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Financial Vulnerability Assessment using Data Analytics: Evidence from the Rural Households of 3 Indian States

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Abstract

Financial Vulnerability is defined as the failure of a household to meet its financial obligations timely and completely, thus incurring financial distress. Following the 2008 global financial crisis, academics, policymakers and practitioners from across the world have given greater attention to the assessment of financial vulnerability of households. Our work considers a broader measure of financial vulnerability to analyse financial vulnerability of households and applies machine learning techniques including deep learning to identify the cluster(s) of financially vulnerable households in the rural locations of three Indian states – Tamil Nadu, Odisha, and Uttarakhand. The results indicate that financial vulnerability varies with the education level of the primary earner, primary occupation and income segment of the household, as well as its dependency ratio, gender ratio, and average age. Our research is helpful for policymakers aiming to design appropriate policies and programs for the financially vulnerable households that are likely to have been the most affected by the massive economic disruption caused by COVID-19, by enabling them to target their interventions to those needing financial help the most.

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1 Introduction

Both developed and emerging economies have witnessed a rise in household indebtedness during the past decades (Tiftik et al., 2019). High levels of indebtedness make the households more vulnerable to economic shocks, thereby enhancing the credit risk of the financial institutions and affecting the financial stability of the larger economy (Mian et al., 2017; Ramsay and Williams, 2020). As per the International Monetary Fund's Global Financial Stability Report – 2021, COVID-19 has elevated global financial vulnerability across sectors, including the household sector. The debt-servicing capacity of households has deteriorated in a number of countries, owing to increased debt levels during the pandemic because of income/employment loss. The report further states that there is a sharp rise in the debt to GDP ratio among emerging economies from 21 per cent in 2008 to 44 per cent in 2020. The pandemic has turned the people's lives upside down as governments and civil societies across the world put their best efforts to safeguard lives and the livelihoods. The International Monetary Fund (IMF) has warned that COVID-19 is further amplifying the existing financial vulnerabilities of households in many countries.

While financial vulnerability or financial distress has been defined by different researchers in different ways, the most appropriate definition of financial vulnerability is the failure of a household to meet its financial obligations timely and completely, thus incurring financial distress. Analysing the financial vulnerability of households has been an important research agenda during the past two decades (Johansson and Persson, 2006; Dey et *al.*, 2008; Alfaro and Gallardo, 2012; Michelangeli and Pietrunti, 2014; Cifuentes et *al.*, 2020). The global financial crisis of 2008 uncovered the financial risks that households are exposed to and how household-level financial distress can have a huge impact on the stability of financial institutions as well as the larger economy. Financial vulnerability of households has both economic and social consequences (Campbell, 2006) as it not only affects the health of financial institutions and the economy as a whole but also determines the households' future poverty level with its negative effects on the standard of living. Thus, any effort made towards analysing and reducing financial vulnerability also has the potential to reduce future poverty levels. Researchers across the world have thus stepped up efforts to assess and understand the financial vulnerability of households across regions, with a special focus on rural areas.

The existing studies on analysing the financial vulnerability of households have many shortcomings. Since financial vulnerability is a multidimensional concept, researchers in the past have defined it in different ways and have attempted to measure it using different approaches. One approach has been to use indicators such as debt to income ratio, debt to asset ratio, and debt-service to income ratio. However, the indicator approach has certain limitations. First, only households with debt may be included in the analysis. Second, it provides a very restricted view of vulnerability since the approach requires an arbitrary threshold for each indicator that considerably changes the proportion of vulnerable households. Another approach has been the financial margin approach which is computed as the income left after making debt payments and basic living costs. However, due to joint constraints on income, consumption, and financial wealth, this approach requires a larger sample and multiple waves of data for analysis. Further, having understood the state of financial vulnerability of households using the above approaches, researchers have also attempted to identify the various determinants of financial vulnerability across countries.

The present work attempts to provide a broad measure of financial vulnerability by including liquid assets in the financial margin approach and identifies the household-level characteristics that differentiate the cluster of financially vulnerable households from that of other households. It adds to the existing literature on financial vulnerability in two ways. Firstly, our work is the first in India that analyses household-level financial vulnerability at rural level using machine learning techniques. We conduct a profiling of the financially vulnerable households and identify the household-level characteristics of the financially vulnerable households. Secondly, our research proposes to measure vulnerability using a broader measure of financial margin (including jewelry as a liquid asset) and thus is more rigorous in nature. Thirdly, by using the evidence from our assessment of financial vulnerability of households, we provide appropriate policy recommendations to address financial vulnerability in the Indian context.

2 Literature Review

While the concept of vulnerability measured at any level is multidimensional, difficult to understand, and without much uniformity (Bernard, 2004; Anderloni et al., 2012; Feeny and McDonald, 2016) with its applications across range of disciplines, its assessment at household level has attracted much attention from the academicians and policymakers as it has direct implications on the standard of living of the households and their future poverty levels (Povel, 2015) and an indirect effect on the stability of financial institutions and the overall health of the economy (Ampudia et al., 2016). Financially vulnerable households are not only more likely to default on their debt repayments but because such households are more likely to reduce their consumption expenditure in times of financial distress, it also affects the profitability of the firms and businesses in the economy due to the reduced sales and loss of revenue resulting in increased likelihood of corporate defaults (Vatne, 2006; Albacete and Fessler, 2010). This eventually exposes the entire financial sector of a country to a great risk.

The terms financial vulnerability, financial distress, and financial fragility are used interchangeably in research (Ampudia et al., 2016; Leika and Marchettini 2017; Daud et al., 2019; Giordana and Ziegelmeyer 2020). It is the failure or inability of an indebted household to make debt repayments (Poh and Sabri, 2017). For non-indebted households, it is their failure to meet basic living costs and thus suggests their inability to manage the household budget (Anderloni et al., 2012). A great deal of research has been carried out in order to measure financial vulnerability at the household level and analyse its determinants across countries (Vatne, 2006; Herrala and Kauko, 2007; Dey et al., 2008; Faruqui, 2008; Sugawara and Zalduendo, 2011; Albacete and Lindner, 2013; Bankowska et al., 2015). The studies primarily focus on debt repayments and analyse issues pertaining to the financial vulnerability of households (Jappelli et al., 2013).

The existing research on financial vulnerability at the household level mostly relies on two key approaches. One is the solvency approach and the other is the liquidity approach. The indicators under solvency approach measure financial vulnerability considering the total debt level of the household. The indicators include debt-to-income ratio (DIR) and debt-to-asset ratio (DAR). Debt-to-income ratio indicates the ability of the household to make payment of its total debt out of its total annual income (Lee and Kim, 2016) and is measured as a ratio of total debt to the total income of the household. The studies that use DIR to measure financial vulnerability across countries include Persson (2009), Cateau et al. (2015), Clercq et al. (2015), Ampudia et al. (2016), Lee and Kim (2016), Fessler et al. (2017). Debt-to-asset ratio indicates the adequacy of assets in meeting the total debt payments of a household and is measured as a ratio of total debt to the total assets of a household (Ampudia et al., 2016; Fessler et al., 2017) The indicators under the liquidity approach measure financial vulnerability considering the monthly debt repayment commitments of a particular household. Most of the studies use debt-service to income ratio and financial margin to analyse financial vulnerability under the liquidity approach. Debt-service-to-income (DSI) ratio measures the ability of a household to meet its monthly debt payment with the available income without having to sell off any of its assets (Ampudia et al., 2016). It is the ratio of monthly loan commitment, including principal and interest, to the household's disposable income (Djoudad, 2012) and has been used by various studies to estimate financial vulnerability (Dey et al., 2008;

Jappelli et al., 2013; Michelangeli, 2014; Bilston et al., 2015). Another measure, financial margin, is defined as the income left after making payment on basic living costs and debt payment or loan installments (Albacete and Fessler, 2010; Bilston et al., 2015; Ampudia et al., 2016; Room and Merikull, 2017). Financial margin also indicates at the ability of a household to absorb any income or interest rate shock (Vatne, 2006) that occurs at a macro level. A financially vulnerable household has a negative financial margin as its income is insufficient to meet its expenses and debt repayments, and is thus more likely to default.

However, the biggest drawback of measuring financial vulnerability with solvency or liquidity approach (except financial margin) is that it requires a threshold to be decided for the financial vulnerability value in order to categorise a particular household as vulnerable or otherwise. Thresholds have been fixed by different researchers using different criteria (May and Tudela, 2005; Dey et al., 2008; Tiongson et al., 2009; Michelangeli and Pietrunti, 2014;). Thus, the proportion of households that are estimated to be vulnerable is dependent on the decided threshold. Moreover, the existing indicators under the solvency or liquidity approach provide incomplete information on the vulnerability status of households as they do not consider the liquid assets held by a household. During financially difficult times, when their incomes are not sufficient to meet monthly expenses and debt repayments, households may avoid defaulting by drawing down their liquid assets. In such cases, even highly indebted households may have lower default rates (Costa and Farinha, 2012; Dietsch and Welter-Nicol, 2014). Households may even sell-off their assets or borrow against collateral in order to pay-off their debt (Ampudia et *al.*, 2016). Another drawback of the existing approaches (except financial margin) is that only indebted households are analysed, excluding the non-indebted households who may also be financially vulnerable, particularly the low-income households (Bridges and Disney, 2004).

Having identified the vulnerable households, researchers have also attempted to determine the household-level characteristics that play a key role in the determination of financial vulnerability such as the number of dependents, age, gender, education, employment status of the household head, and location (rural/urban) of the household (Worthington, 2006; Hollo and Papp, 2007; McCarthy and McQuinn, 2011; Kim et al., 2014; Yusof, Rokis, and Jusoh, 2015)

Our work attempts to find the determinants of financial vulnerability after addressing the above shortcomings in its estimation. Firstly, using the liquidity approach, we use financial margin as an indicator to measure financial vulnerability as this does not require a threshold to be decided. Secondly, we also include liquid assets as an additional variable while measuring financial vulnerability.

3 The Case of India

The COVID-19 pandemic has once again highlighted the risk that the household sector is exposed to through income and job losses, especially during macreconomic shocks. In the aftermath of COVID-19 outbreak, not only is the household sector at risk but the financial institutions have also become fragile as the likelihood of default from households and enterprises has increased. While household indebtedness is on the rise globally, Asia has witnessed a sharp rise in household debt as a share of gross domestic product (GDP) from nearly 45 per cent in 2008 to more than 60 per cent in 2020. In India, as per the Reserve Bank of India (RBI) data, there has been a steady rise in the household debt to GDP ratio in the last few years, reaching 37.3 per cent in 2020-21 from 32.5 per cent in 2019-20.

On March 24, 2020, the Government of India imposed a strict twelve-week nationwide lockdown, restricting the movement of its population in order to contain the spread of COVID-19. This brought the economic activities in the country to a complete halt resulting in widespread loss of income and jobs. This was followed by another three consecutive phases of lockdown with certain restrictions lifted in a phased manner till May 30, 2020. This prolonged lockdown has made a massive impact on the livelihood of low-income households, largely working in the informal sector and often relying on irregular sources of income with little to no social safety nets. The Gross Domestic Product (GDP) data from the first quarter of Financial Year 2020-21 suggests that the Indian economy contracted by 23 per cent due to the initial impact of COVID-19 and lockdowns. In order to provide relief to the borrowers during this COVID-19 induced financial crisis, the Reserve Bank of India (RBI) announced a three-month moratorium on term loan EMIs and this was further extended by another three months.

As per the Centre for Monitoring Indian Economy's data from the Consumer Pyramids Household Survey (CPHS), in May 2020, 84 per cent of the surveyed households reported a decrease in monthly income and more than one-fourth of the working-age population reported being unemployed. The survey results also report that the fall in household income was in line with a sharp increase in the unemployment to 25.5 per cent as on May 5, 2020, from 7.4 per cent on March 21, 2020. While the restrictions in several parts of the country have been eased out, the negative impact of the halt in economic activities on vulnerable sections of the society is likely to continue in the medium to long-term. Several studies in India have found that the pandemic has left the low-income households in deep financial distress, pushing them to borrow money from various sources. Thus, India provides an appropriate case to estimate financial vulnerability at the household level and identify the household-level characteristics that determine financial vulnerability.

4 Data, Variables and Methodology

The study uses a dataset maintained by a Non-Banking Financial Company (NBFC) about its customers, along with household-level information on their demographic characteristics, income, expenditure, savings, debt and repayments, assets, etc. The study focuses on households from the states of Tamil Nadu, Odisha, and Uttarakhand. A total of 91,093 records of households from Tamil Nadu, Odisha, and Uttarakhand are analysed.

We analyse financial vulnerability at the household-level in two steps. In the first step, we use financial margin (inclusive of liquid assets) as a measure of financial vulnerability at the household level using the following formula:

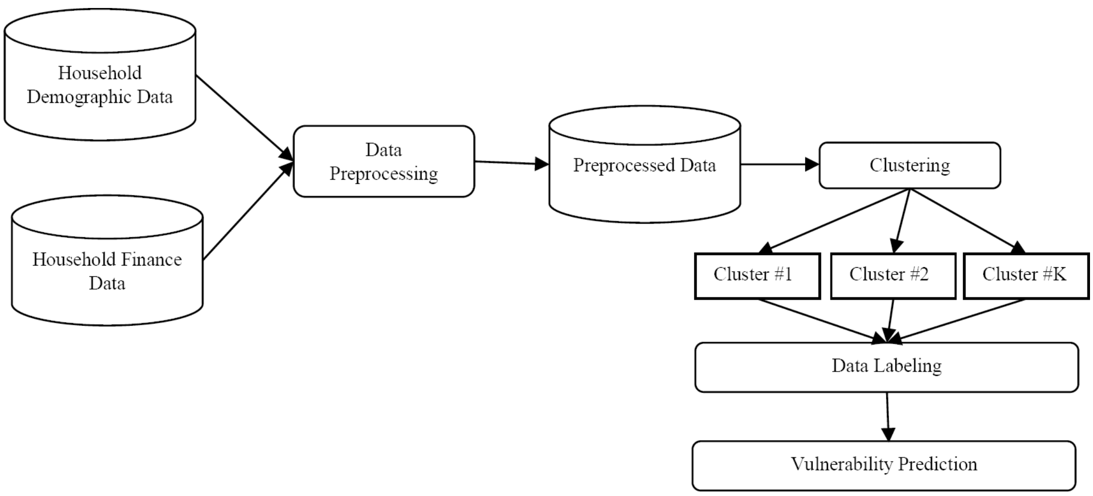
$$FM_h = Y_h + LA_h - LC_h - DP_h \tag{1}$$

where Y_h, LC_h, and DP_h are household h's annual income, living costs, and debt payments and LA_h is the liquid assets held by a household. Since the dataset has information only on the jewellery value of the household, the same is included in eq. (1) as liquid assets.

In the second step, we predict the vulnerability status of households. The approach is further divided into two parts. In the first part, we use an unsupervised machine learning algorithm to identify clusters of financially vulnerable households. The characteristics considered while clustering include location of the household (district), education of the primary earner, primary occupation, Income segment, dependency ratio (dependents/income earners), gender ratio (male/female), and average household age. Time series clustering approach is used for this purpose. In the second part, we predict the vulnerability status of households considering the household characteristics. The classification approaches used include Logistic Regression (LR), Decision Tree (DT), Random Forest (RF) and Multi-layer Perceptron (MLP).

The prediction approach is summarized in Figure 1 below.

Figure 1: Approach for Household Vulnerability Prediction



Data Collection and Preprocessing: The foremost step in this proposed approach is data collection and preprocessing. Let $X = \{X_1, X_2, \ldots, X_N\}$ be the collection of household characteristics and financial variables. Once the data is collected, we apply various preprocessing activities such as data imputation, feature selection and feature extraction. Data imputation helps in filling the missing values of a feature, feature selection helps in selecting relevant features from X, and feature extraction helps in creating new features from existing features.

Clustering and Data Labeling: Post preprocessing, the clustering algorithm, an unsupervised machine learning algorithm, helps break down the preprocessed dataset into several subsets having similar characteristics. An exploratory analysis of the characteristics of each cluster is done and appropriate labels are created with a new variable (y) holding the labels.

Prediction: After labelling, a classifier is built to predict the status of vulnerability of a household. The data is partitioned into 'training set' and 'test set' and a classification model, y=f(X), is fit to the training set. The function f(.) maps the input features (X) to the target variable (y). The predictions for the test set are obtained using the trained classifier. In the end, the fitness of the classifier for test set is computed using the performance metric.

5 Results and Discussion

5.1 *Cluster Characteristics*

Our dataset is a multi-variate time series dataset for which we use 'Time series K-Means' clustering algorithm to cluster time series of similar shapes. To obtain the time series clusters, Dynamic Time Warping (DTW) is used. DTW calculates optimal match between two time series subsequences. After thorough experimentation of K values, it is found that K=7 is the optimal one out of {3,4,5,6,7,8} which suggests that the 'Time series K-Means' clustered the data into 7 clusters. The clusters vary from each other with respect to different characteristics whereas the households within these clusters are homogenous. Table 1 summarises the variation between clusters in terms of characteristics:

TABLE 1: Classification of Clusters

Cluster No.	**Size (%)**	**Characteristics**
0	11.5	Relatively more dependents; greater representation of labour as primary occupation; over-representation of low-and middle-income segment; relatively greater 'no male' households;
1	21.8	Relatively more dependents; low grads and PG income earners; over-representation of labour/agriculture /business low-income segment; about 2/3rd HH with dependency ratio >=1; over representation of HH with gender ratio < = 1;
2	22.5	Highest representation from 'Tehri Garhwal' district; Highest no. of dependents; More illiterate primary earners with least grads and PG; highest representation of labour and agri low-income segment; high dependency ratio with lowest representation of 'no dependents' households; over representation of HH with gender ratio < =1; half of the households are young (up to 24)
3	13.2	$1/3^{rd}$ least educated (1-5 grade); greater representation of business-low and labour-mid income segment; 40% HH with dependency ratio >=1; about 1/4th HH with females outnumbering males; more than $1/4^{th}$ young households (up to 24).
4	8.2	More literate primary earners; greater representation of business mid and labour high-income segment; lower dependency ratio; low representation of young households (up to 24).
5	16.4	Over-representation of illiterates and least educated; over-representation of business-low and labour-low income segment; low representation of 'no dependents' households; more than 1/4th HH with females outnumbering males; greater representation of young households (upto 24)
6	6.4	Lowest representation from 'Thanjavur' and 'Ganjam' district; Least dependents; More graduate and PG primary earners; greater representation of shop and business owners in high income segment; lower dependency ratio; lowest representation of gender ratio < 1 with 'no female' households greater than 'no male' households; low representation of young households (upto 24).

Since a significant income shock may considerably affect the vulnerability status of the households and may turn even non-vulnerable households vulnerable, we categorise and label the clusters based on their characteristics as vulnerable, high-risk, medium-risk, and low-risk households. The households belonging to cluster '2' are identified as vulnerable;

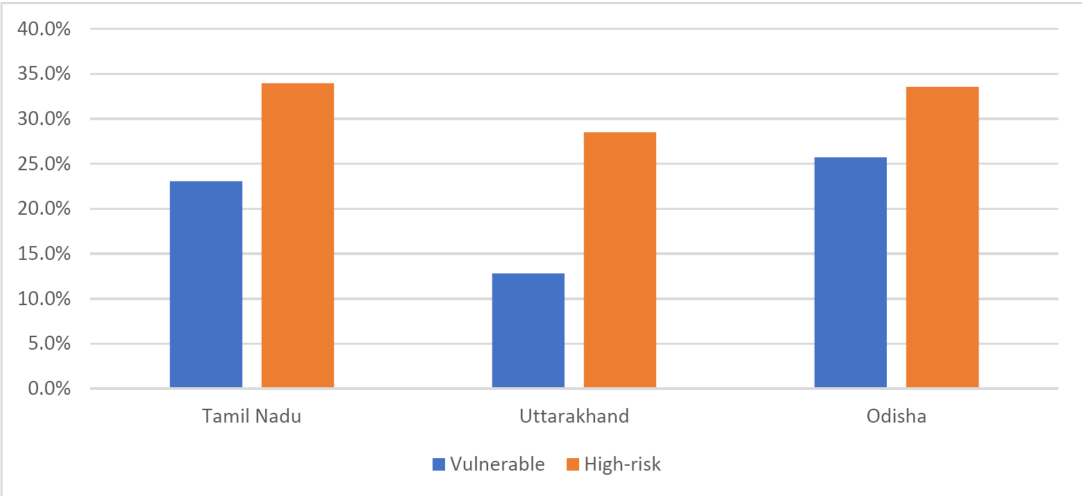
households in cluster '0' and '1' are identified as high-risk households; households in cluster '3' and '5' are identified as moderate-risk households; and households in cluster '4' and '6' are identified as low-risk households.

The above categorisation suggests that 22.5 per cent of the households in our sample are vulnerable, 33.3 per cent are high-risk, 29.6 per cent are moderate-risk, and 14.6 per cent households are low-risk.

5.2 *Descriptive Analysis*

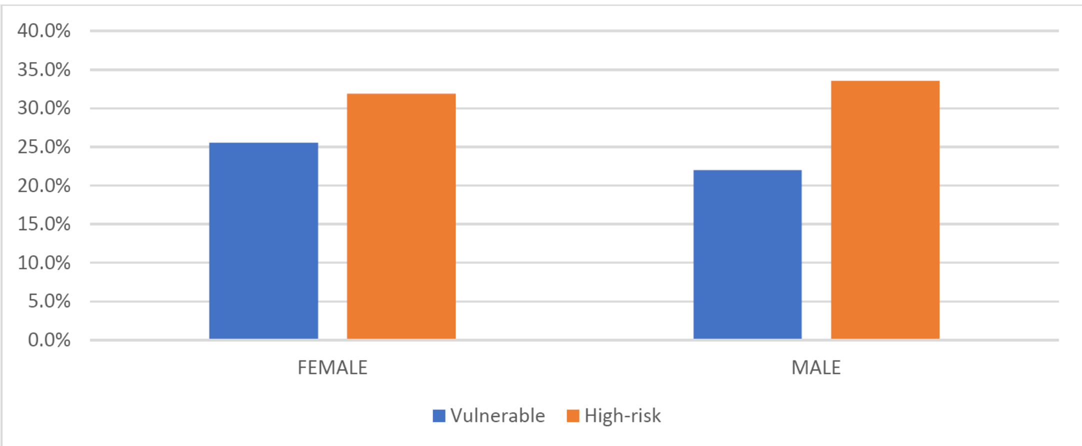
Among the three states, the proportion of financially vulnerable households is the highest in Odisha, followed by Tamil Nadu, and Uttarakhand (Figure 2).

FIGURE 2: Financial Vulnerability across 3 states



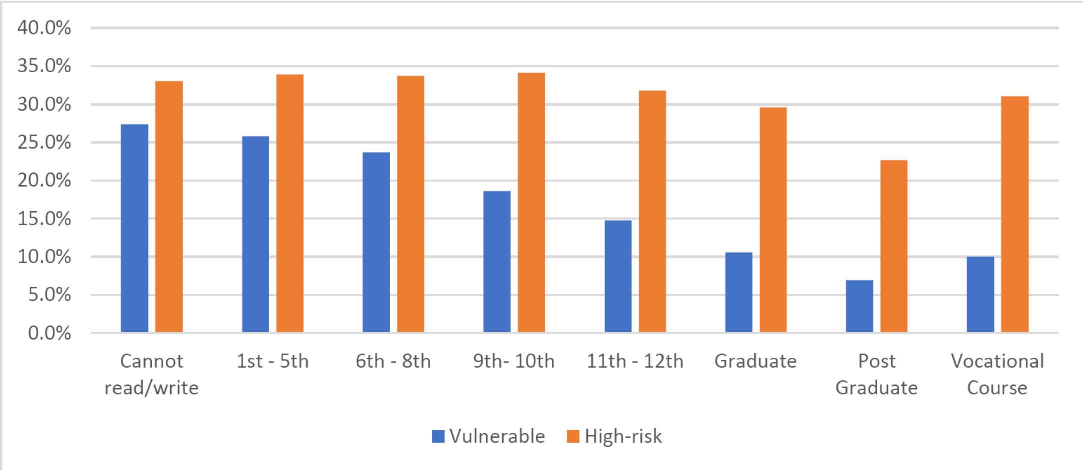
The gender of the primary income earner has a moderate association with the financial vulnerability of the household, with female primary earners being more financially vulnerable than their male counterparts (Figure 3).

FIGURE 3: Primary Earner's Gender and Financial Vulnerability



Financial vulnerability also varies with the education level of the primary earner of the household (Figure 4). A greater share of households with illiterate primary earners is financially vulnerable when compared to households with literate primary earners. Among households with literate primary earners, increase in the educational level is associated with decreasing financial vulnerability.

FIGURE 4: Primary Earner's Education and Financial Vulnerability



The primary occupation of the household is also associated with the level of financial vulnerability (Figure 5). Households with 'Agriculture' as the primary occupation are the most vulnerable ones followed by 'Labour', 'Business', 'Salaried', 'Shop Owner', and 'Working Abroad'.

FIGURE 5: Primary Occupation and Financial Vulnerability

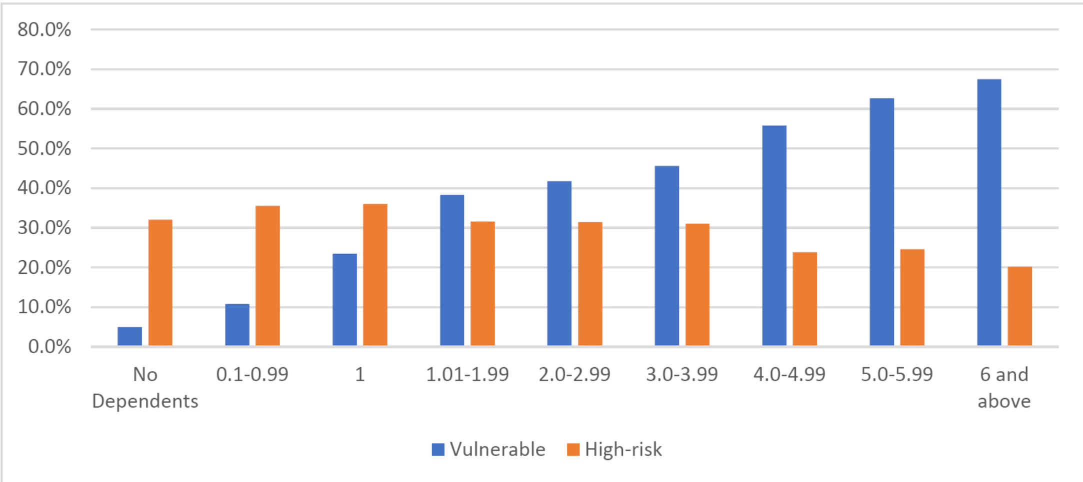
Household income remains a key variable in deciding their vulnerability status. Households belonging to the low-income segment are the most vulnerable ones (Figure 6). Among the low-income segment households, the financial vulnerability is highest for 'agriculture low-income segment' households followed by 'labour', 'salary', 'business', and 'working abroad'.[1]

[1] Households are classified into low-income, middle-income, etc. in the Customer Management System data of the NBFC. We use the same classification for this analysis

FIGURE 6: Income Segment and Financial Vulnerability

The dependency ratio of the household, which is measured as the ratio of number of dependents to the number of income earners, is also associated with its financial vulnerability status (Figure 7). Households with no dependents are the least financially vulnerable. A dependency ratio of less than 1, indicating that income earners outnumber the dependents, is associated with low financial vulnerability. Financial vulnerability increases with increasing dependency ratio.

FIGURE 7: Dependency Ratio and Financial Vulnerability



The 'Gender ratio' of a household, which is measured as the ratio of male members to the female members of a household, is also associated with the household's financial vulnerability (Figure 8). Households where female members outnumber the male members (with gender ratio < 1) are the most financially vulnerable. Households with an increasing gender ratio above 1 are less vulnerable. Households with 'no males' are more vulnerable than households with 'no females'.

Analysing financial vulnerability with the average household age suggests that younger households (with more young members) are more vulnerable relative to older households (Figure 9). Households with average age up to 24 are most vulnerable followed by '25-34', '35-44', and '45-54' average age group.

FIGURE 8: Gender Ratio and Financial Vulnerability

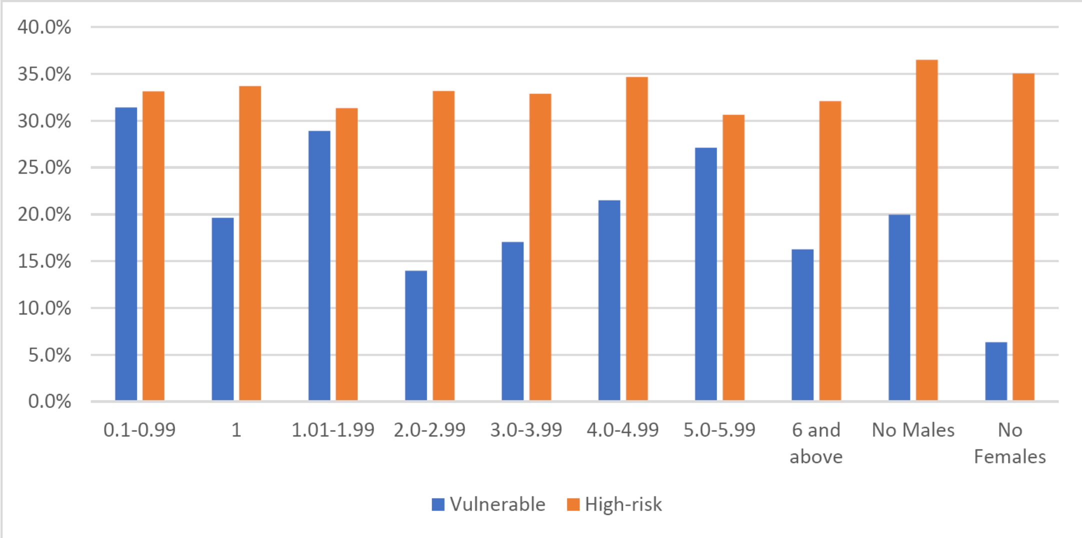
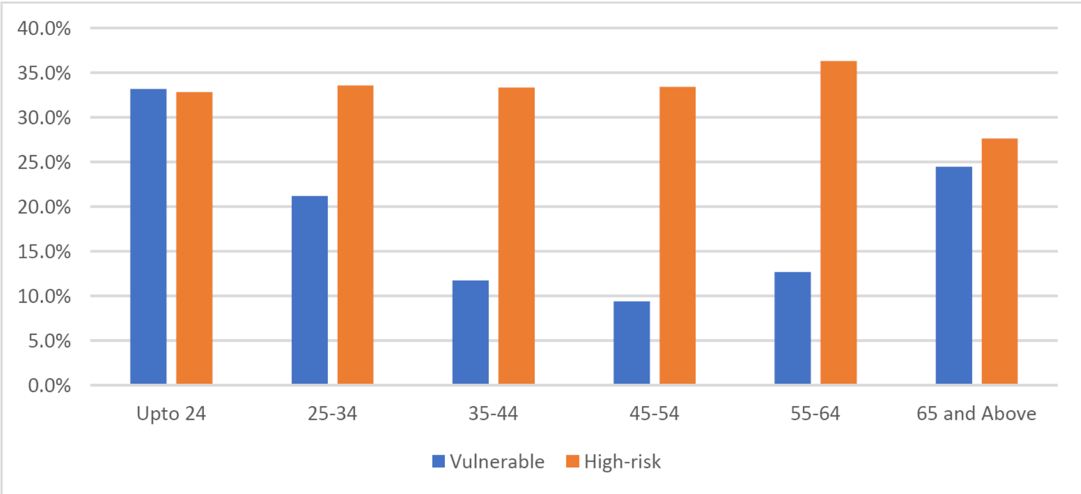


FIGURE 9: Average HH Age and Financial Vulnerability



5.3 *Prediction*

The overall sample is partitioned into a training set (70%) and a test set (30%). The test set consists of 27,327 observations. Of these observations, 14,045 observations are of 'Medium-risk' class, 6,698 observations are of 'Low-risk' class, 4,366 observations are of 'High-risk' class, and 2,218 observations are of 'Vulnerable' class. As there are multiple labels, the problem turns out to be a multi-class classification problem. The classification algorithms applied to address the multi-class classification problem include Logistic Regression (LR), Decision Tree (DT), Random Forest (RF) and Multi-layer Perceptron (MLP) are used.

Multinomial logistic regression algorithm is an extension of the logistic regression model that involves changing the loss function to cross-entropy loss and predicts probability distribution to a multinomial probability distribution to natively support multi-class classification problems. Out of 27,327 observations, Logistic Regression classifier correctly classifies 26,994 observations whereas 333 observations are classified incorrectly (Table 2). Hence, the accuracy level is 99%.

Table 2: Confusion Matrix using Logistic Regression

Actual↓ / Predicted→	**High-risk**	**Low-risk**	**Medium-risk**	**Vulnerable**
High-risk	4322	0	40	4
Low-risk	0	6606	92	0
Medium-risk	70	100	13875	0
Vulnerable	27	0	0	2191

Decision Tree (DT) predicts the labels based on node splitting concept. For each split node, a best attribute or a best split point is chosen. The impurity of child nodes is computed using Gini index. Out of 27,327 observations, the Decision Tree classifier correctly classifies all 27,327 observations (Table 3). Hence, its accuracy is 100%.

Table 3: Confusion Matrix using Decision Tree

Actual↓ / Predicted→	**High-risk**	**Low-risk**	**Medium-risk**	**Vulnerable**
High-risk	4366	0	0	0
Low-risk	0	6698	0	0
Medium-risk	0	0	14045	0
Vulnerable	0	0	0	2218

Random Forest (RF) is an ensemble of decision trees, usually trained with the "bagging" method. It predicts the class labels based on majority voting of predictions obtained from decision tree. Out of 27,327 observations, the Random Forest classifier could correctly classify all 27327 observations (Table 4). Hence, its accuracy is also 100%.

Table 4: Confusion Matrix using Random Fores

Actual↓ / Predicted→	**High-risk**	**Low-risk**	**Medium-risk**	**Vulnerable**
High-risk	4366	0	0	0
Low-risk	0	6698	0	0
Medium-risk	0	0	14045	0
Vulnerable	0	0	0	2218

Multi-layer Perceptron (MLP) is a feed-forward neural network in which each node is connected to all the nodes in the previous layer except the input layer. It predicts the probabilities using the activation function in the output nodes. It updates the weights of connections using a learning algorithm. The probabilities are cut off using threshold to obtain predicted class labels. Out of 27,327 observations, MLP classifier could correctly classify 14,049 observations whereas 13,278 observations are classified incorrectly (Table 4). Hence, its accuracy is only 51%.

Table 5: Confusion Matrix using Multi-layer Perceptro

Actual↓ / Predicted→	**High_Risk**	**Low_or_No_Risk**	**Medium_Risk**	**Vulnerable**
High_Risk	0	0	4366	0
Low_or_No_Risk	0	0	6698	0
Medium_Risk	0	0	14045	0
Vulnerable	0	0	2214	4

Out of these four classifiers, Logistic Regression, DT, and RF yield accurate predictions. However, MLP does not yield better predictions because even though neural networks are universal approximators, they may not always yield an optimal solution. The linear nature of data is captured very well by Logistic Regression, whereas MLP, a non-linear classifier, does not capture linearity very well.

6 Conclusion

The past few decades have seen an increased interest among academicians, policymakers, and the practitioners to understand financial vulnerability of households and identify its determinants. Adding to the existing literature on household-level financial vulnerability, the present work uses a broader measure of financial margin (including liquid assets) to assess the financial vulnerability of households and employs machine and deep learning techniques to identify cluster(s) of financially vulnerable as well as high, medium and low-risk households in the rural areas of three Indian states – Tamil Nadu, Odisha, and Uttarakhand. Our results suggest that out of a total sample of 91,093 households, 22.5 per cent are found to be financially vulnerable, followed by 33.3 per cent high risk, 29.6 per cent medium risk, and 14.6 per cent low-risk households. The share of financially vulnerable households is the highest in Odisha followed by Tamil Nadu, and Uttarakhand. The clustering of households based on household characteristics suggests that financially vulnerable households tend to have illiterate or less educated primary earners, females outnumbering males or have 'no males' at all, agriculture or labour as their primary occupation, a higher dependency ratio, belong to low-income segment, and are younger households with an average household age of up to 24 years.

Our results are important for policymakers who design financial sector policies with a focus on reducing financial vulnerability of households. The study suggests that policymakers should explore ways to systematically monitor the vulnerability levels of households with identified characteristics, specifically low-income households in the 'agriculture' and 'labour' sector, and to enhance their debt management practices. Since more educated primary earners are less financially vulnerable, providing adequate financial education may also help the households in managing their finances well. Since COVID-19 has affected both rural and urban sectors in India on an unprecedented scale, policies and programs aimed at strengthening the risk management strategies of households assume greater importance. The results may also be useful in assessing the impact of income and credit shocks on household welfare, including their effects on poverty and income distribution, and thus motivates additional research to further inform future policymaking.

References

1. Albacete, N., & Fessler, P. (2010). Stress testing Austrian Households. *Financial stability report*, *19*, 72-91.

2. Albacete, N., & Lindner, P. (2013). Household Vulnerability in Austria–A Microeconomic Analysis based on the Household Finance and consumption survey. *Financial stability report*, *25*, 57-73.

3. Alfaro, R., & Gallardo, N. (2012). The determinants of household debt default. *Economic Analysis Review*, *27*(1), 55-70.

4. Ampudia, M., van Vlokhoven, H., & Żochowski, D. (2016). Financial fragility of euro area households. *Journal of Financial Stability*, *27*, 250-262.

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

6. Bankowska, K., Lamarche, P., Osier, G., & Perez-Duarte, S. (2015). *Measuring household debt vulnerability in the euro area.* In Indicators to Support Monetary and Financial Stability Analysis: Data Sources and Statistical Methodologies, *39*, Bank of International Settlements, European Central Bank.

7. Bernard, G. S. (2004). Toward the construction of a social vulnerability index–Theoretical and methodological considerations. *Social and Economic Studies*, *53*(2), 1-29.

8. Bettocchi, A., Giarda, E., Moriconi, C., Orsini, F., & Romeo, R. (2018). Assessing and predicting financial vulnerability of Italian households: a micro-macro approach. *Empirica*, *45*(3), 587-605.

9. Bilston, T., Johnson, R., & Read, M. (2015). *Stress testing the Australian household sector using the HILDA survey*, Research Discussion Paper 2015-01. Economic Research Department, Reserve Bank of Australia.

10. Bridges, S., & Disney, R. (2004). Use of credit and arrears on debt among low-income families in the United Kingdom. *Fiscal Studies*, *25*(1), 1-25.

11. Brunetti, M., Giarda, E., & Torricelli, C. (2016). Is financial fragility a matter of illiquidity? An appraisal for Italian households. *Review of Income and Wealth*, *62*(4), 628-649.

12. Campbell, J. Y. (2006). Household finance. *The journal of finance*, *61*(4), 1553-1604.

13. Cateau, G., Roberts, T., & Zhou, J. (2015). Indebted households and potential vulnerabilities for the Canadian financial system: A microdata analysis. *Financial system review,* Bank of Canada.

14. Cifuentes, R., Margaretic, P., & Saavedra, T. (2020). Measuring households' financial vulnerabilities from consumer debt: Evidence from Chile. *Emerging Markets Review*, *43*.

15. Clercq, B. D., Tonder, J. A. V., & Aardt, C. J. V. (2015). Consumer financial vulnerability: identifying transmission linkages that could give rise to higher levels of consumer financial vulnerability. *Southern African Business Review*, *19*(1), 112-136.

16. Costa, S., & Farinha, L. (2012). Households' Indebtedness: A Microeconomic Analysis based on the results of the Households' Financial and consumption survey. *Financial Stability Report.* Bank of Portugal.

17. 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.

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

19. Dietsch, M., & Welter-Nicol, C. (2014). Do LTV and DSTI caps make banks more resilient?. *Débats économiques et financiers*, *13*, Banque de France.

20. Djoudad, R. (2012). *A framework to assess vulnerabilities arising from household indebtedness using microdata.* Bank of Canada Discussion Paper No. 2012-3, Bank of Canada.

21. Faruqui, U. (2008). *Indebtedness and the household financial health: an examination of the Canadian debt service ratio distribution* Working Paper No. 2008-46, Bank of Canada, Ottawa.

22. Feeny, S., & McDonald, L. (2016). Vulnerability to multidimensional poverty: Findings from households in Melanesia. *The journal of development studies*, *52*(3), 447-464.

23. Fessler, P., List, E., & Messner, T. (2017). How financially vulnerable are CESEE households? An Austrian perspective on its neighbors. *Focus on European Economic Integration*, (Q2/17), 58-79.

24. Giordana, G., & Ziegelmeyer, M. (2020). Stress testing household balance sheets in Luxembourg. *The Quarterly Review of Economics and Finance*, *76*, 115-138.

25. Herrala, R., & Kauko, K. (2007). Household loan loss risk in Finland-Estimations and simulations with micro data. *Bank of Finland Research Discussion Paper*, (5).

26. Hollo, D., & Papp, M. (2007). Assessing household credit risk: evidence from a household survey, Magyar Nemzeti Bank Occasional Papers, No. 70.

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

28. Johansson, M. W., & Persson, M. (2006). Swedish households' indebtedness and ability to pay: a household level study. *Press & Communications CH 4002 Basel, Switzerland*, *30*, 234.

29. Kim, H. J., Lee, D., Son, J. C., & Son, M. K. (2014). Household indebtedness in Korea: Its causes and sustainability. Japan and the World Economy, 29, 59-76.

30. Lee, J. M., & Kim, K. T. (2016). Assessing financial security of low-income households in the United States. *Journal of Poverty*, *20*(3), 296-315.

31. Leika, M., & Marchettini, D. (2017). *A generalized framework for the assessment of household financial vulnerability.* International Monetary Fund.

32. May, O., & Tudela, M. (2005). When is mortgage indebtedness a financial burden to British households? A dynamic probit approach. Working Paper No. 277, Bank of England.

33. McCarthy, Y., & McQuinn, K. (2011). How are Irish households coping with their mortgage repayments? Information from the Survey on Income and Living Conditions. *The Economic and Social Review*, *42*(1), 71-94.

34. Mian, A., Sufi, A., & Verner, E. (2017). Household debt and business cycles worldwide. *The Quarterly Journal of Economics*, *132*(4), 1755-1817.

35. Michelangeli, V., & Pietrunti, M. (2014). A Microsimulation Model to evaluate Italian Households' Financial Vulnerability. *International Journal of Microsimulation*, *7*(3), 53-79.

36. Persson, M. (2009). Household indebtedness in Sweden and implications for financial stability–the use of household-level data. *BIS Papers*, *46*, 124-135.

37. Poh L.M., & Sabri, M. F. (2017). Review of financial vulnerability studies. *Archives of Business Research*, *5*(2), 127-133.

38. Povel, F. (2015). Measuring exposure to downside risk with an application to Thailand and Vietnam. *World Development*, *71*, 4-24.

39. Ramsay, I., & Williams, T. (2020). Peering forward, 10 years after: International policy and consumer credit regulation. *Journal of Consumer Policy*, *43*(1), 209-226.

40. Room, T., & Merikull, J. (2017). *The financial fragility of Estonian households: Evidence from stress tests on the HFCS microdata,* Working Paper No. wp2017-4. Bank of Estonia.

41. Sugawara, N., & Zalduendo, J. (2011). *Stress-Testing Croatian Households with Debt-Implications for Financial Stability.* Working Paper No. 5906, The World Bank.

42. Tiftik, E., Mahmood, K., & Gibbs, S. (2019). Global debt monitor: Devil in the details. International Institute of Finance.

43. Tiongson, E., Gueorguieva, A. I., Levin, V., Subbarao, K., Sugawara, N., Sulla, V., & Taylor, A. (2009). *The crisis hits home: Stress testing households in Europe and Central Asia.* The World Bank.

44. Vatne, B. H. (2006). How large are the financial margins of Norwegian households? An analysis of micro data for the period 1987–2004, Economic Bulletin, *77*(4/06), 173-180.

45. Worthington, A. C. (2006). Debt as a source of financial stress in Australian households. *International Journal of Consumer Studies*, *30*(1), 2-15.

46. Yusof, S. A., Rokis, R. A., & Jusoh, W. J. W. (2015). Financial fragility of urban households in Malaysia. *Jurnal Ekonomi Malaysia*, *49*(1), 15-24.