based on the ownership of various asset by the household using PCA.[6] Other characteristics considered are $Children_{i,t}$ and

[6]The asset index includes ownership of houses, air conditioners, cars, two wheelers, computers, refrigerators, washing machines, televisions, tractors and cattle.

Seniors$_{i,t}$ that measure the proportion of children less younger than 10 years old and senior members aged more than 64, respectively, *Femaleheaded*$_{i,t}$ is a dummy for households with a female household head, and *HohAge*$_{i,t}$ is the age of the household head. 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. The sample considered for the above estimation for the pre-COVID period includes CPHS waves from wave 13 through wave 19.

Table 3 presents results for correlates of the FVI in the pre-COVID period. Column 1 considers baseline correlates that include household asset index, proportion of dependent members in the household, age of the household head, and the household head's gender. The next three columns gradually introduce the three main correlates of household financial vulnerability, i.e., household income, education of the household head, and the occupation group. The results show that household asset index negatively affects the FVI implying that if a household owns higher number of assets they tend to be less vulnerable. Similarly, age of the household head has a negative coefficient suggesting that households with older household heads are less vulnerable. This can be attributed to higher income for older members and greater experience, as compared to younger household heads who may have lower professional experience. The coefficients for proportion of dependent members, both children and senior members, are positive indicating that higher the number of dependent members, higher is the household's FVI since dependent members do not usually contribute to the household income. Column 2 in Table 3 shows that households in higher income group are less financially vulnerable as compared to households in lower income quintiles. The results in Column 3 suggest that households whose household heads have no education, less than high school education, or high school education, are more financially vulnerable as compared to households whose heads have a college degree or higher education. This implies that higher the level of education, lower is the household FVI. This is possibly due to the impact of improved education on the household head's income, as well as on the level of education and income of other household members. Finally, column 4 in Table 3 explains the role of occupation of the household heads in determining the household's FVI. Here, households whose heads are white collar employees are taken as the reference group. The results imply that households with heads employed as daily wagers and those with non-earning household heads are the most financially vulnerable, followed by small traders or home-based workers, small farmers, and blue collar employees. Households with heads employed as self-employed professionals, entrepreneurs, businessmen, and organised farmers are less vulnerable compared to others while the households with white collar employees are the least vulnerable.

4.1.2. *Correlates of the FVI during* COVID-*19*

We extend the above analysis to include COVID-19 time period and observe the changes in the correlates of the household FVI during this period. The following equation is used for the analysis:

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

In the above equation, $Post_t$ is a COVID-19 indicator which takes on the value 1 for CPHS waves during the COVID-19 time period, and 0 otherwise. COVID-19 period includes two CPHS waves, waves 20 and 21 covering the time period between May 2020 and December 2020. The COVID-19 outbreak in India began in March, 2020 and the nationwide lockdown was announced on 21st March 2020. However, the number of cases began to rise after the lockdown was relaxed. Therefore, we consider the period from May, 2020 as the COVID-19 period for the initial analysis. However, we also create an alternate COVID-19 indicator with the full year defined as the COVID-19 period from January, 2020 to December, 2020. This includes three CPHS waves that cover the initial lockdown period as well (see results in Table 6).

$CovidCases_{v,t}$ measures the number of COVID-19 cases per 100,000 population in each district.[7] $\boldsymbol{X}_{i,t}$ includes all the other control variables used in Equation 2 i.e. asset index, proportion of

[7]District population is estimated using the data for per capita district GVA for the year 2020.

children and seniors in the household, and age and gender of the household head. μ_i, θ_v, τ_{st}, and γ_t are the household fixed effects, district fixed effects, state-year fixed effects, and district specific time trends, respectively and are included to account for household, state, and district specific time-invariant effects. $\varepsilon_{i,t}$ is the error term that measures unobserved characteristics. This estimation extends the time period used in the previous analysis to include the CPHS waves conducted during the COVID-19 period.[8] Therefore, the CPHS waves considered for the analysis include wave 13 through wave 21 i.e. the time period from January, 2018 to December, 2020.

The results presented in Table 4 measures the impact of COVID-19 on the correlates of household FVI. Figure 1 plots the interaction coefficients for income quintiles. The results in the table and the figure show that the FVI for households in all five income groups was higher during the COVID-19 period as compared to the pre-COVID period, implying that households in all income quintiles were more financially vulnerable during the pandemic. However, households in higher income quintiles were less vulnerable as compared to those in the lower quintiles. Column 2 suggests that as compared to households with household heads who had college or higher degree in the pre-COVID period, all the other households are more vulnerable during COVID-19. Figure 2 plots the interaction coefficients which suggests that higher is the level of education of the household head, lower is the vulnerability during the pandemic. Finally, Column 3 in Table 4 presents the results for occupation groups of the household heads during COVID-19 and Figure 3 plots the coefficients. Here, we observe 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.

[8]The surveys were conducted through telephonic interviews due to the restrictions in movements during this period.

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 the households' financial vulnerability based on variation in the intensity of the pandemic, as measured by COVID-19 cases, across districts in India. An alternate indicator for the impact of the pandemic on district-level economic activity using satellite based night-time lights is also used in the analysis.

4.2.1. *Impact of* COVID-*19 based on district-level variation in cases per 100,000 population*

We use a difference-in-differences (DID) estimation to analyse 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:

$$\begin{aligned}
FVI_{i,t} = \alpha + \beta_0 Post_t + \beta_1 HighCasesDist_v + \beta_2 Post_t * HighCasesDist_v \\
+ \beta_3 \sum_{k=i}^{k=K} HohEdu_{i,t,k} + \beta_4 \sum_{j=1}^{j=J} IncQuin_{i,t,j} + \beta_5 \sum_{l=1}^{l=L} HohOccup_{i,t,l} \\
+ \beta_6 CovidCases_{v,t} + \beta_7 \boldsymbol{X}_{i,t} + \mu_i + \theta_v + \tau_{st}\gamma_t + \varepsilon_{i,t} \quad (4)
\end{aligned}$$

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 conisdered 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, 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 that affect the outcome variable. μ_i, θ_v, τ_{st}, and γ_t are the household fixed effects, district fixed effects, state-year fixed effects, and district specific time trends, respectively. As discussed earlier, the household and district fixed effects represent time-invariant unobserved household- and district-specific characteristics. The state-year fixed effects account for time-varying state-level factors. We also include district specific linear time trends for longer-term trends in the dependent variable at the district-level. $\varepsilon_{i,d,t}$ is the error term that measures unobserved characteristics.

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). CEM reduces the imbalance between treated and untreated observations. This method depends on fewer assumptions as compared to other matching estimators. To get the matched sample, the data is temporarily coarsened, then the treated observations are matched with the untreated observations and finally the sample is uncoarsened. Here, we match the treated and untreated households on the following characteristics: asset index, household income, education of the household head, and occupation group of the household head. 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).

An assumption underlying a DID analysis is that the treatment and control groups should be on parallel trends prior to the shock. Therefore, we test for the parallel trends in household FVI for high and low cases districts graphically. Figure 4 plots the average household FVI for high and low cases districts for CPHS waves 13 through 21 (Jan., 2018 to Dec., 2020). The figure shows that pre-COVID, the average FVI for households in both high and low cases districts followed a fairly similar trend. It also shows that the average FVI for households in high cases districts was lower before the pandemic. However, during the COVID-19 period, the average FVI for households in high cases districts increased exponentially and was higher than the average FVI for households in low cases districts. This suggests that the households in both treatment and control groups followed similar trends pre-COVID, but households in high cases districts (treatment group) were more affected by the pandemic as compared to households in other districts.

Table 5 presents the DID results for the heterogeneous impact of COVID-19 on FVI across districts using the number of COVID-19 cases per 100,000 population. The COVID-19 indicator is a time dummy which takes on the value one for the CPHS waves during the COVID-19 time period. However, the variable is dropped from the results since the regressions also include state-year fixed which absorbs the time dummy. *High cases dist.* is a dummy variable indicating districts with the highest number of COVID-19 cases per 100,000 population during the two CPHS COVID-19 waves, i.e, wave 20 and 21 which consists of the time period from May, 2020 to Dec, 2020. The coefficient for the DID estimator term is positive implying that as compared to districts with lower number of COVID-19 cases per 100,000 population, households in the top one-third districts with highest 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. In the main estimation the COVID-19 indicator covers the time period between May, 2020 to December, 2020. This leave out two months of initial COVID-19 outbreak and the nationwide lockdown in India. Therefore, to check the robustness of the results, the alternate COVID-19 indicator is used which covers the initial pandemic months. The regression results for this alternate definition of COVID-19 indicator are presented in Table 6. The findings show that households in the top-third districts with higher COVID-19 cases have higher FVI and are more affected by the pandemic. These results are consistent with the earlier findings.

4.2.2. *Impact of economic disruption due to* COVID-*19 on household FVI*

Here, 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. Night-time lights has been used extensively to measure economic activities in the literature (see, for instance, Beyer et al. (2018); Keola et al. (2015)). Further, districts with higher night-time light and thus higher economic activities can be expected to have different response to the pandemic as compared to districts with lower levels of economic activity. Therefore, we use a DID analysis (similar to that mentioned in the previous section) to capture the impact of COVID-19 on household FVI for districts with different levels of night-time lights. Here, the treatment group consists of districts that have the lowest economic activity. The variable takes on the value 1 for the bottom one-third districts with lowest night-time lights value, and 0 otherwise. A matching technique similar to the one described in the previous section is used to create the sample for the analysis. Households in the control group are matched with those in the treatment group based on the following characteristics: asset index, income of the household, education of the household head, and occupation group of the household head. In this regression we use the COVID-19 indicator with the full year defined as the COVID-19 period (January, 2020 to December, 2020). This is done to capture the negative impact of the initial lockdown on the economic activities since the economic activities were most affected during the complete lockdown period in March and April.

Table 7 presents the the DID results for heterogeneous impact of COVID-19 based on night-time lights. Here, *low NTL dist.* is a binary variable that indicates the bottom one-third districts with the lowest value for night-time lights indicating the largest disruption to economic activity. The results in column 1 show that households in the districts with lower economic activity were more financially vulnerable during COVID-19, as compared to other districts. The results in the subsequent columns remain robust to controlling for different sets of household characteristics.

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

In this section, we consider the impact of out-migration and gender of the household head on households' financial vulnerability during COVID-19. Migration out of the household for reasons related to work and employment can affect their financial vulnerability since events and situations faced by the migrated members differ from those faced by members staying in the household. Therefore, in the event of an aggregate shock that affects all households in a particular region or district, households with out-migrant members, would be less vulnerable as compared to those households with no out-migrant members. For example, Yang and Choi (2007) find that households in Philippines with out-migrant members are able to deal with income decline due to rainfall shocks much better than those households with no out-migrants. Thus, we test the hypothesis that households with out-migrant members are less vulnerable as compared to households without out-migrant members.

To further understand the importance of out-migration on the households' FVI, we create an alternate indicator for households with out-migrant members. During the COVID-19 pandemic when the government of India announced a nationwide lockdown, many out-migrants (especially out-migrant labourers) moved back to their hometowns (Guadagno, 2020). Therefore, we create a variable that takes on the value 1 if the household had an out-migrant in the pre-COVID period but the member has returned home during the pandemic, and 0 otherwise. Here, to account for seasonality, we compare migration status of the members during COVID-19 to corresponding waves in the pre-COVID period.

Finally, since the gender of the household head with out-migrant workers could have an effect on the financial vulnerability, we consider households with male/female heads and out-migrant workers. Usually, if there is a male out-migrant worker, the females in the household assume the position of the household head in their absence. Here, the following categories are included: households with male heads and no out-migrants, with male heads and out-migrants, with male heads and out-migrants only in the pre-COVID period, with female heads and no out-migrants, with female heads and out-migrants, and with female heads and out-migrants only in the pre-COVID period.

To test the above hypotheses 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. Here, the treatment group is defined as having out-migrant members in the household. Hagen-Zanker (2008) shows that migration decision is dependent on various individual, household, and aggregate characteristics. Thus, the treatment being assigned here is not perfectly random. Therefore, we employ the matching technique to compare households with and without out-migrant members. Once we have the matched dataset, we analyse the effect of having out-migrant members in the household on the financial vulnerability index of the household using a difference-in-differences (DID) estimation. 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. 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 time period. We also consider the effect on households that had an out-migrant in the pre-COVID period but no out-migrants during the pandemic.

Column 2 in Table 8 shows 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 aggregate shocks such as COVID-19 affected different regions differently. Therefore, if there was an out-migrant worker in a household working in regions that were less affected by the pandemic, such households would be able to better smooth the shock. The columns 3 and 4 in Table 8 includes the impact on households that had an out-migrant in the pre-COVID waves but did not have an out-migrant during the corresponding COVID-19 waves. 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 9 presents the impact of COVID-19 on the household FVI based on both the gender of the household head and out-migration status. We observe from columns 1 and 2 that household FVI is lower for households in the presence of a 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 the current migrant 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 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 builds on the literature on measures of household financial vulnerability and creates for Indian households using objective and subjective indicators and analyses the changes in the FVI due to the COVID-19 pandemic. The paper uses multiple correspondence analysis (MCA) to create the index given the categorical nature of the variables. We have used the frequency of sources household has borrowed from and the number of instruments they have saved in, since CPHS data does not provide the amount borrowed or saved by the households. The study exploits the heterogeneous impact of COVID-19 in different regions based on the number of cases per 100,000 population and the effect on the economic activities proxied using night-time lights. We use DID analysis for a matched sample created using the coarsened exact matching (CEM) technique. We find a higher increase in the financial vulnerability of households in the top-third districts with the highest number of COVID-19 cases and the lowest night-time lights in the pre-COVID period. This suggests that households in districts that were impacted more severely by the pandemic became more financially vulnerable as compared to households in other districts.

Further, the study also considers the impact of having out-migrant members in households and the gender of household heads on the FVI during the COVID-19 period. We find that households with at least one out-migrant member during the COVID-19 period, especially those with a female head, are less financially vulnerable during the pandemic, as compared to households with no out-migrant members. 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, 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. Studying the correlates of financial vulnerability and the impact of COVID-19 has some broader policy implications since household financial vulnerability also affects their spending and consumption behaviour, which in turn, impact the overall growth of the economy. More financially distressed households might lead to decreased consumption which will have a negative impact on the overall growth of the economy. Further, possible loan defaults by households due to greater financial vulnerability also influence banks and other financial institutions by negatively affecting their balance sheets. Hence, it is important to study the impact of shocks on household financial vulnerability in order to maintain financial stability and economic growth.

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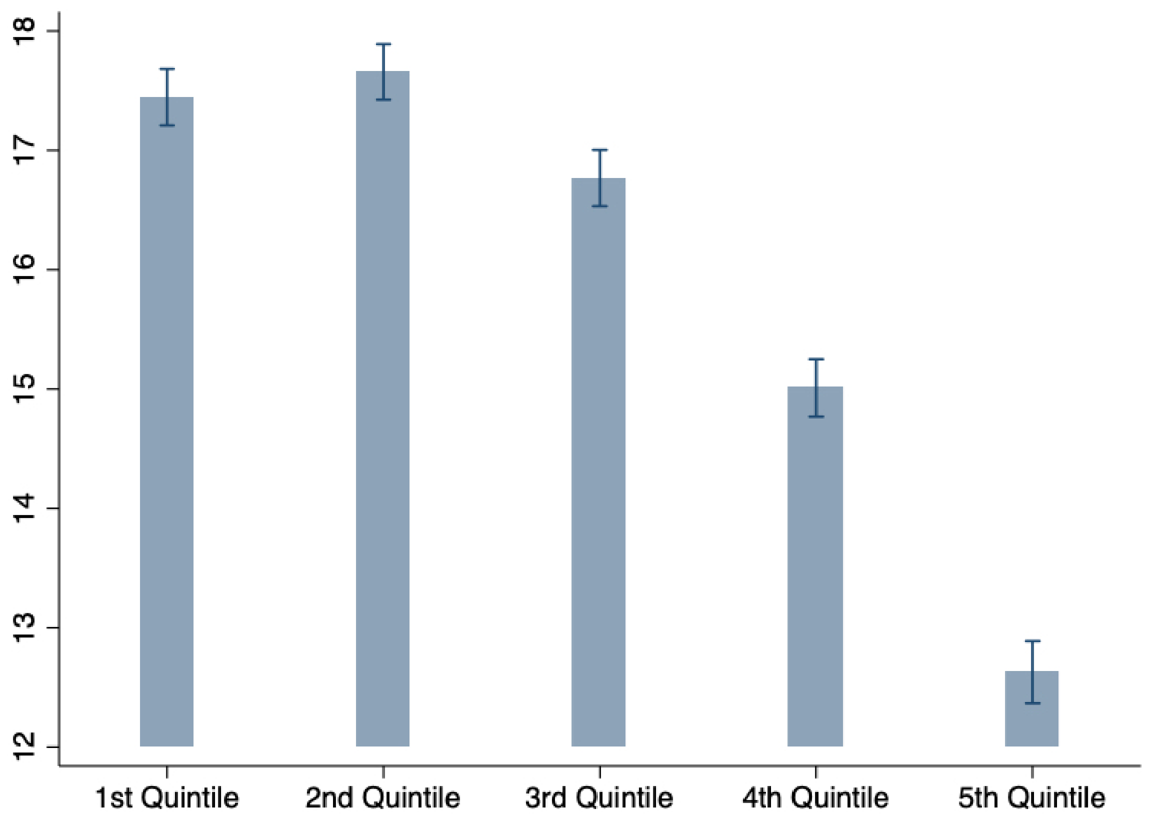
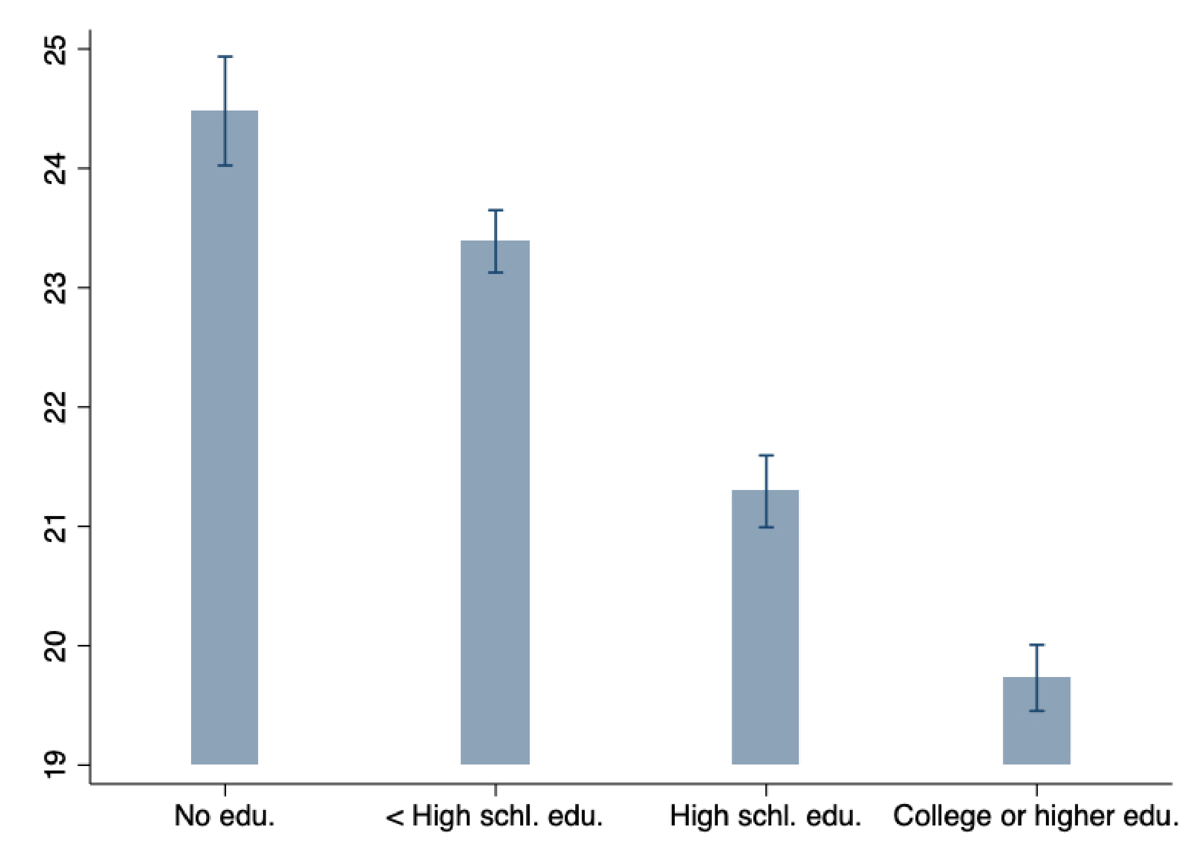
Figure 1: Correlates of household FVI during COVID-19: Income groups



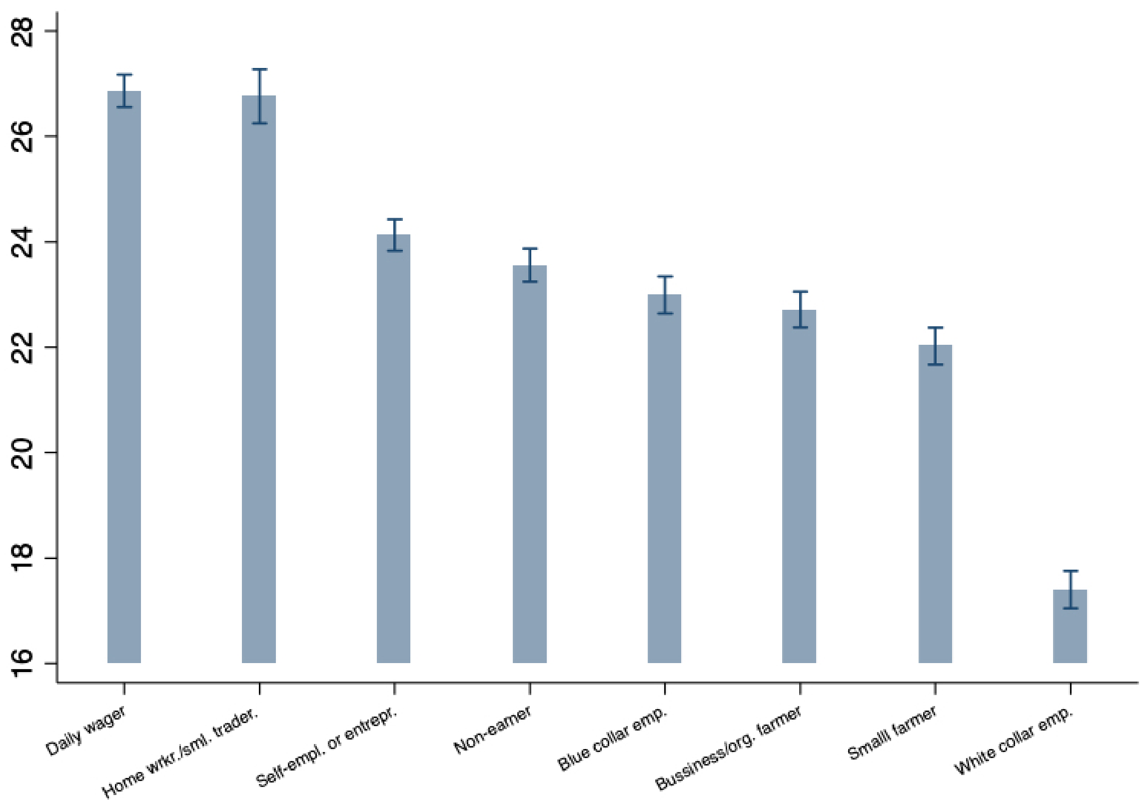
This figure presents regression coefficients for the impact of COVID-19 on household FVI for various income quintiles (see column 1 in Table 4). The coefficients presented are an interaction between income quintiles and the COVID-19 indicator. 1st income quintile consists of households with the lowest income and 5th quintile consists of households in the highest income group. 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 regression includes household and district fixed effects, state-year fixed effects, and district-specific time trends.

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



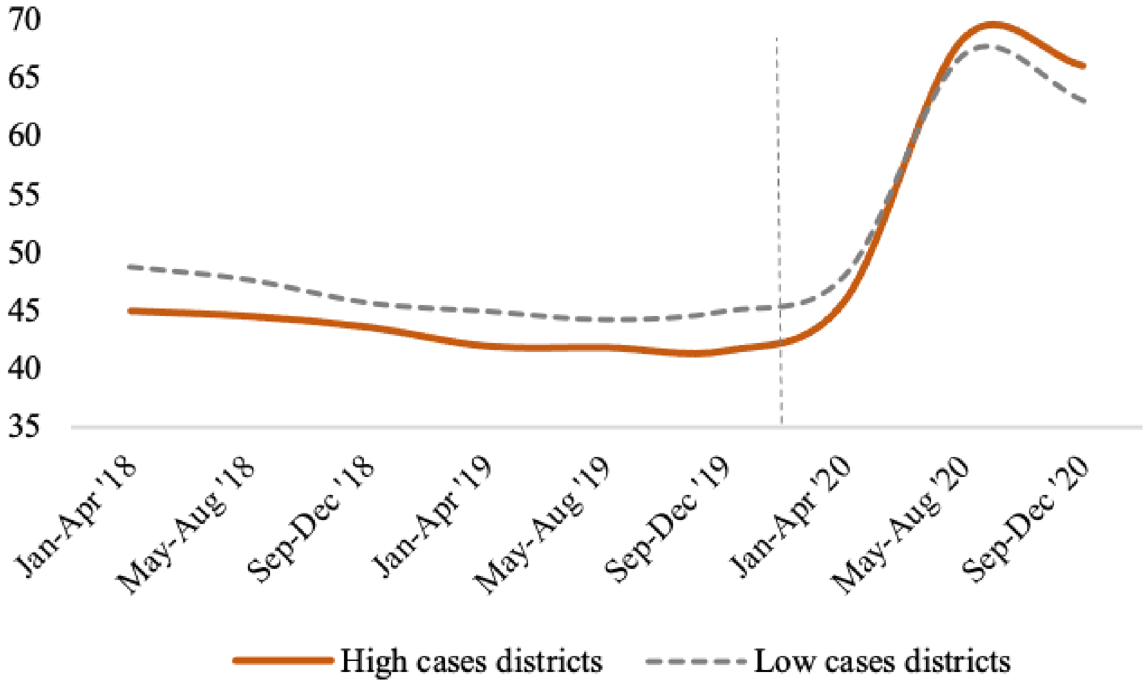
This figure presents regression coefficients for the impact of COVID-19 on household FVI for different level of education of household heads (see column 2 in Table 4). The coefficients presented are an interaction between education level and the COVID-19 indicator. COVID-19 is an indicator for the COVID time-period which takes the value 1 for CPHS waves 20 (May to August, 2020) and 21 (Sept. to Dec., 2020). The regression includes household and district fixed effects, state-year fixed effects, and district-specific time trends.

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



This figure presents regression coefficients for the impact of COVID-19 on household FVI based on household head's occupation (see column 3 in Table 4). The coefficients presented are an interaction between occupation indicator and the COVID-19 indicator. 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 regression includes household and district fixed effects, state-year fixed effects, and district-specific time trends.

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). FVI is the index for household financial vulnerability created using MCA. 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 indicates the beginning of the COVID-19 pandemic 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 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 individuals 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.	Individuals 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.	The individuals 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 individuals 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 individuals who perform professional, desk, managerial, or administrative work.	CPHS
Non-earning	Non-earning members are categorised as all the individuals 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 group includes support staff such as peons, janitors, lift-man, door keepers, watch-persons, drivers, gardeners, garbage collectors, cooks, housekeepers, delivery boys, and similar persons who 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	Individuals 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 individual 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 group includes self-employed entrepreneurs and qualified self-employed professionals who 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	Businessman is defined as a person who owns and runs a proprietorship concern or is a partner in a partnership concern. A businessman is expected to own and/or manage some fixed premises. While, organised farmers are those farmers who undertake farming as a regular business and generate surplus agricultural produce that can be sold in the markets.	CPHS
Daily wager	The individuals 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

FVI is the household financial vulnerability index created using multiple correspondence analysis (MCA). Use of financial instruments variables include 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. Businessmen include people who invest in a business and own fixed premises while small traders are those who do not own a fixed premise.

	(1) Obs.	(2) Mean	(3) Std. dev.	(4) Min.	(5) Max.
FVI	1,133,916	47.74	20.65	0.00	100
Components of FVI					
Borrowing for debt repayment	1,133,916	0.04	0.20	0.00	1.00
Borrowing for cons. exp.	1,133,916	0.26	0.44	0.00	1.00
Financial condition (compared to last year)					
Better	1,133,916	0.30	0.46	0.00	1.00
Same	1,133,916	0.52	0.50	0.00	1.00
Worse	1,133,916	0.19	0.40	0.00	1.00
Use of financial instruments					
Saved in>1 instrument	1,133,916	0.27	0.44	0.00	1.00
Saved in 1 instrument	1,133,916	0.25	0.43	0.00	1.00
No savings	1,133,916	0.48	0.50	0.00	1.00
Willingness to buy consumer good					
Better	1,133,916	0.24	0.43	0.00	1.00
Same	1,133,916	0.53	0.50	0.00	1.00
Worse	1,133,916	0.23	0.42	0.00	1.00
Explanatory variables					
COVID-19 Indicator	1,133,916	0.16	0.37	0.00	1.00
High cases dist.	1,133,916	0.45	0.50	0.00	1.00
Low NTL dist.	1,133,916	0.37	0.48	0.00	1.00
Household asset index	1,133,916	0.44	3.02	0.00	100
Share of members aged<10	1,133,916	0.06	0.13	0.00	1.00
Share of members aged>64	1,133,916	0.07	0.17	0.00	1.00
Log of income	1,133,916	11.11	0.78	1.10	16.09
Age of household head	1,133,916	50.94	11.53	18.00	110
Female-headed household	1,133,916	0.11	0.31	0.00	1.00
COVID-19 cases per 100,000 population (only COVID-19 period)	185,065	0.05	0.11	0.00	1.49
Income quintiles					
1st Quintile	1,132,756	0.19	0.39	0.00	1.00
2nd Quintile	1,133,916	0.20	0.40	0.00	1.00
3rd Quintile	1,133,916	0.20	0.40	0.00	1.00
4th Quintile	1,133,916	0.20	0.40	0.00	1.00
5th Quintile	1,133,916	0.20	0.40	0.00	1.00
Educ.					
No educ.	1,133,916	0.03	0.17	0.00	1.00
Less than high school educ.	1,133,916	0.72	0.45	0.00	1.00
High school educ.	1,133,916	0.10	0.30	0.00	1.00
College degree or higher	1,133,916	0.15	0.36	0.00	1.00
Occup. group					
White collar empl.	1,133,916	0.07	0.26	0.00	1.00
Daily wager	1,133,916	0.18	0.38	0.00	1.00
Blue collar employee	1,133,916	0.11	0.31	0.00	1.00
Small farmer	1,133,916	0.09	0.29	0.00	1.00
Small trader or home-based wkr.	1,133,916	0.03	0.18	0.00	1.00
Self-empl. profess. or entrepr.	1,133,916	0.14	0.35	0.00	1.00

Table 2 – *Continued from previous page*

	(1)	(2)	(3)	(4)	(5)
Businessman or org. farmer	1,133,916	0.12	0.33	0.00	1.00
Non-earning	1,133,916	0.25	0.43	0.00	1.00

Table 3: Correlates of household financial vulnerability in the pre-COVID period

The dependent variable in all estimations is the household financial vulnerability index (FVI). All columns include household and district fixed effects, state-year fixed effects, and district-specific time trends. The standard errors are clustered at the household level. ***, ** , * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Income quintiles (Ref.: 1st Quin.)					
2nd Quintile		-1.923***			-1.825***
		(0.070)			(0.071)
3rd Quintile		-2.973***			-2.790***
		(0.080)			(0.080)
4th Quintile		-5.188***			-4.891***
		(0.089)			(0.090)
5th Quintile		-7.398***			-6.975***
		(0.107)			(0.109)
Educ. (Ref.: College or higher)					
No educ.			3.492***		2.402***
			(0.334)		(0.332)
Less than high school educ.			1.495***		0.441
			(0.287)		(0.285)
High school educ.			0.683***		0.110
			(0.341)		(0.338)
Occup. (Ref.: White collar empl.)					
Daily wager				3.764***	2.123***
				(0.156)	(0.158)
Blue collar employee				2.276***	1.239***
				(0.147)	(0.147)
Small farmer				2.617***	1.273***
				(0.170)	(0.171)
Small trader or home-based wkr.				2.713***	1.478***
				(0.185)	(0.186)
Self-empl. profess. or entrepr.				2.023***	0.944***
				(0.147)	(0.148)
Businessman or org. farmer				0.306*	-0.128
				(0.157)	(0.157)
Non-earning				3.340***	1.537***
				(0.164)	(0.166)
Baseline controls					
Household asset index	-0.142***	-0.126***	-0.142***	-0.128***	-0.117***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Share of members aged>64	2.587***	1.687***	2.659***	2.553***	1.750***
	(0.270)	(0.268)	(0.270)	(0.269)	(0.268)
Share of members aged<10	0.106	0.429	0.090	-0.060	0.322
	(0.318)	(0.315)	(0.318)	(0.317)	(0.315)
Age of household head	-0.010*	0.003	-0.020***	-0.037***	-0.013**
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Female-headed household	0.274	-0.093	0.051	-0.245	-0.375**
	(0.171)	(0.170)	(0.174)	(0.179)	(0.180)
Household FE	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes	Yes
District specific time trends	Yes	Yes	Yes	Yes	Yes
Observations	838,741	838,741	838,741	838,741	838,741
Adjusted R-squared	0.400	0.406	0.400	0.401	0.406

Table 4: Correlates of household financial vulnerability in the COVID-19 period

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). Baseline controls are the controls included in Table 3 and also include number of COVID-19 cases per 100,000 population at the district level. All columns include household and district fixed effects, state-year fixed effects, and district-specific time trends. 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	17.447***		
	(0.121)		
2nd Quintile	-2.675***		
	(0.064)		
2nd Quintile*COVID-19	17.659***		
	(0.119)		
3rd Quintile	-3.802***		
	(0.071)		
3rd Quintile*COVID-19	16.767***		
	(0.121)		
4th Quintile	-6.316***		
	(0.077)		
4th Quintile*COVID-19	15.010***		
	(0.123)		
5th Quintile	-8.731***		
	(0.089)		
5th Quintile*COVID-19	12.627***		
	(0.132)		
Educ. (Ref.: College or higher pre-COVID)			
College or higher*COVID-19		19.729***	
		(0.142)	
No educ.		6.593***	
		(0.189)	
No educ.*COVID-19		24.480***	
		(0.232)	
Less than high school educ.		3.207***	
		(0.117)	
Less than high school educ.*COVID-19		23.388***	
		(0.134)	
High school educ.		2.033***	
		(0.151)	
High school educ.*COVID-19		21.293***	
		(0.154)	
Occup. (Ref.: White collar empl. pre-COVID)			
White collar empl.*COVID-19			17.401***
			(0.180)
Daily wager			5.644***
			(0.125)
Daily wager*COVID-19			26.865***
			(0.158)
Blue collar employee			3.241***
			(0.124)
Blue collar employee*COVID-19			22.993***
			(0.178)
Small farmer			4.629***

Table 4 – *Continued from previous page*

	(1)	(2)	(3)
			(0.138)
Small farmer*COVID-19			22.022***
			(0.178)
Small trader or home-based wkr.			4.168***
			(0.158)
Small trader or home-based wkr.*COVID-19			26.763***
			(0.262)
Self-empl. profess. or entrepr.			2.986***
			(0.120)
Self-empl. profess. or entrepr.*COVID-19			24.129***
			(0.153)
Businessman or org. farmer			1.391***
			(0.127)
Businessman or org. farmer*COVID-19			22.715***
			(0.174)
Non-earning			4.363***
			(0.132)
Non-earning*COVID-19			23.556***
			(0.161)
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	1,133,916	1,133,916	1,133,916
Adjusted R-squared	0.461	0.455	0.458

Table 5: 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). The sample is created using coarsened exact matching (CEM) and balanced using entropy balancing. Column 2 controls for the education group of the household head. Columns 3 and 4 include controls for income quintiles and household heads' occupation, respectively. Column 5 includes all the controls. All columns include household and district fixed effects, state-year fixed effects, and district-specific time trends. 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	19.130***	18.999***	19.217***	19.068***	19.060***
	(0.104)	(0.104)	(0.103)	(0.103)	(0.103)
High cases dist.*COVID-19	3.245***	3.302***	3.097***	3.218***	3.116***
	(0.142)	(0.142)	(0.142)	(0.142)	(0.141)
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	1,168,453	1,168,453	1,168,453	1,168,453	1,168,453
Adjusted R-squared	0.462	0.464	0.469	0.465	0.470

Table 6: 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 4. The sample is created using coarsened exact matching (CEM) and balanced using entropy balancing. Column 2 controls for the education group of the household head. Columns 3 and 4 include controls for income quintiles and household heads' occupation, respectively. Column 5 includes all the controls. All columns include household and district fixed effects, state-year fixed effects, and district-specific time trends. 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	1.208***	1.202***	1.045***	1.186***	1.037***
	(0.168)	(0.168)	(0.167)	(0.168)	(0.166)
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	1,168,453	1,168,453	1,168,453	1,168,453	1,168,453
Adjusted R-squared	0.418	0.420	0.425	0.422	0.427

Table 7: 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 pre-COVID average night-time lights per square meter. 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 4. The sample is created using coarsened exact matching (CEM) and balanced using entropy balancing. Column 2 controls for the education group of the household head. Columns 3 and 4 include controls for income quintiles and household heads' occupation, respectively. Column 5 includes all the controls. All columns include household and district fixed effects, state-year fixed effects, and district-specific time trends. 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	3.606***	3.554***	3.566***	3.665***	3.551***
	(0.267)	(0.267)	(0.264)	(0.266)	(0.264)
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	1,238,675	1,238,675	1,238,675	1,238,675	1,238,675
Adjusted R-squared	0.462	0.464	0.470	0.465	0.472

Table 8: 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). Out-migrant households are defined as households where one or more members have migrated out for purposes other than marriage, education and family split. 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. Out-migrants' status is compared for the same months in the previous year to account for seasonal migration. In the estimations presented in the table, the COVID-19 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 4. All columns include household and district fixed effects, state-year fixed effects, and district-specific time trends. 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	-2.543***	-2.621***	-0.099	-0.356**
	(0.105)	(0.103)	(0.160)	(0.158)
Migrant household*COVID-19	-1.628***	-1.555***	-1.501***	-1.437***
	(0.105)	(0.104)	(0.105)	(0.104)
Pre-COVID mig. household *COVID-19			4.128***	3.832***
			(0.180)	(0.177)
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	708,433	707,683	708,433	707,683
Adjusted R-squared	0.451	0.461	0.452	0.461

Table 9: 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). Out-migrant households are defined as households where one or more members have migrated out for purposes other than marriage, education and family split. 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. Out-migrants' status is compared for the same months in the previous year to account for seasonal migration. 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). 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 4. All columns include household and district fixed effects, state-year fixed effects, and district-specific time trends. 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.	-2.591***	-2.682***	-0.170	-0.424***
	(0.110)	(0.108)	(0.166)	(0.164)
Female-headed with mig.	-2.197***	-2.193***	0.401	0.138
	(0.250)	(0.247)	(0.322)	(0.318)
Male-headed with mig.*COVID-19	-1.518***	-1.433***	-1.381***	-1.308***
	(0.111)	(0.109)	(0.110)	(0.109)
Female-headed with mig.*COVID-19	-2.372***	-2.374***	-2.304***	-2.302***
	(0.251)	(0.247)	(0.251)	(0.248)
Male-headed with pre-COVID mig.*COVID-19			4.059***	3.796***
			(0.186)	(0.183)
Female-headed with pre-COVID mig.*COVID-19			4.625***	4.106***
			(0.400)	(0.395)
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	708,433	707,683	708,433	707,683
Adjusted R-squared	0.452	0.461	0.452	0.461

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