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The Ability of Households to Repay Financial Liabilities in the Face of Unscheduled Events: Insights from the COVID-19 Pandemic

Keywords: repayment of financial liabilities; COVID-19; logistic regression; decision trees; Shapley Additive exPlanations method

JEL: D12; G51; C35

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Abstract

Theoretical background: Unscheduled events, such as illnesses, disasters, or pandemics, can significantly impact households' ability to meet their financial obligations. The resilience of households to such events depends on their characteristics. While existing literature primarily focuses on individual characteristics,

a noticeable research gap remains regarding the impact of interactions between these factors on household financial situations.
Purpose of the article: This study aims to identify and assess the importance of factors determining the repayment of household financial obligations during the COVID-19 pandemic.
Research methods: The study applied a logistic regression model and a decision tree. Since logistic regression does not provide information on the importance of variables used in the model, and decision trees do not provide information on the direction of the impact of the factors being examined, the Shapley Additive exPlanations method has been applied to evaluate the results obtained using these models. The study used data from the Household Budget Survey for 2020 and 2021.
Main findings: We established that the greatest impact on the inability to meet financial obligations due to the COVID-19 pandemic was the change in total income caused by the pandemic, subjectively assessed by the respondents. Other key factors influencing difficulties in repaying obligations were education level and the household's available income. However, the importance of these two factors was influenced by the subjective opinions of respondents about the change in total income due to the COVID-19 variable.

Introduction

The losses and harm resulting from unscheduled events, such as natural disasters, pandemics, and other similar occurrences, might significantly affect the region's economy and individual households (Okuyama et al., 1999). The negative effects of the COVID-19 pandemic primarily affected finances and debt, both public and private, with some of these effects still observable today (Wąsiński & Wnukowski, 2020). The appearance of the SARS-CoV-2 coronavirus in 2019 prompted governments worldwide, including Poland, to introduce business activity restrictions.

Moreover, anti-crisis shields were structured as a set of governmental measures aimed at safeguarding the Polish state and its residents from the impact of the crisis. These instruments were founded on essential principles, such as job and employee protection, along with the fortification of the financial system. The changes implemented included tax exemptions and reliefs, temporary benefits, subsidies, and tax deferments or arrangements for instalment payments (Korzeniowska et al., 2023).

Existing literature predominantly examines individual factors influencing household indebtedness during periods of crisis; however, a significant research gap remains regarding the interactions between these factors. This study aims to identify and assess the importance of factors determining the ability of households to repay financial liabilities in the context of unscheduled events, using the COVID-19 pandemic as an example, including an examination of the interactions between such factors. Therefore, in our study, it is crucial to use models that enable the explanation of the phenomenon under study. The logistic regression model is a common research tool used to analyse meeting financial liabilities (Cramer, 2003; Hosmer et al., 2013). However, in some applications, regression models may be insufficient due to the nature of the training sample, and then machine learning algorithms may provide better predictions. Decision trees are machine learning methods that also provide interpretable results (Breiman et al., 1984). However, both logistic regression models and decision tree models have certain limitations regarding the interpretability of the obtained results, even if they are considered interpretable by themselves (Ribeiro et al., 2016). Based on the estimated parameter values of logistic regression models, it is not possible to assess the importance of the variables used in the model. On the other hand, the importance of variables determined for decision tree models does not provide information about the direction of their impact on the studied phenomenon.

The importance of variables in the model reflects their impact on the obtained model result. Thus, it is essential to understand how machine learning models make predictions as the deployment of artificial intelligence systems increases (Arya et al., 2019, p. 1; Chen et al., 2023). In the field of finance, it is crucial to ensure that models depend on the right factors, making interpretability particularly essential (Gramegna & Giudici, 2021). In our study, we used the Shapley Additive exPlanations (SHAP) approach. The SHAP method adapts a concept from game theory and possesses many appealing properties. It enables the assessment of each explanatory variable's contribution to each prediction, regardless of the underlying model (Lundberg & Lee, 2017; Mangalathu et al., 2020). With the usage of the SHAP method not only a local explanation is provided but also a global one by aggregating the local SHAP values. Thus, local accuracy is preserved while capturing global trends, resulting in more comprehensive representations of the model's behaviour (Lundberg et al., 2020).

In our study, using the interpretability of the logistic regression model and the decision tree we identify the factors that affect the repayment of fixed financial obligations due to the COVID-19 pandemic. Furthermore, we go beyond previous findings by establishing a hierarchy of these factors using the SHAP method. The innovation of our approach lies in combining these modelling techniques with the SHAP method, we enhance the explanation of the impact of individual variables in the models. In the study, we used the data from household budget surveys conducted in Poland in 2020 and 2021.

Literature review

The COVID-19 pandemic had and still has significant implications for not only the broader economy, but also for public finances, business viability, and the financial stability of individual households (Witoń, 2024). The shift in household financial behaviours in response to the shock of the pandemic included a decrease in spending compared to the pre-pandemic period, a decline in income, and a freeze on expenditures due to concerns about an uncertain future (Waliszewski & Warchlewska, 2021). Yannelis and Amato (2023) focused on household behaviour during and after the pandemic, particularly concerning consumption, credit, and investment patterns. They referred to the study by Horvath et al. (2023) regarding the dynamic impact of the COVID-19 shock on credit card usage in 2020. It has been concluded that among creditworthy borrowers, changes in their higher credit spending aligned and followed higher outstanding credit balances. Conversely, among the riskiest borrowers, the recovery in their credit card transactions coincided with a persistent decline in their outstanding credit balances. This phenomenon is consistent with the idea that a positive income boost, possibly stemming from government support programs, allowed them to use their credit cards more without accumulating additional debt. Puszer and Czech (2021) explored the dynamics and changes in consumer credit values in the Eurozone during the COVID-19 pandemic. The study focused on identifying pandemic-related factors that directly influenced consumer credit. The findings demonstrate that COVID-19 shaped the value of consumer credit across the Eurozone and influenced households' debt-related decisions. The key conclusion of the study is that the impact of COVID-19-related factors, including the number of cases, tests, deaths, and vaccinations, on household consumer credit varied significantly across countries.

Li et al. (2020) showed that in the case of Chinese households, the pandemic has increased the likelihood of financial constraints and reduced liquidity. This likelihood intensified as the pandemic became more severe. During that time, as household income and employment were affected, the likelihood of saving increased while spending on consumption decreased. Albuquerque and Green (2023) conducted a representative survey of UK households to investigate how concerns about future finances influenced their marginal propensity to consume (MPC) during the COVID-19 pandemic. Specifically, the MPC was derived from a question asking participants how they would spend a hypothetical one-off transfer of GBP 500. The primary measure of household expectations, or financial concerns, was the self-reported probability of being unable to pay usual bills and expenses over the next three months. Households were classified as financially concerned if their reported probability of financial distress was above the median in the sample. To examine differences in MPC between households, probit panel regressions were used. They found that households that fear not being able to make ends meet had a 20% higher MPC than other households (Albuquerque & Green, 2023).

Mamatzakis et al. (2023) examined how COVID-19 affected households' debt repayments in the UK. Using a vector autoregressive (VAR) model with neural networks and Mixed Data Sampling (MIDAS), they analyzed financial data related to the pandemic. The results showed that household debt repayments decreased slightly in response to overall COVID-19 shocks. However, when governments focused on specific factors related to vaccines and testing, repayments increased, highlighting complex underlying dynamics. Confirmed deaths and hospitalizations in households were found to reduce debt repayments, though this effect was short-lived. As lockdowns eased and COVID-19's impact lessened, household finances gradually returned to pre-pandemic levels, but with some delays.

A study by Achou et al. (2020) investigated the COVID-19 impact on the Canadian household's financial situation. The study utilized data from a survey of 3,009 respondents who were asked about their employment status, debts, and spending. The analysis focused on how individuals adapted to reduced income during COVID-19, including strategies such as deferring debt payments. Results revealed that homeowners were more likely to defer mortgage payments than renters who missed or deferred rent payments. Additionally, 7.3% of households deferred other debts. Women and older individuals were less likely to miss mortgage payments or increase credit card debt. Overall, homeowners primarily used mortgage deferrals, while non-homeowners faced fewer options and turned to other financial strategies. This confirms that the pandemic particularly impacted the financial situation of renters, resulting in many falling behind on their rent payments. Airgood-Obrycki et al. (2022) utilised data from the US Census Bureau's Household Pulse Survey and logistic regression model to explore how renters managed their finances after losing income during the pandemic. Their findings revealed that renters, especially those with lower incomes and renters of colour, relied on a mix of government support, personal savings, credit, and borrowing from family and friends to cover rent and other expenses.

The literature provides substantial evidence of the worsening financial situation of households during the COVID-19 pandemic. However, less well-recognized are the factors that determine why some households cope better or worse with such unexpected events. Thus, our study seeks to answer two key research questions: Which factors influenced households' ability to meet their financial obligations during the COVID-19 pandemic? What was the hierarchy of these factors? Our results contribute to research on the resilience of households to unscheduled events.

Research methodology

Data

The data for our study was obtained from the Polish Household Budget Surveys (HBS) from 2020–2021. The data obtained from the HBS makes it possible to analyse the living conditions of the population and to assess the impact of various factors on the level and diversification of the material situation of households. The survey is conducted using the representative method across the country among a randomly selected group of households. Compared to previous surveys, data from 2020–2021 provide additional information regarding selected aspects of the functioning of households in conditions of an epidemic threat of an infectious disease caused by the SARS-COV-2 virus, called COVID-19. The dataset for the study was limited based on the question about the characteristics of household debt.

Respondents could choose one of five possible answers: 1 = "household is not in debt", 2 = "debt is not a burden and repayments are made on time", 3 = "debt is somewhat a burden, but repayments are made on time", 4 = debt is a heavy burden and repayments are not always made on time", 5 = "household is unable to pay off its liabilities at all". According to the purpose of our study, it was selected only indebted households. Thus, our study included 11,616 households.

To assess the impact of unplanned events, such as the COVID-19 pandemic, on the ability of households to meet their financial liabilities we used the following question: As a result of the COVID-19 pandemic lasting from 2020, was household forced to make decisions on resigning from repayment of fixed financial liabilities (e.g. payments related to housing, repayment instalments, and credits, alimony payments)?. Respondents could choose one of 5 possible answers: 1 = "no", 2 = "yes, slightly", 3 = "yes, moderately", 4 = "yes, largely", 8 = "hard to say". It turned out that most households (97%) had no problems with repaying their financial liabilities. Taking into account the distribution of answers to this question, the target variable with two levels was constructed: 0 = 11,253 (97%) and 1 = 363 (3%). Moreover, the households that answered "hard to say" to this question were not included in the study. The selection of the remaining variables for the model was based on a literature review, considering that the anti-crisis measures primarily focused on the financial aspects of individuals (Korzeniowska et al., 2023). We determined the characteristic of available income as a categorical variable based on the quartiles. The set of characteristics of households included in the study is presented in Table 1.

Table 1. Sample characteristics (in %)

Variable	Category	Percentage
Available income	<= 3,724	25.02
	(3,724 ; 6,000>	26.21
	(6,000 ; 8,300>	23.87
	(8,300 ; 17,4438>	24.90
As a result of the COVID-19 pandemic lasting from 2020, according to the subjective opinion of respondents' total income	decreased significantly	8.03
	decreased insignificantly	15.31
	remained at the same level	73.34
	increased	2.32
	hard to say	1.00
Socio-economic groups	employees	64.41
	farmers	2.88
	self-employed	11.05
	retirees and pensioners	19.48
	any unearned income	2.18
Number of household members	1	14.99
	2	27.13
	3	22.60
	4	24.53
	5 and more	10.75
The education level of the highest educated household member	lower secondary, primary, incomplete primary	2.52
	basic vocational	13.32
	general secondary	7.48
	postsecondary and vocational secondary	25.90
	higher	50.78
Macroregion	south	18.56
	northwest	14.73
	southwest	15.42
	northwest	16.76
	central	8.66
	eastern	9.98
	Mazowieckie Voivodeship	15.89

Source: Authors' own study based on (Statistics Poland, 2021, 2022).

Logistic regression model

The study examines a binary dependent variable describing being unable to fully meet financial liabilities. Therefore, we used the logistic regression model (Hosmer et al., 2013). Let y denotes a binary dependent variable taking two values: $y_i = 1$ or $y_i = 0$, for $i = 1, \dots, n$, with $y_i = 1$ denoting the occurrence of an event, and $y_i = 0$ non-occurrence of the event. If p_i denotes probability of event occurrence: $p_i = P(y_i = 1)$, and $1 - p_i$ probability of the opposite: $1 - p_i = P(y_i = 0)$, for $i = 1, \dots, n$, then the response variable y follows the binomial distribution with probability function:

$$f(y_i) = p_i^{y_i}(1 - p_i)^{1-y_i}, \ for \quad y_i = 0,1 \tag{1}$$

Furthermore, let $\mathbf{x}_i = [x_{i1}, \dots, x_{ik}]^T$ denotes the vector of observed covariates, and $\boldsymbol{\beta} = [\beta_1, \dots, \beta_k]$ is a vector of estimated model parameters. Then p_i is given as a linear function of covariates:

$$p_i = F(\boldsymbol{\beta x}_i). \tag{2}$$

If the F function is a cumulative distribution logistic function, then the logit model is considered, also called logistic regression (Cramer, 2003; Greenberg, 2012; Hosmer et al., 2013), where:

$$p_i = P(y_i = 1) = F(\boldsymbol{\beta x}_i) = \frac{exp(\boldsymbol{\beta x}_i)}{1+exp(\boldsymbol{\beta x}_i)}. \tag{3}$$

Then logit probability p_i is expressed by the formula:

$$\text{logit}(p_i) = ln\left(\frac{P(y_i=1)}{P(y_i=0)}\right) = ln\left(\frac{p_i}{1-p_i}\right), \tag{4}$$

where:

$$F^{-1}(p_i) = ln\left(\frac{p_i}{1-p_i}\right) = \boldsymbol{\beta x}_i \tag{5}$$

F^{-1} denotes then, inverse function. For k independent variables and n analysed individuals, logit probability of success is given as linear combination of explanatory variables:

$$\text{logit}(p_i) = \boldsymbol{\beta}\mathbf{x}_i \tag{6}$$

A maximum likelihood method is commonly adopted to estimate model coefficients (Maddala, 1983).

Decision trees

A decision tree is a non-parametric supervised learning method, commonly used for classification problems but also regression ones (Breiman et al., 1984). A decision tree is a graphical representation of the recursive partitioning method, it consists of a root node, branches, and leaf nodes which represent the outcomes. The input space is broken into regions, and each node of the decision tree is associated with a region in the input space. The internal nodes break that region into one subregion for each child of the node. In this way, the space is subdivided into non-overlapping regions, with a one-to-one correspondence between leaf nodes and input regions (Goodfellow et al., 2016). Decision trees are trained, in general, with an algorithm:

Input Training set $\{(\mathbf{x}_1, y_1),\ldots, (\mathbf{x}_n, y_n)\}$

1. Initialize T to be a single unlabeled node
2. **While** there are unlabeled leaves in T **do**
3. Navigate data samples to their corresponding leaves
4. **For all** unlabeled leaves v in T **do**
5. **If** v satisfies the stopping criterion or there are no samples reaching v **then**
6. Label v with the most frequent label among the samples reaching v
7. **else**
8. Choose candidate splits for v and estimate Δ for each of them
9. Split v with the highest estimated Δ among all possible candidate splits
10. **End if**
11. **End for**
12. **End while**

The general algorithm of tree construction starts with the training examples $\{(\mathbf{x}_1, y_1),\ldots, (\mathbf{x}_\mathrm{n}, y_n)\}$, where $\mathbf{x}_1,\ldots, \mathbf{x}_{nz} \in \mathbf{R}^d$ are the features vectors and $y_1,\ldots, y_n \in \{1,\ldots, c\}$ are the labels. Every internal node is split into child nodes and has a decision rule formed $\mathbf{x}(i) < a$, where $\mathbf{x}(i)$ is the i-th attribute and a states for real number. Feature vectors are subject to the decision rule and if satisfied – are directed to the left child node, otherwise they are directed to the right one. In each iteration, the new level of nodes is appended to the tree until a stopping criterion is met. The stopping criterion stands for the threshold defined by the number of samples in the node, or the impurity of the node, expressed by a homogeneity function G. The most popular impurity functions are the Gini and entropy functions (Ben-Haim & Tom-Tov, 2010).

To provide feature importance, the measure of mean decrease impurity (MDI) is calculated. The MDI is a widely known and used measure of feature importance (Li et al., 2019) and was originally defined by Breiman et al. (1984) for a single decision tree. Decision tree is one of the most popular and well-known classification algorithms. However, decision tree-based models do not manage well the imbalanced or skewed data sets. It means that they tend to classify instances to the majority class (Li et al., 2018). Our data is imbalanced since the majority class is outnumbered and accounts for 97%, while the minority class accounts for 3% only. Therefore, undersampling was introduced, an effective technique for dealing with such data. Undersampling is the method that decreases the frequency of one class in the dataset. Thus, no change is made to the algorithm itself but only to the training data (Drummond & Holte, 2003). The main idea is to randomly sample the subset to obtain a balance between minority and majority classes. Namely, given the minority set P and the majority training set N, the undersampling method randomly samples a subset N' from N, where| N'| ≤ | N (Liu et al., 2008). Thus, in our study, we obtained a sample of 1,089 observations, where 363 households had target = 1 and 726 households had target = 0.

Shapley Additive exPlanations (SHAP) method

The SHAP framework is based on the Shapley values and is used to explain individual predictions, as well as global ones. Shapley's values are derived from coalitional game theory and aim to evaluate each player's contribution to a game. This concept was proposed by Lloyd Shapley in 1953. Shapley value is the way of allocating the profit among individual players depending on their contribution to the overall game's result. The Shapley value reflects the average marginal contribution of an individual instance (player) in all possible coalitions and is based on four assumptions: efficiency, symmetry, dummy, and additivity. The Shapley value is determined according to the formula:

$$\phi_i(v) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N \setminus S| - 1)!}{|N|!} [v(S \cup \{i\}) - v(S)], \tag{7}$$

where N is set of all players, $S \subseteq N \setminus \{i\}$ is the subset of all but i-th features from subset S, $v(S)$ is the function assigning the subset of agents S with a total payoff contributed by co-working and $v(S \cup \{i\})$ is the function with the i-th feature present (Strumbelj & Kononenko, 2010). It is also assumed that $v(\emptyset) = 0$, as nothing is produced for free (Roth, 1988).

The general concept of the Shapley value is as follows, i-th player's marginal payout share represents the difference between payout from playing with all players and the profit without i-th player. All possible coalitions (sets) of player values have to be evaluated with and without the i-th player to calculate the exact Shapley value. As the number of all possible coalitions equals 2N, the exact solution to this problem becomes numerically problematic as the number of possible coalitions exponentially increases with the number of players.

The SHAP method, proposed by Lundberg and Lee (2017), is a framework that explains individual model outputs. It attributes an effect ϕ_i to each feature and summing the effects of all features provides an approximation of the original model output $f(x)$ based on the single input x. Thus, the SHAP approach is one of the additive feature attribution methods. It is also a method that has an explanation model that is a linear function of binary variables:

$$g(z') = \phi_o + \sum_{i=1}^{M} \phi_i z_i', \quad (8)$$

where g is the function for explanation model of the original prediction model with function f, $z' \in \{0, 1\}^M$, M is the number of input features and $\phi_i \in$ R (Lundberg & Lee, 2017, p. 2).

Lundberg and Lee (2017) proved that there is only one explanation model with function g which follows the definition of additive feature attribution methods and satisfies properties of missingness and consistency. It also satisfies local accuracy, since the explanation model approximation of the original model with function f for a single input x, at least matches the output of f for a simplified input x'. This model is given by the formula:

$$\phi_i(f, x) = \sum_{z' \subseteq x'} \frac{|z'|!(M - |z'| - 1)!}{M!} [f_x(z') - f_x(z' \setminus i)], \quad (9)$$

where $|z'|$ – number of non-zero entries in z', $z' \subseteq x'$ – all z' vectors where the non-zero entries are a subset of the non-zero entries in x'.

SHAP values use conditional expectations to define simplified inputs. Moreover, SHAP values are based on Shapley values, thus, they satisfy their desirable properties. What follows from the definition is that SHAP values are a simplified input mapping $h_x(z') = z_S$, where z_S has missing values for features not in the set S. As most models are incapable of effectively addressing arbitrary missing input value patterns, $f(z_S)$ is approximated with $E[f(z)|z_S]$.

SHAP values might be perceived as the Shapley values of a conditional expectation function of the original model. Therefore, they are not calculated directly but the approximation might be done by several model-agnostic or model-specific methods (Chlebus et al., 2020, p. 249). Nevertheless, such model-agnostic approaches come with certain limitations, including the potential for misinterpretations when there is dependence between features (Molnar et al., 2020). In this paper, SHAP frameworks for decision trees as well as linear SHAP were employed.

Results

Results of the logistic regression model

In the first stage of this research, using the logistic regression model, using the Scikit library (Pedregosa et al., 2011), we identified characteristics that influence the ability of households to repay financial liabilities in the context of the COVID-19 pandemic. The results obtained from this model are presented in Table 2.

Table 2. Estimated parameters, standard error, *p*-value, and odds ratio

Covariate	Parameter estimate	Standard error	*p*-value	Odds ratio
Macroregion (*ref. central*)				
south	-0.086	0.216	0.691	0.918
northwest	-0.116	0.228	0.611	0.890
southwest	-0.438	0.235	0.062	0.646
northwest	-0.230	0.221	0.300	0.795
eastern	0.019	0.246	0.938	1.019
Mazowieckie Voivodeship	0.007	0.220	0.974	1.007
Available income (*ref.* <= 3,724)				
(3,724; 6,000>	-0.504	0.153	0.001	0.604
(6,000; 8,300>	-0.685	0.182	<.0001	0.504
(8,300; 17,4438>	-0.532	0.187	0.005	0.587
The highest education level (*ref. lower secondary, primary, incomplete primary*)				
basic vocational	-0.008	0.313	0.979	0.992
general secondary	-0.765	0.366	0.037	0.466
postsecondary and vocational secondary	-0.412	0.313	0.188	0.662
higher	-0.625	0.317	0.048	0.535
As a result of the COVID-19 pandemic lasting from 2020, according to the subjective opinion of respondents' total income (*ref. decreased significantly*)				
decreased insignificantly	-1.242	0.149	<.0001	0.289
remained at the same level	-2.499	0.136	<.0001	0.082
increased	-1.765	0.398	<.0001	0.171
hard to say	-1.979	0.596	0.001	0.138
Number of household members (*ref.* 1)				
2	-0.076	0.170	0.653	0.927
3	-0.243	0.190	0.200	0.784
4	-0.486	0.202	0.016	0.615
5–12	-0.111	0.232	0.633	0.895
Socio-economic groups (*ref. employees*)				
farmers	0.218	0.294	0.458	1.244
self-employed	0.026	0.170	0.881	1.026
retirees and pensioners	-0.059	0.167	0.722	0.943
any unearned income	0.422	0.249	0.090	1.525

Source: Authors' own study based (Statistics Poland 2021, 2022).

The results of the logistic regression model revealed that the risk of lack of ability of households to repay financial liabilities due to unscheduled events was lower when available income was greater. In particular, households with available income between PLN 3,724 and PLN 6,000 had 0.604 times the odds of having issues with repayment financial liabilities due to unscheduled events than households with available income below PLN 3,724. The households with available income between PLN 6,000 and PLN 8,300 had 0.504 times the odds of having issues with repayment financial liabilities than households with available income lower than PLN 3,724. While households with available income above PLN 8,300 had 0.587 times the odds for the same risk than households with available income below PLN 3,724.

Considering the subjective assessment of the level change of household income due to the pandemic, we see a similar relation. Namely, households that reported lower decreases, no change or increase in income, had less odds of risk of lack of ability to meet financial liabilities due to the pandemic. Households whose income remained at the same level, exhibited the fewest odds of the same risk, compared with the households whose income dropped significantly.

As regards the number of members in the household, the results can be concluded that if the household had more than one member, then the less often the household had issues with meeting their financial liabilities because of COVID-19.

When it comes to the education level of the person holding the highest educational attainment, each category of education level that is higher than the reference category of lower secondary, primary, and incomplete primary, is associated with less odds of having issues with meeting financial liabilities. However, only the estimates for general secondary and higher education were statistically significant.

In respect of the socio-economic groups, results showed that there is a dissimilarity between employees and those with any unearned income. Accordingly, households with unearned income as the only or prevailing source of income were 1.525 times the odds of having issues with repayment financial liabilities due to the pandemic than households where employees provide the only or prevailing source of income.

Outcomes indicated that households in the southwest macroregion had 0.646 times the odds of risk of inability to meet financial liabilities than households located in the central part of Poland. For the rest of the macroregions, the odds ratio estimation was not statistically significant.

Next, for this model, a global explanation has been presented, which explains the entire behaviour of the predictive model (Arya et al., 2019, p. 2). Figure 1 presents the SHAP bar plot with the mean of the absolute SHAP values and, thus, the average impact of the independent variables on the model output. Results revealed that the subjective opinion of respondents about the change in total income due to COVID-19 influenced model output the most. Its mean SHAP value equals 1.51. The mean SHAP value of education level, available income, number of members in the household, microregion, and socio-economic group equals, respectively: 0.26, 0.2, 0.08, 0.07, and 0.6.

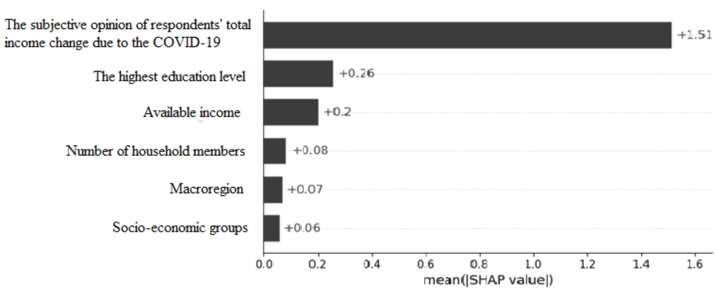

Figure 1. SHAP bar plot for the independent variables from the logistic regression model

Source: Authors' own study based on (Statistics Poland 2021, 2022).

Results of decision trees

In the second stage of the research, we considered a decision tree (Figure 2), utilizing the Scikit library (Pedregosa et al., 2011). Using this model, we distinguished three most important features of the division. In order of importance based on the mean decrease impurity, they were as follows: subjective opinion of respondents about the change in total income due to COVID-19 (score = 0.80208), available income of household (score = 0.13613), education level of the person holding the highest educational attainment (score = 0.06178) (Figure 3).

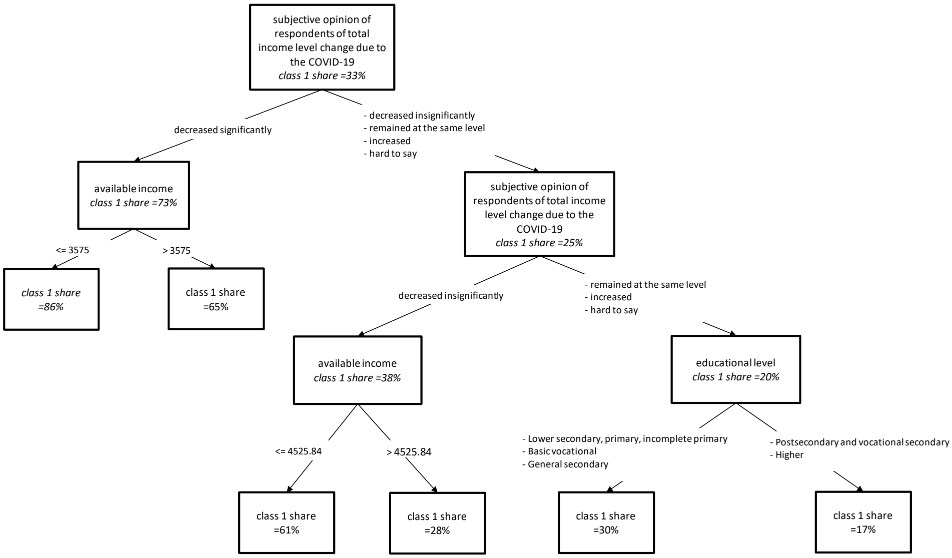

Figure 2. The decision tree for individual characteristics

Source: Authors' own study based on (Statistics Poland 2021, 2022).

It was revealed that the key factor influencing the ability of households to repay financial liabilities due to unscheduled events was the subjective opinion of respondents about the change in total income due to COVID-19 (Figure 2). So, the subset of households whose income decreased significantly was separated from the rest of the households. For this group, the split was further done based on the available income with the split point of PLN 3,575. In the case of households whose available income was less than PLN 3,575, 86% of households had problems with repaying their financial liabilities due to the pandemic. However, in the case of households whose income was higher than PLN 3,575, the share of households that had issues with repaying their financial liabilities was smaller and amounted to 65%.

Whilst, at the right side of the decision tree (Figure 2), with households reporting an insignificant decrease, no change or increase in their income, the further split was done based on the same factor, the subjective opinion of respondents about the change in

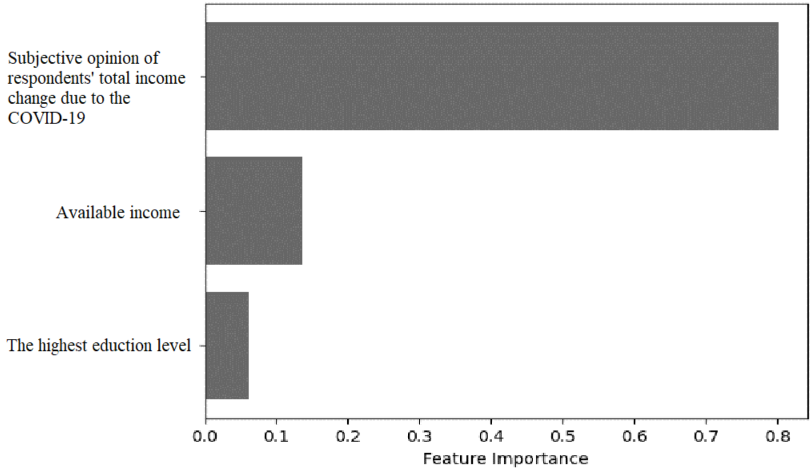

Figure 3. Feature importance for characteristics in the decision tree

Source: Authors' own study based on (Statistics Poland 2021, 2022).

total income due to COVID-19. For the subset of households that subjectively assessed their total income increased, remained at the same level or it was hard to state, the education level was employed in further node. The one subset involved households whose members' highest education level was one of the following: lower secondary, primary, incomplete primary, basic vocational or general secondary. Such a group consisted of 30% of households that had issues with repayment of financial liabilities when facing the pandemic. A lower share (17%) of households that had problems with repaying their financial liabilities was observed in the subset of households where the highest educated member holds a postsecondary, vocational secondary, or higher education level.

The households with reported insignificant decrease in their total income, according to the subjective opinion, were further divided by the available income. The left leaf included households with available income lower than or equal to PLN 4,252.84 and 61% of all such households had issues with repayment financial liabilities due to the pandemic. On the other side, in the subset of households with available income higher than PLN 4,252.84, only 28% had issues with meeting financial liabilities when facing an unscheduled event.

Explanations for this model were obtained with the usage of the Tree SHAP method, which is a variant of the SHAP method for tree-based models and has a fast implementation. We received, that the main factor influencing the prediction of the decision tree was the subjective opinion of respondents about the change in total income due to the pandemic (Figure 4). Moreover, available income and the education level of the person holding the highest educational attainment affected this model output to a lesser extent. The SHAP summary plot, additionally showed that both situations, the ability to meet financial liabilities when facing COVID-19, and the lack of such ability, were explained by the same features equally.

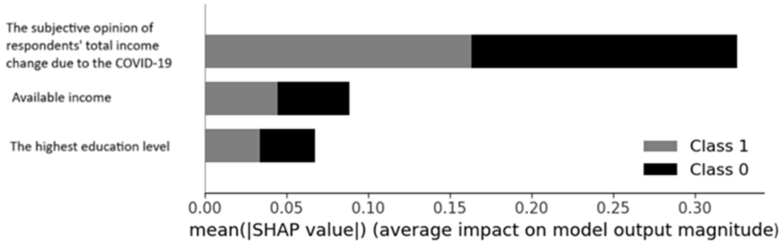

Figure 4. The SHAP summary plot for the decision tree characteristics

Source: Authors' own study based on (Statistics Poland 2021, 2022).

Furthermore, with the use of, so-called decision plot, we presented the changes in predicted value across a set of feature values. The *x*-axis represents the model's outputs, while on the *y*-axis all features are listed (Figure 5). The lines strike the bottom part of the plot, which corresponds to the predicted share of households that had problems with repaying their financial liabilities in each decision tree leaf. Most of all, it is noticeable that the subjective opinion of respondents impacted the most decision tree output, thus, classifying each household to the class of households having issues with repaying financial liabilities when facing unscheduled events or to the opposite class.

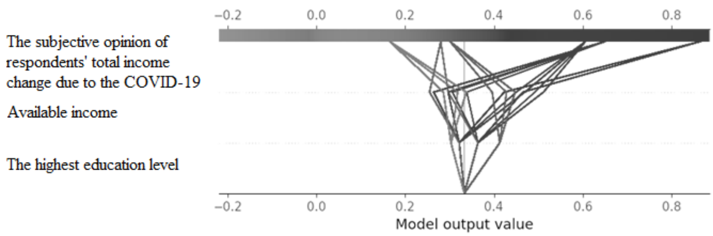

Figure 5. The SHAP decision plot for the decision tree characteristics and model's results

Source: Authors' own study based on (Statistics Poland 2021, 2022).

Results of logistic regression with interaction

With the results of logistic regression, decision tree, and SHAP analysis we found it necessary to examine the interaction between available household income and subjectively perceived changes in household income due to COVID-19. This is because the household's available income can moderate the effect of the subjective opinion of respondents' total income on repayment difficulties. Thus, while income change due to COVID-19 reflects respondents' subjective assessment, household income serves as an objective measure. The results obtained from the model with interaction terms are presented in Table 3.

Table 3. Estimated parameters, standard error, *p*-value, and odds ratio

Covariate	Parameter estimate	Standard error	*p*-value	Odds ratio
Macroregion (*ref. central*)				
south	-0.082	0.217	0.7040	0.921
northwest	-0.110	0.229	0.6320	0.896
southwest	-0.436	0.236	0.0640	0.647
northwest	-0.220	0.222	0.3220	0.802
eastern	0.013	0.246	0.9590	1.013
Mazowieckie Voivodeship	0.002	0.221	0.9940	1.002
Available income (*ref.* <= 3724)				
(3724 ; 6000>	-0.621	0.243	0.0100	0.537
(6000 ; 8300>	-0.766	0.291	0.0080	0.465
(8300 ; 174438>	-0.582	0.284	0.0410	0.559
The highest education level (*ref. lower secondary, primary, incomplete primary*)				
basic vocational	0.296	0.348	0.3960	1.344
general secondary	-0.466	0.396	0.2400	0.627
postsecondary and vocational secondary	-0.117	0.348	0.7370	0.890
higher	-0.322	0.352	0.3600	0.725
Number of household members (*ref.* 1)				
2	-0.074	0.171	0.6650	0.929
3	-0.241	0.190	0.2060	0.786
4	-0.487	0.203	0.0160	0.615
5–12	-0.107	0.232	0.6470	0.899
Socio-economic groups (*ref. employees*)				
farmers	0.224	0.295	0.4470	1.251
self-employed	0.034	0.170	0.8430	1.034
retirees and pensioners	-0.016	0.167	0.9220	0.984
any unearned income	0.426	0.251	0.0900	1.531
Interaction term: As a result of the COVID-19 pandemic lasting from 2020, according to the subjective opinion of respondents' total income (*ref. decreased significantly*) with available income				
decreased insignificantly: <= 3,724	-1.209	0.240	<.0001	0.299
remained at the same level: <= 3,724	-2.642	0.214	<.0001	0.071
increased: <= 3,724	-1.636	0.744	0.0280	0.195
hard to say: <= 3,724	-1.720	0.745	0.0210	0.179
decreased insignificantly: (3,724; 6,000>	-1.365	0.305	<.0001	0.255
remained at the same level: (3,724; 6,000>	-2.331	0.260	<.0001	0.097
increased: (3,724; 6,000>	-1.365	0.749	0.0690	0.255
hard to say: (3,724; 6,000>	-32.030	4.32E+06	1.0000	0.000
decreased insignificantly: (6,000; 8,300>	-1.151	0.340	0.0010	0.316
remained at the same level:(6,000; 8,300>	-2.398	0.327	<.0001	0.091
increased: (6,000; 8,300>	-38.644	2.17E+07	1.0000	0.000
hard to say: (6,000; 8,300>	-0.946	1.055	0.3700	0.388
decreased insignificantly: (8,300; 17,443.8>	-1.238	0.347	<.0001	0.290
remained at the same level: (8,300; 17,443.8>	-2.487	0.310	<.0001	0.083
increased: (8,300; 17,443.8>	-1.606	0.629	0.0110	0.201
hard to say: (8,300; 17,443.8>	-31.821	4.38E+06	1.0000	0.000

Source: Authors' own study based on (Statistics Poland 2021, 2022).

The results revealed that incorporating the interaction term impacted the significance of other independent variables. The odds ratio of each category of interaction, that occurred to be statistically significant, showed that households included in a category other than the reference one had fewer odds of risk of inability to meet financial liabilities due to the pandemic compared with the households whose income dropped significantly.

To compare the models with and without the interaction term, we used the likelihood-ratio test. The null hypothesis is that the competing models are equally close to the true data-generating process. The alternative hypothesis is that one of the models is closer to the true process (Vuong, 1989). The test revealed a significant difference between the two models, indicating that the model with interaction provides a better fit and justifies the inclusion of the interaction term.

Discussion

Unscheduled events such as natural disasters, and pandemics can result in substantial and profound ramifications for an economy. Simultaneously, evaluating their effects is accompanied by inherent difficulties and uncertainties (Hewings & Mahidhara, 2019, p. 216). Therefore, effective interpretations and explanations of the results obtained from models are extremely important in this type of analysis. In this study, we propose a micro-level approach, focusing attention on determinants of the ability of households to repay financial liabilities in the context of unscheduled events, using the example of the COVID-19 pandemic. However, the use of interpretable logistic regression models and decision tree models turned out to be insufficient due to certain limitations regarding the interpretation results from these models. So, we used the SHAP method at a global level to indicate the hierarchy of the importance of key factors affecting the ability to repay financial liabilities. The SHAP is a model-agnostic method (Lundberg & Lee, 2017, p. 5), thus, it can be applied to a wide range of models, including logistic regression and decision trees (Lundberg et al., 2020). However, the order of factors' importance may vary between different models (Fisher et al., 2019). The importance of variables in logistic regression indicates the extent to which a given factor influences the logit (log-odds), which is a linear combination of the variables. In contrast, decision trees are models capable of capturing complex, non-linear interactions between variables. Thus, the importance of variables in decision trees is determined by the splits within the tree, considering all possible paths through the tree.

Based on the results obtained from both the logistic regression model and the decision tree at the global level, it was found that the key factor determining households' ability to repay financial liabilities due to unforeseen events was respondents' subjective opinion on changes in total income due to COVID-19. In the logistic regression model, the second most important variable was education level, followed by available income.

Other significant variables included the number of household members, microregion, and socio-economic group. However, in the decision tree model, only three variables were selected as the best for partitioning the data. The second most important variable was available income, followed by education level. The observed differences suggest that the impact of education level depends on the value of the variable representing respondents' subjective opinion on changes in total income due to COVID-19. This means that the most significant factors affecting the inability to repay fixed financial obligations due to the COVID-19 pandemic were respondents' subjective opinions on the change in total income caused by COVID-19 and the available income. Moreover, the results obtained from the logistic regression model, including the interaction term, confirm that the impact of one of these variables on the ability to repay financial obligations due to COVID-19 depends on the value of the second variable.

We found that the households with lower total income or perceived decrease in income were more often forced to defer repayment of fixed financial obligations due to the COVID-19 pandemic. This confirms that the greater sensitivity to the effects of COVID-19 is mainly driven by, the lower, in statistical terms, income level and worse financial condition of households (Jędrzejczyk, 2021). Furthermore, financial factors could be associated with the psychological distress of individuals during the pandemic, which may be linked to both their objective financial situation, such as income and debt levels, and their subjective perception of their financial situations (Sekścińska et al., 2022). The understanding of repayment difficulties during the COVID-19 pandemic hinges on the interaction between available household income and subjectively perceived income change, emphasizing the necessity of considering both objective and subjective financial measures when evaluating household debt burden (Keese, 2012).

Our study also confirmed the significance of education in managing financial obligations during unexpected events such as COVID-19 (Li et al., 2020). We found that the percentage of households in Poland struggling with the repayment of financial obligations, where the most educated individuals had at least a secondary education, was nearly half that of other households. Therefore, it can be concluded that education is one of the key factors determining the resilience of households to unforeseen events.

The data analysis methods used in this study have certain limitations. Tools for assessing variables importance evaluate how much a model's accuracy depends on each determinant (Fisher et al., 2019). Although the SHAP framework explains model prediction results at both global and local levels, it does not imply a causal relationship. Moreover, SHAP is a post hoc explanation technique that, based on biased classifiers and their biased predictions, can provide misleading yet seemingly correct explanations (Slack et al., 2020). Employing various research methods and comparing their results can provide a deeper understanding of the studied phenomenon. The analysis of the determinants of repayment of financial liabilities in the context of unscheduled events presented in this work also has certain limitations. Firstly, such unscheduled events may have both direct and indirect effects, which could not be fully captured in the model due to data limitations. Furthermore, the study could only include subjective assessments of both changes in household income levels and the ability of households to meet their financial liabilities.

Conclusions

The study highlights the significant impact of unscheduled events, such as the COVID-19 pandemic, on households' ability to repay financial liabilities. Through a micro-level approach, we examined key determinants, with a focus on subjective perceptions of income changes as well as the available income. The results, derived from both logistic regression and decision tree models, underscore that households perceiving a decline in income or having lower available income were more likely to struggle with financial repayments. Notably, the study also confirms the role of education in mitigating the effects of unforeseen events, as households, where the highest educated member was more educated, were better equipped to manage their financial obligations. Although both logistic regression and decision tree models provided valuable insights, the SHAP method was essential for a more nuanced interpretation of the variables' importance, revealing differences in the factors affecting repayment of household liabilities in the face of unscheduled events. These findings suggest that income level, feeling offinancial stability, and education are key factors influencing household resilience to economic shocks. These findings provide valuable insights for policymakers, enabling development support programs designed to maintain financial stability and enhance the resilience of households during crises. The significance of the results is further emphasized by the lasting pandemic's impact on the household financial situation, despite its subsidence, and the enduring relevance of household resilience in responding to unforeseen events.

Future research could be extended by incorporating panel data analysis, facilitating a more in-depth examination of the dynamic influence of various factors on household financial situations in response to unforeseen events. This approach would allow for the longitudinal tracking of individual household circumstances over time.

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