Investigating the Determinants of Local Indebtedness in Slovakia: The Machine Learning Approach[1]

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Abstract

The paper aims to investigate local indebtedness determinants in a sample of Slovak municipalities using machine learning methods based on decision trees. The sample covers all 2,926 municipalities listed by the Ministry of Finance of the Slovak Republic in 2005 – 2022. Using the QUEST, CRT, CHAID, and exhaustive CHAID growing methods, our results point to a significant effect of current expenditure, subsidies, size category, and crises on local indebtedness. Based on the results of decision trees, significant variables are treated as regressors in logit and probit econometric estimations, to check their statistical significance. The results of the estimations correspond to the results of decision trees and provide us with a further view of the determinants of local indebtedness in Slovakia.

Keywords: *local government, local indebtedness, machine learning, decision trees*

JEL Classification: H72, H74

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Introduction

Slovakia still considered a young democracy with a small and open economy, is by no means exempt from economic development in the world. In periods of worsening economic landscape (now we are witnessing the multi-crisis, and before it was the Global Financial Crisis in 2009), governments at all levels struggle with cuts in revenues and higher pressure on the resources of public spending.

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In this paper, we focus on the governments that are the closest to the citizens, i.e. local governments. They cope with the allocation function of public finance and provide 70% of public goods to the general public. Local elected authorities have to face the citizens' opinions, reservations, and questions every day, especially in small municipalities that present a majority among municipalities in Slovakia, thus the elector-decision-maker interaction is more intensive and visible.

However, in the recent era, increases in public debts have been observed in many EU countries due to the need to perform the stabilization and redistribution function of public finance at the national level. At the local level of the government, when providing public goods (allocation function of public finance), the worsening of economic conditions increases pressure on local budgets, too, and correspondent answers on the side of local expenditure (cutback management and impoverishment of public services) should be provided by the local authorities. They might consider returnable financial resources, similarly to national governments when increasing public debt. Local authorities must usually operate within the legislatively arranged boundaries of local indebtedness to avoid the destabilization of the macroeconomic environment in the country. Hence, to consider the determinants of the indebtedness at the local government level is as important as it is in the case of the national level. Over-indebtedness at the local level has a detrimental effect on local financial management and local development, on the other side it could be harmful to macroeconomic stability, too.

In this paper, the examination of local indebtedness determinants of Slovak municipalities is provided using machine learning methods, which is quite an unconventional approach in this field of scientific research. To confront the results with a more conventional analysis (mentioned e.g. in Elith, Leathwick and Hastie, 2008; Mullainathan and Spiess, 2017; and Masci, Johnes and Agasisti, 2018), we provide a regression analysis to investigate the determinants of local indebtedness in Slovakia, too, when economists still consider the information about scale and sign of coefficients and p-values important (Chen, 2021). The sample consists of 2,926 Slovak municipalities in the period 2005 – 2022. The paper's motivation originates from the need to monitor indebtedness in the turbulent period we live in, while the increase in public debts is frequently discussed and considered detrimental. As Elith, Leathwick and Hastie (2008) mention, growing sophistication in the methodology is observed in past decades. Since then, machine learning methods, as an emerging field of data science, have enjoyed increasing popularity (Masci, Johnes and Agasisti, 2018; Dahiya, Gupta and Singh, 2022; Guo, Li and Qian, 2022). In recent research, e.g. in Guo, Li and Qian, (2022), and Lin and Bai (2022), the interdisciplinary application of machine learning methods to the political economy is observed.

However, machine learning methods are not a novelty in empirical research; they are widely used in academia and industry, but their use in local public finance is not so common. This paper contributes to the existing literature on local indebtedness by extending the use of machine learning methods in public finance. The paper aims to identify Slovak municipalities' characteristics that are related to their indebtedness. Since the previous research on local indebtedness does not use these kinds of methods to examine the local indebtedness determinants, in the further analysis we compare the results obtained by machine learning methods with the results of econometric estimations.

The paper is organized as follows. After the introduction, the literature review provides an overview of the literature on local indebtedness and its determinants with a remark on methods used in this field of research. Methods and data provide information about used methods used, data, and basic assumptions of the research. The main findings are presented in the chapter on results and discussion. The paper ends with a conclusion.

1. Literature Review

The literature on public debt focuses more on the increase of debt generated at the central level of the government, while local levels of government and their debts enjoy less attention (Bröthaler, Getzner and Haber, 2015; Butoracova Šindleryova, Cíbik and Turčan 2023). However, local public debts present a serious treatment when providing local public goods, too (Bröthaler, Getzner and Haber, 2015; Němec and Špaček, 2020). The question of growing public debts in Europe is still intensively discussed (Bequiraj, Fedeli and Forte, 2018), because the policymakers, corporations, academia, and the public react to changes in economic circumstances in their countries.

Anyway, local indebtedness is the focal point of many country-specific research, e.g. Spain (Bolívar et al., 2014; Balaguer-Coll, Prior and Tortosa-Ausina, 2016; Ballaguer-Coll and Ivanova-Toneva, 2021), Spain and Italy (Brusca, Rossi and Aversano, 2015), Portugal (Veiga and Veiga, 2014; Ribeiro, Jorge and Nogueira, 2019; Basílio and Borralho, 2022), Germany (Zabler, 2022), Austria (Bröthaler, Getzner and Haber, 2015), England (De Widt, 2021), Ireland (Turley, McNena and Robbins, 2018), Poland (Wichowska, 2019; Kozera, Standar and Satoła, 2020; Galinski, 2023b), Hungary (Kovács and Stion, 2013; Lentner, 2014), China (Bo, Yao and Mear, 2021; Guo, Li and Qian, 2022), New Zealand (Ehalaiye, Botica-Redmayne and Laswad, 2017) and for the EU (Galinski, 2023a). The local indebtedness in Slovakia is investigated by only several authors e.g. Maličká (2017), Němec and Špaček (2020), and Maličká (2021). Butoracova Šindleryova, Cíbik

and Turčan (2023) examine the sub-national level of government in Slovakia, too, but focusing on the regional indebtedness.

Determinants of local indebtedness include a variety of variables, usually referring to the economic circumstances in the country, socio-economic conditions in the municipalities, and their demography. An important part of regressors are fiscal variables derived from local budgets. Besides, institutional, and political variables are considered to affect local indebtedness.

Referring to the socio-economic variables of the municipalities, the literature on local indebtedness employs mainly the unemployment variable (e.g. Veiga and Veiga, 2014; Bröthaler, Getzner and Haber, 2015; Brusca, Rossi and Aversano, 2015; Maličká, 2017; Wichowska, 2019; Galinski, 2023a and 2023b) and variables on family disposable income to refer to the economic level in the municipality (Ballaguer-Coll and Ivanova-Toneva, 2021; Basílio and Borralho, 2022).

De Widt (2021), Valkama and Oulasvirta (2021), and Ferreira et al. (2021) consider demographic variables as an important determinant of local indebtedness. Among, them, the municipalities' population is broadly employed (e.g. Bröthaler, Getzner and Haber, 2015; Brusca, Rossi and Aversano, 2015; Wichowska, 2019; Ballaguer-Coll and Ivanova-Toneva, 2021; Basílio and Borralho 2022; Galinski 2023a). Besides the age structure of the population is considered, while the empirical research focuses on pre-productive and post-productive populations, the aging index (e.g. Veiga and Veiga 2014; Rodríguez et al. 2016; Wichowska, 2019; Ferreira, Caldas and Marques, 2021; Valkama and Oulasvirta, 2021; Galinski, 2023b) and migration (Kozera, Standar and Satoła, 2020).

Fiscal variables of different natures are involved in the research because they directly enter the potential creation of indebtedness (Ehalaiye, Botica-Redmayne and Laswad, 2017). Ehalaiye, Botica-Redmayne and Laswad (2017) and Wichowska (2019) use a municipal revenue, Kozera, Standar and Satoła (2020) discuss the effect of income and property taxes, Galinsky (2023b) discusses the personal income tax, Maličká (2017) computes the indicators of fiscal autonomy using items such as local tax revenue, local non-tax revenues, subsidies, and total local revenues. Ehalaiye, Botica-Redmayne and Laswad (2017) consider local capital expenditures, revenues from shared taxes, and own municipal income. Ribeiro, Jorge and Nogueira (2019), tax revenue negative effect on indebtedness.

The literature on local indebtedness proves the effect of political variables such as mayor party orientation, gender of the mayor or re-elected mayor (e.g. Veiga and Veiga, 2014; Bröthaler, Getzner and Haber, 2015; Chortareas, Logothetis and Papandreou, 2016; Basílio and Borralho, 2022). Voters award mayors with good economic outcomes with re-elections (Benito, Martínez-Córdoba and Guillamón López, 2023; Ballesteros et al., 2019) and punish those with bad outcomes. Mayor

party orientation is discussed in Veiga and Veiga (2014), when left-wing mayors tend to incur less debt. They also observe an increase of mayors without any political affiliation (independent mayors). Considering the gender perspective, women mayors tend to be risk averse, thus better fiscal discipline is evidenced in municipalities with women mayors (Ballaguer-Coll and Ivanova-Toneva, 2021; Cuadrado-Ballesteros, Guillamón and Ríos, 2022; Cuadrado-Ballesteros, Ríos and Guillamón, 2023).

The effect of crises is taken into account in myriad of studies. For the Global financial crisis in 2009, it is e.g. Afonso (2014), Ringa and Kattel, (2013), Bröthaler, Getzner and Haber (2015), Balaguer-Coll, Prior and Tortosa-Ausina (2016), Ehalaiye, Botica-Redmayne and Laswad (2017), Turley, McNena and Robbins (2018), Bequiraj, Fedeli and Forte (2018), Wichowska (2019). For the multi-crisis tied to the COVID-19 pandemic, the war conflict in Ukraine, and the energy crisis after 2020 it is e.g. Němec and Špaček (2020), Zabler (2022), and Ferreira Soares and Souza Gonçalves (2022).

Besides, the election period at the local government level is the external factor, that determines the local indebtedness, too. It is known as the political budget cycle as mentioned e.g. Bastida, Beyaert and Benito, (2013), Veiga and Veiga (2014), Chortareas, Logothetis and Papandreou (2016), Ballaguer-Coll and Ivanova-Toneva (2021), Basílio and Borralho (2022) and Maličká and Mourao (2023).

The most employed research method when analyzing the local indebtedness determinants is the regression analysis (e.g. Brusca, Rossi and Aversano, 2015; Wichowska, 2019). Usually, the research is conducted on a panel of municipalities or countries (e.g. Bequiraj, Fedeli and Forte, 2018; Galinski, 2023a), thus models based on the panel data approach are used. Ehalaiye, Botica-Redmayne and Laswad (2017) run a pooled ordinary least squares (OLS) regression model. Bröthaler, Getzner and Haber (2015) ran a panel Estimated Generalize Least Square (EGLS, cross-section weights) model, including cross-section (fixed) effects (constants). Galinski (2023a) employs the fixed effect model (FEM) and random effect models (REM), Galinski (2023b) runs the FEM, Basílio and Borralho (2022) FEM and REM. Veiga and Veiga (2014), besides the FEM, run a dynamic panel data model based on the generalized method of moments estimator (GMM) of a Blundell-Bond type (known as system GMM) too. Similarly proceeds Maličká (2017) and Maličká (2021) when running a dynamic panel data estimation using the system GMM. Bequiraj, Fedeli and Forte (2018) employ the Error-corrected model (ECM) and Vector auto-regressive model (VAR). Kovács and Stion (2013) use the OLS Auto-regressive moving average model (ARIMA). Kozera, Standar and Satoła (2020) run an ordered logit model to set the local indebtedness determinants. Ballaguer-Coll and Ivanova-Toneva (2021) use a Tobit model because they refer to the local indebtedness limits. Guo, Li, and Qian (2022) use a textual and sentiment analysis based on deep learning-based methods when searching for debt risk of Chinese local

governments. Lin and Bai (2022) use machine learning methods when investigating debt determinants of corporations. In the research of Guo, Li and Qian, (2022), and Lin and Bai (2022), the interdisciplinary application of machine learning methods to the political economy is observed.

2. Methods, Data, and Assumptions

In this research, the local indebtedness of Slovak municipalities is examined using machine learning methods. The sample of Slovak municipalities covers all 2,926 municipalities listed by the Ministry of Finance of the Slovak Republic (from now on MF SR) in the period 2005 – 2022. After using the data mining methods of research, we conduct an econometric analysis to compare the results.

2.1. Methods

As shown in the literature review, the empirical research focuses more on using parametric methods, predominantly regression analysis. In this research, we apply the data mining employing the decision trees that present a non-parametric supervised machine learning. The graphical result of the analysis is a tree-shaped schematic model of information, which provides us with significant determinants of the dependent variable. Decision trees are used to detect the associations between the dependent variable and multiple independent variables (Piramuthu, 2008; Elith, Leathwick and Hastie, 2008; Ture, Tokatli and Kurt, 2009; Masci, Johnes and Agasisti, 2018; Lin and Fan, 2019).

In this paper, four types of decision trees are used to analyze the determinants of the local indebtedness of Slovak municipalities – Chi-squared Automatic Interaction Detection (CHAID) introduced by Kaas (1980), Exhaustive CHAID – a modification of CHAID proposed by Biggs, De Ville and Suen (1991), Classification and Regression Tree (CRT) growing method that attempts to maximize within-node homogeneity (Breiman et al., 1984), and Quick, Unbiased and Efficient Statistical Tree (QUEST) introduced by Loh and Shin (1997). As mentioned by Lin and Fan (2019), these algorithms use different methods of how the attribute criteria of the root and child nodes are split and in the number of split child nodes.

In the case of CRT, the splitting condition is based on the Gini Index (Gini Impurity Measure, the generalization of the binomial variance; Loh, 2011). The smaller the Gini index, the higher the homogeneity inside the subset (Lin and Fan, 2019). After the CRT is trained, the pruning can be conducted. It serves to minimize the misclassification error (Loh, 2011). The QUEST growing method is based on the chi-square and F test used as a branching method, where the strongest association is selected, again. It can be pruned in the same manner as CRT. In the CHAID and

exhaustive CHAID, the selection of relevant independent variables is based on the chi-square test method. In the tree-like hierarchically arranged structure the first selected independent variable has the smallest p-value; thus, it is the most associated with the dependent variable. When there is not a significant difference between branches, they are merged into the same branch (Lin and Fan, 2019). The limitation of the use of decision trees on datasets with missing observations is considered important. In the case of CRT, missing values are treated by surrogates, QUEST inputs the missing values locally and CHAID creates a missing value branch (Loh, 2011). Further comparison of hereinbefore mentioned growing methods is provided e.g. by Ture, Tokatli and Kurt (2009), Loh (2011), and Lin and Fan (2019).

The decision trees based on the QUEST growing method require the binary dependent variable. For this reason, we transformed the data on local indebtedness, i.e. received loans to a binary variable denoting 1 of the municipality reports a received loan in a respective year, otherwise 0. However, in the case of CRT, CHAID, and exhaustive CHAID, it is possible to compute with a scale variable (as is the nature of this budget item), or categorical variable (when setting intervals for the level of indebtedness).

When considering the strengths of the chosen methodological approach, Dahiya, Gupta and Singh (2022) mention that machine learning methods work with raw data and generate results without human intervention. In a similar vein, Breiman et al. (1984) highlight that decision trees can deal with the multidimensionality of data and mixed data types. Lin and Bai (2022) stay that machine learning methods deal with the multidimensionality of data and reduce them.

When mentioning the advantages of decision trees, according to Sarker (2021), supervised machine learning methods as decision trees present the task-driven approach. As mentioned in Elith, Leathwick and Hastie (2008), Mullainathan and Spiess (2017), and Masci, Johnes and Agasisti (2018), decision trees differ from conventional techniques (classical statistics, Masci, Johnes and Agasisti, 2018) because they learn about the relationship between input and output. Classical regression is a data-model (Masci, Johnes and Agasisti, 2018), that starts with a selection of the appropriate data model to estimate the parameters. However, forcing the input-output relationship in a data-model to be linear might bias the results (Mullainathan and Spiess, 2017; Masci, Johnes and Agasisti, 2018). The advantage of tree-based methods is that they allow the predictors to interact. They identify which interactions are relevant in affecting the outcome (Mullainathan and Spiess, 2017; Masci, Johnes and Agasisti, 2018; Lin and Fan, 2019) and try to identify dominant patterns by observing inputs and responses (Piramuthu, 2008; Elith, Leathwick and Hastie, 2008; Ture, Tokatli and Kurt, 2009; Masci, Johnes and Agasisti, 2018; Lin and Fan, 2019). Additionally, the machine learning approach based on decision trees learns the relationship between response and predictors

considering past experience (Breiman et al., 1984; Masci, Johnes and Agasisti, 2018) summarized by a learning sample when partitioning data. It allows us to take into account that the data-generating process is unknown and complex, as mentioned in Elith, Leathwick and Hastie (2008), and Masci, Johnes and Agasisti (2018). Besides, as mentioned in Mullainathan and Spiess (2017) and Pawliczek, Kozel and Vilamová (2018) the graphical presentation of the results is another advantage of decision trees.

The results of tree-based machine learning methods are often compared to those of logistic regression in different research fields such as education and medicine (using CHAID e.g. Miller et al., 2014; Aksu and Keceoglu, 2019). Pawliczek, Kozel and Vilamová (2018) apply CHAID decision trees in the field of economics. In their study, they compare the use of CRT, QUEST, and CHAID and mention the advantages of all growing methods, which we employ in our research, similar to Lin and Fan (2019). CRT and QUEST create binary trees (nodes have two branches when splitting) while CHAID-based trees are non-binary (nodes have more than two branches when splitting) and, therefore grow wider. According to Pawliczek, Kozel and Vilamová (2018), CRT and QUEST binary trees are more accurate. The advantage of CRT and CHAID is, that they work with categorical and continuous dependent variables, while QUEST works with binary outcomes. Our sample contains missing data, which could be dealt with by the CRT decision tree (Loh, 2011; Boonamnuay, Kerdprasop and Kerdprasop, 2018).

Consequently, in the further analysis, we run regression models on local indebtedness determinants using estimation techniques that work with binary dependent variables – logit models, and probit models to robustness check (Wooldridge, 2012; Liu, 2016) Logistic regression assumes the logistic distribution, the probit model assumes the normal distribution. So, we proceed similarly to e.g. Miller et al. (2014), and Aksu and Keceoglu, (2019) in other fields of science.

3. Data and Assumptions

We seek inspiration in the related research when considering the potential determinants of local indebtedness. Socio-economic variables usually provide us with an insight into the economic conditions. However, when researching the municipal level of the government certain limitations are imposed by the data availability for this level of government. Therefore, using the available data, we employ the variables on unemployment and productive population. The same variables were employed in the research of Veiga and Veiga (2014), Bröthaler, Getzner and Haber (2015), Brusca, Rossi and Aversano (2015), Maličká (2017), Wichowska, 2019, Galinski (2023a and 2023b).

Considered demographic variables refer to the municipality's size measured by its population (used e.g. by Bröthaler, Getzner and Haber, 2015; Brusca, Rossi and Aversano, 2015; Wichowska, 2019; Ballaguer-Coll and Ivanova-Toneva, 2021; Basílio and Borralho 2022; Galinski 2023a), aging index (Ferreira, Caldas and Marques, 2021; Valkama and Oulasvirta, 2021; Galinski, 2023b; Veiga and Veiga 2014; Rodríguez et al. 2016 and Wichowska, 2019, uses a variable on post-productive age), and the population moving in the municipality (Kozera, Standar and Satoła, 2020). The municipality's size is expressed using the categorization into 10 size categories as referred to in Maličká and Mourao (2023) or Lukáčová and Maličká (2023) dealing with an analysis at the municipal level of the government in Slovakia (for more details see the note in Table 1). The Aging index is employed due to the pronounced increase in the population's aging in Slovakia (like in other EU countries, too, e.g. Portugal – Ferreira, Caldas and Marques, 2021; Finland – Valkama and Oulasvirta, 2021), which has a twofold impact on municipalities in Slovakia. The higher age of the population points to lower levels of tax collection based on income taxes at the national level. It leads to cuts in shifted receipts from shared taxes to sub-national levels of government (in Slovakia the shared tax is personal income tax since 2005, the moment of fiscal decentralization). Besides, certain limits on tax base when considering immovable property taxes are imposed on municipal taxation, when the disposable income of aged people, meaning their pensions, is lower than those in productive age employed). Another question, intuitively related to the age of the population, too, is the rate of urbanization when people are moving into bigger cities for better job opportunities and living conditions. It is mirrored in the variable on the population moving in the municipality, which also regards the attractiveness of the municipality. However, higher rates of the population moving into the municipalities are observed in the case of bigger towns and cities of local and regional importance (based on data from SO SR 2023). In the research of Kozera, Standar and Satoła (2020), the migration of the population was the local indebtedness determinant, too.

To catch the effect of the geography of municipalities, we dispose of data on altitude and area in square kilometers. Data on altitude are in the Slovak circumstances under consideration when arranging the design of the tax sharing. Slovakia is a mountainous country, and a prevalent part of municipalities is located in a mountainous landscape that imposes additional costs related to basic daily tasks of municipalities, such as road maintenance, public lighting, etc. The area of municipalities refers to the geographical size of the municipality when the positive correlation between the geographical size and population size of the municipalities in Slovakia is proven by Lukáčová and Maličká (2023).

When considering the fiscal variables, we follow the literature on local indebtedness determinants under the standard classification of budget items into basic

groups of revenues and expenditures. We employ variables on different types of local tax revenues (like Ehalaiye, Botica-Redmayne and Laswad, 2017; Maličká, 2017; Wichowska, 2019; Kozera, Standar and Satoła, 2020; Galinski, 2023b) from which we use shared tax (personal income tax), immovable property tax and other local taxes that in Slovak conditions present tax on goods and services, local non-tax revenues, subsidies and the share of current expenditures on total local expenditures (as negative to capital expenditures; e.g. Ehalaiye, Botica-Redmayne and Laswad, 2017; Maličká, 2017).

In our research, we include political variables, too. The mayor's party orientation, gender of the mayor or re-elected mayor present a standard political variables used in the literature on local indebtedness (e.g. Veiga and Veiga, 2014; Bröthaler, Getzner and Haber, 2015; Chortareas, Logothetis and Papandreou, 2016; Ballesteros et al., 2019; Ballaguer-Coll and Ivanova-Toneva, 2021; Basílio and Borralho, 2022; Cuadrado-Ballesteros, Guillamón and Ríos, 2022; Benito, Martínez-Córdoba and Guillamón López, 2023; Cuadrado-Ballesteros, Ríos and Guillamón, 2023). In Slovakia, the increase of mayors without any political affiliation is observed (independent mayors) and it is already examined in related literature (e.g. Veiga and Veiga, 2014). Besides, the number of women mayors increased in Slovakia, too, as evidenced by Maškarinec and Klimovský (2017), Maličká (2022) and Lukáčová and Maličká (2023).

External factors, that could influence the local indebtedness in Slovakia are defined concerning the economic crises (Global financial crisis in 2009 and the multi-crisis tied to the COVID-19 pandemic, the war conflict in Ukraine, and the energy crisis after 2020; e.g. Afonso, 2014; Bröthaler, Getzner and Haber, 2015; Balaguer-Coll, Prior and Tortosa-Ausina, 2016; Ehalaiye, Botica-Redmayne and Laswad, 2017; Turley, McNena and Robbins, 2018; Wichowska, 2019; Němec and Špaček, 2020; Zabler, 2022; Ferreira Soares and Souza Gonçalves, 2022) and with the relation in the local elections (e.g. Bastida, Beyaert and Benito, 2013; Veiga and Veiga, 2014; Chortareas, Logothetis and Papandreou, 2016; Ballaguer-Coll and Ivanova-Toneva, 2021; Basílio and Borralho, 2022; Maličká and Mourao, 2023).

To express the dependent and independent variables, several sources of information are employed. Data on municipal budgets which served to create the fiscal variables, are collected from the DataCentrum database provided by MF SR (2023). Data on the socio-economic, demographic, and geographic characteristics of Slovak municipalities are collected from the DataCube database provided by the Statistical Office of the Slovak Republic (from now on SO SR, 2023a). Data focusing on political indicators are derived from the SO SR (2023b) when semi-structured data on winning mayoral candidates and political affiliation were transformed into structured data in the form of binary dummy variables. The most discussed structural breaks (exogenous shocks) are defined as dummy variables, too.

The list of variables and their characterization is displayed in Table. 1. Descriptive statistics of dependent and independent variables are shown in Table 2.

T a b l e 1

Definition and Source of the Research Variables

Variables	Characteristics	Source
Dependent variable		
Indebted	Local indebtedness; dummy variable; 1 if indebted, otherwise 0	Own, Based on data from MF SR (2023)
Independent variables		
Socio-economic variables		
Unemployment	Share of unemployed persons in the municipal population	SO SR (DataCube, 2023)
Productive Population	Share of population less than 14 and over 65 on population between 14 – 65 (unproductive to productive population)	SO SR (DataCube, 2023)
Demographic variables		
Aging Index	The share of the population over 65 to less than 14 years old	SO SR (DataCube, 2023)
Moving In	Share of the population moving in the municipality on municipal population	SO SR (DataCube, 2023)
Size Category*	Categorical; 1 – 10; derived from the municipal population	Own based on Population – SO SR (DataCube, 2023)
Geographical variables		
Altitude	The altitude of the geographical center of the municipality	SO SR (DataCube, 2023)
Area km2	The area of the municipality in square kilometers	SO SR (DataCube, 2023)
Fiscal variables (Budget data approach)		
Current Expenditure	The share of current expenditures on total municipal expenditures	MF SR (2023)
Shared Taxes	The share of personal income tax receipts on municipal tax revenue	MF SR (2023)
Immovable Property Taxes	The share of tax on land, apartments, and buildings on municipal tax revenue	MF SR (2023)
Other Local Taxes	The share of other local taxes on municipal tax revenue	MF SR (2023)
Non-Tax Revenues	The share of non-tax revenues on total municipal revenues	MF SR (2023)
Subsidies	The share of grants and transfers on total municipal revenues	MF SR (2023)
Political variables		
Independent Mayor	Dummy variable; 1 if mayor without party affiliation, otherwise 0	Own based on SO SR (2023)
Mayor Party Orientation	Dummy variable; 1 if right-wing affiliation, otherwise 0	Own based on SO SR (2023)
Reelected Mayor	Dummy variable; 1 if the reelected mayor, otherwise 0	Own based on SO SR (2023)
Woman Mayor	Dummy variable; 1 if woman mayor, otherwise 0	Own based on SO SR (2023)
Structural breaks		
Crises	Dummy variable; 1 if crisis 2009 or 2020, otherwise 0	Own
Elections	Dummy variable; 1 if election year, otherwise 0	Own

Note: *1 if population <199; 2 if 199< population <499; 3 if 499< population <999; 4 if 999< population <1,999; 5 if 1,999< population <4,999; 6 if 4,999< population <9,999; 7 if 9,999< population <19,999; 8 if 19,999< population <49,999; 9 if 49,999< population <99,999; 10 if population >99,999.

Source: Own processing.

T a b l e 2

Descriptive Statistics

Variables	No of obs.	Min.	Max.	Mean	Median	StDev	C.V.
Dependent variable							
Indebted	52,534	0	1	0.2529	0.0000	0.4350	1.7187
Independent variables							
Socio-economic variables							
Unemployment	52,668	0.0000	0.9474	0.0722	0.0573	0.0551	0.7636
Productive Population	52,668	0.2308	1.5982	0.6841	0.6893	0.0447	0.0653
Demographic variables							
Aging Index	52,668	0	5,000	117.96	100	120.39	1.0206
Moving In	52,668	0.0000	0.6154	0.0205	0.0166	0.0191	0.9312
Size Category	52,668	1	10	3.0880	3	1.5166	0.4911
Geographical variables							
Altitude	52,650	0.0000	1,109	307.95	250.00	176.93	0.5746
Area km2	52,668	0.3613	367.63	16.785	11.652	18.791	1.1195
Fiscal variables (Budget data approach)							
Current Expenditure	46,687	0.0128	1.0000	0.7786	0.8411	0.2047	0.2629
Shared Taxes	46,658	0.0000	1.0184	0.7992	0.8273	0.1267	0.1585
Immovable Property Taxes	46,658	–0.3297	0.9553	0.1414	0.1128	0.1099	0.7773
Other Local Taxes	46,658	0.0000	1.3297	0.0587	0.0482	0.0495	0.8431
Non-Tax Revenues	46,665	0.0000	0.9089	0.0955	0.0714	0.0876	0.9172
Subsidies	46,665	0.0000	0.9721	0.2849	0.2722	0.1887	0.6623
Political variables							
Independent Mayor	52,351	0	1	0.3679	0.0000	0.4827	1.3121
Mayor Party Orientation	52,353	0	1	0.2943	0.0000	0.4557	1.5484
Reelected Mayor	52,254	0	1	0.3679	1.0000	0.4714	0.7072
Woman Mayor	52,351	0	1	0.2249	0.0000	0.4175	1.8566
Structural breaks							
Crises	52,668	0	1	0.2778	0.0000	0.4479	1.6125
Elections	52,668	0	1	0.2778	0.0000	0.4479	1.6125

Source: Own processing.

4. Results and Discussion

In decision trees CHAID and exhaustive CHAID, the standard significance level (0.05) is set for splitting nodes (and merging categories in the case of CHAID). Significance values are adjusted using the Bonferroni method. Due to the continuous character of the prevalent part of the independent variables we fixed the intervals for scaling the independent variables to two. Maximum tree depth is set to three because of the software limitations (in the settings on growth limits the maximum three depth is three for CHAID and five for CRT and QUEST). Further growing brings unreadable figures, when this type of tree grows wider because nodes can have more than two branches when splitting. Similarly proceeded e.g. Pawliczek, Kozel and Vilamová (2018). When using the CRT growing method, the impurity measure based on the Gini indicator is employed to maximize the

homogeneity of child nodes. In the case of the QUEST decision tree, the significance level for splitting nodes is standard 0.05. Maximum tree depth is set to three, to make them comparable to those of CHAID and exhaustive CHAID. Both decision trees (based on CRT and QUEST) were pruned to avoid overfitting as suggested e.g. Friedman, Kohavi and Yun (1996).

The total sample of observations was split for validation. Validation was made using a random assignment training sample containing 80% of the 20% of the test sample as suggested by Friedman, Kohavi and Yun (1996), Boonamnuay, Kerdprasop and Kerdprasop (2018), and Han, Jeong and Kim (2023).

Results of machine learning procedures are shown in Table 3 the visualization of the results is projected in Figure 1 – 6.

T a b l e 3

Basic Parameters and Results of Decision Trees

Specifications				
Growing Method	**QUEST**	**CRT**	**CHAID**	**EXHAUSTIVE CHAID**
Dependent Variable	Indebted			
Independent Variables	Moving In, Productive Population, Size Category, Shared Taxes, Immovable Property Taxes, Other Local Taxes, Non-Tax Revenues, Subsidies, Independent Mayor, Reelected Mayor, Mayor Party Orientation, Ageing Index, Altitude, Area km2, Unemployment, Elections, Woman Mayor, Current Expenditure, Crises			
Validation	Split Sample	Split Sample	Split Sample	Split Sample
Maximum Tree Depth	3	3	3	3
Minimum Cases in Parent Node	100	100	100	100
Minimum Cases in Child Node	50	50	50	50
Results				
Independent Variables Included	Size Category, Current Expenditure, Subsidies, *Non-Tax Revenues, *Immovable Property Taxes, *Area km2, *Altitude, *Moving In, *Other Local Taxes, *Productive Population, *Unemployment, *Shared Taxes	Current Expenditure, Subsidies, Unemployment, Non-Tax Revenues, *Other Local Taxes, *Shared Taxes, *Immovable Property Taxes, *Altitude, *Productive Population, *Area km2, *Ageing Index, *Size Category, *Moving In	Current Expenditure, Size Category, Crises, Non-Tax Revenues, Moving In, Ageing Index, Mayor Party Orientation	Current Expenditure, Crises, Size Category, Subsidies
Number of Nodes	9	15	40	34
Number of Terminal Nodes	5	8	25	23
Depth	3	3	3	3

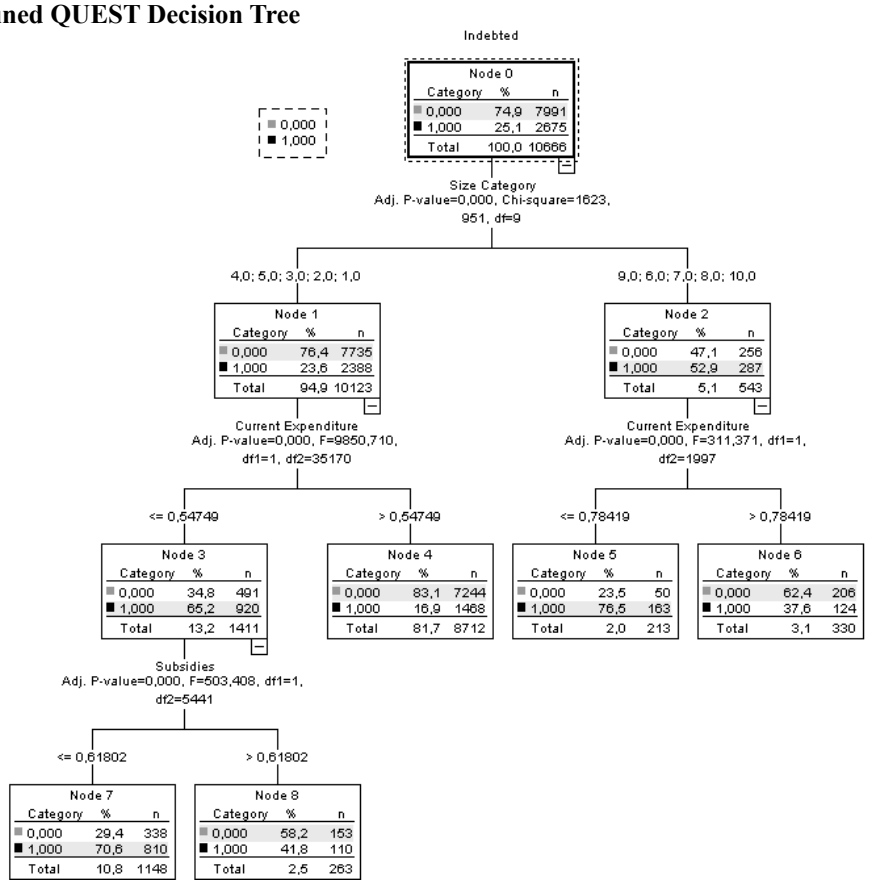
Note: * Not shown in the decision tree due to the limitation in the tree depth, for QUEST and CRT results refer to pruned decision trees.

Source: Own processing based on SPSS.

Results obtained by machine learning provide us with an important insight into the determinants of local indebtedness of Slovak municipalities. According to all growing methods, the variable of current expenditure and the variable of size category are detected as the most significant when determining the local indebtedness in Slovakia. It is mirrored in Figures 1 – 4, too, when the QUEST method splits the nodes according to the size category variable (Figure 1), and the CRT, CHAID, and exhaustive CHAID split the nodes according to the current expenditure variable (Figure 2 – 4) at the highest level of the decision tree. Besides, three of four decision trees signal the significance of the variable of subsidies, when splitting nodes according to this variable in a deeper level of decision trees. According to the decision tree based on the CHAID and exhaustive CHAID growing methods, the dummy variable referring to the financial crisis in 2009 and multi-crisis after 2020 is considered significant when explaining the local indebtedness in Slovakia and its position when splitting nodes is visible in the Figures 3 – 4, too.

F i g u r e 1

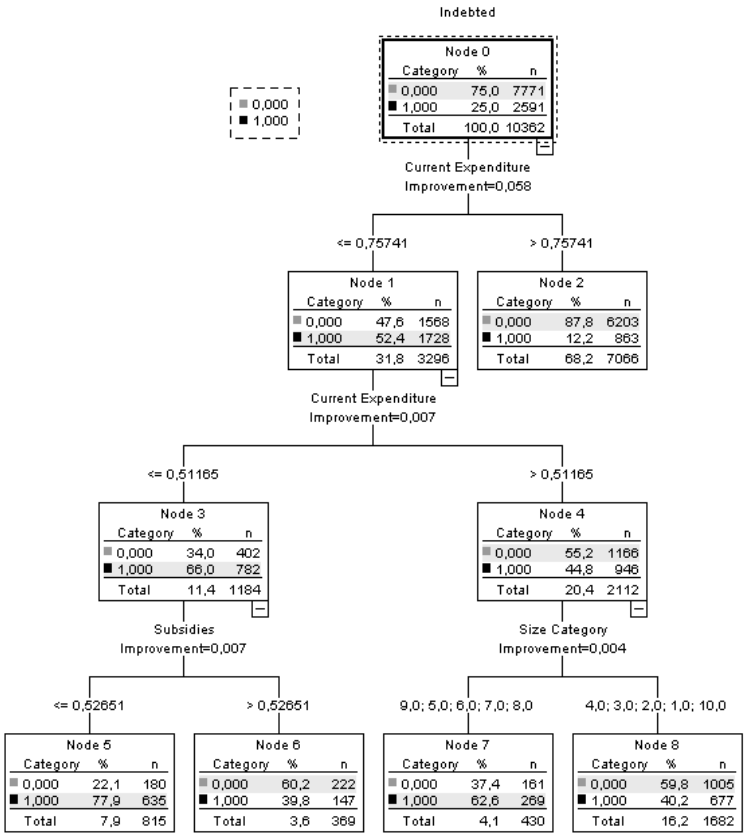
Pruned QUEST Decision Tree



Source: Own processing.

F i g u r e 2

Pruned CRT Decision Tree

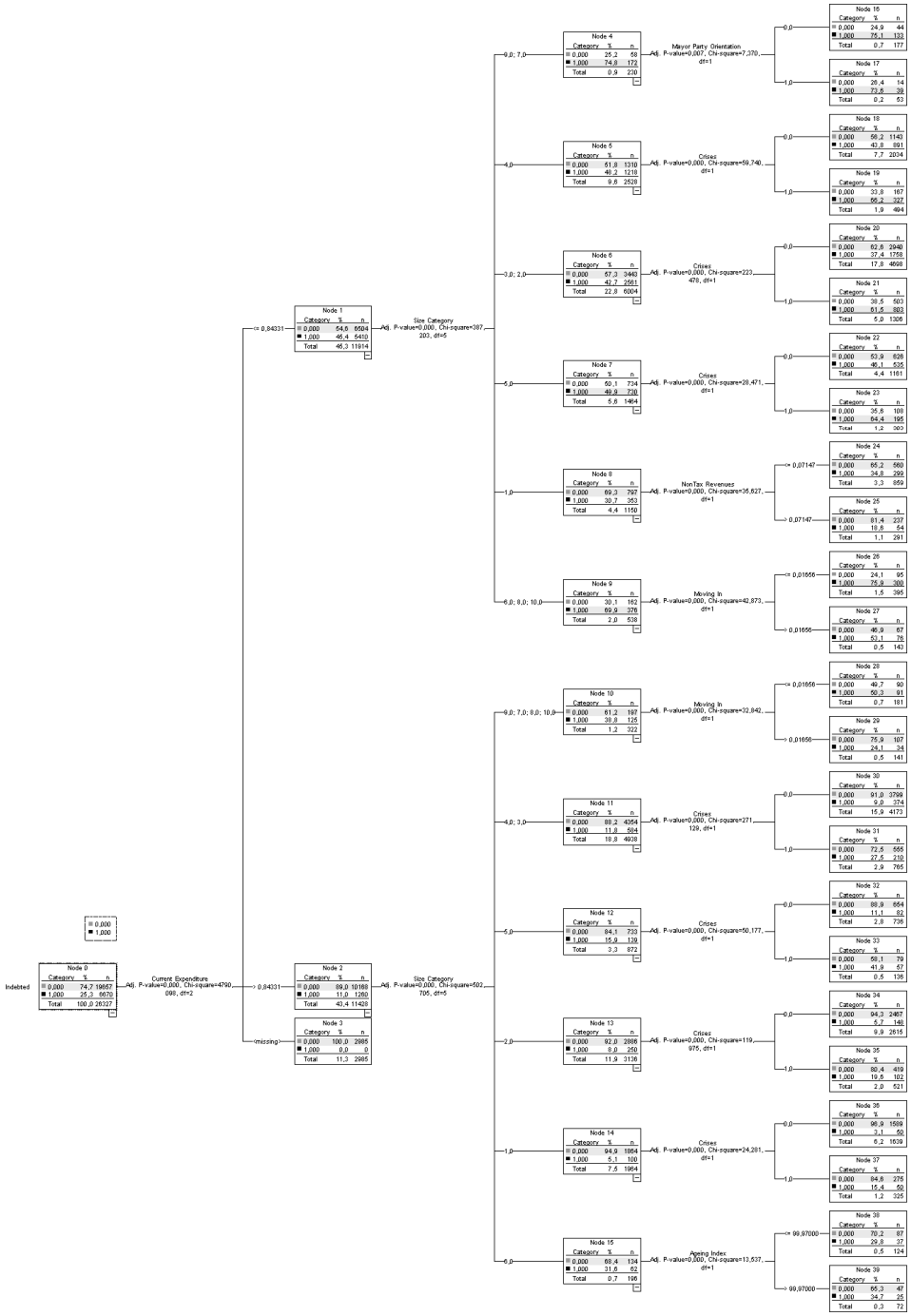


Source: Own processing.

Decision trees based on QUEST, CRT, and CHAID growing methods indicate the significant association of other variables with the dependent variable, too, while more similarities are obvious when comparing the results of decision trees based on QUEST and CRT growing methods. In the results, the most frequently observed are the variables on non-tax revenues and moving in persons. Results of decision trees based on QUEST and CRT growing methods point to the significance of variables on fiscal categories – shared taxes, immovable property taxes, and other local taxes, geographical variables – altitude and area of the municipality, and socio-economic variables – productive population, unemployment, and aging index.

Except for some of them, the results of the decision tree based on the CHAID growing method consider the variable on the mayor's party orientation significant when determining the local indebtedness in Slovakia (see Table 3 for more details on CHAID results).

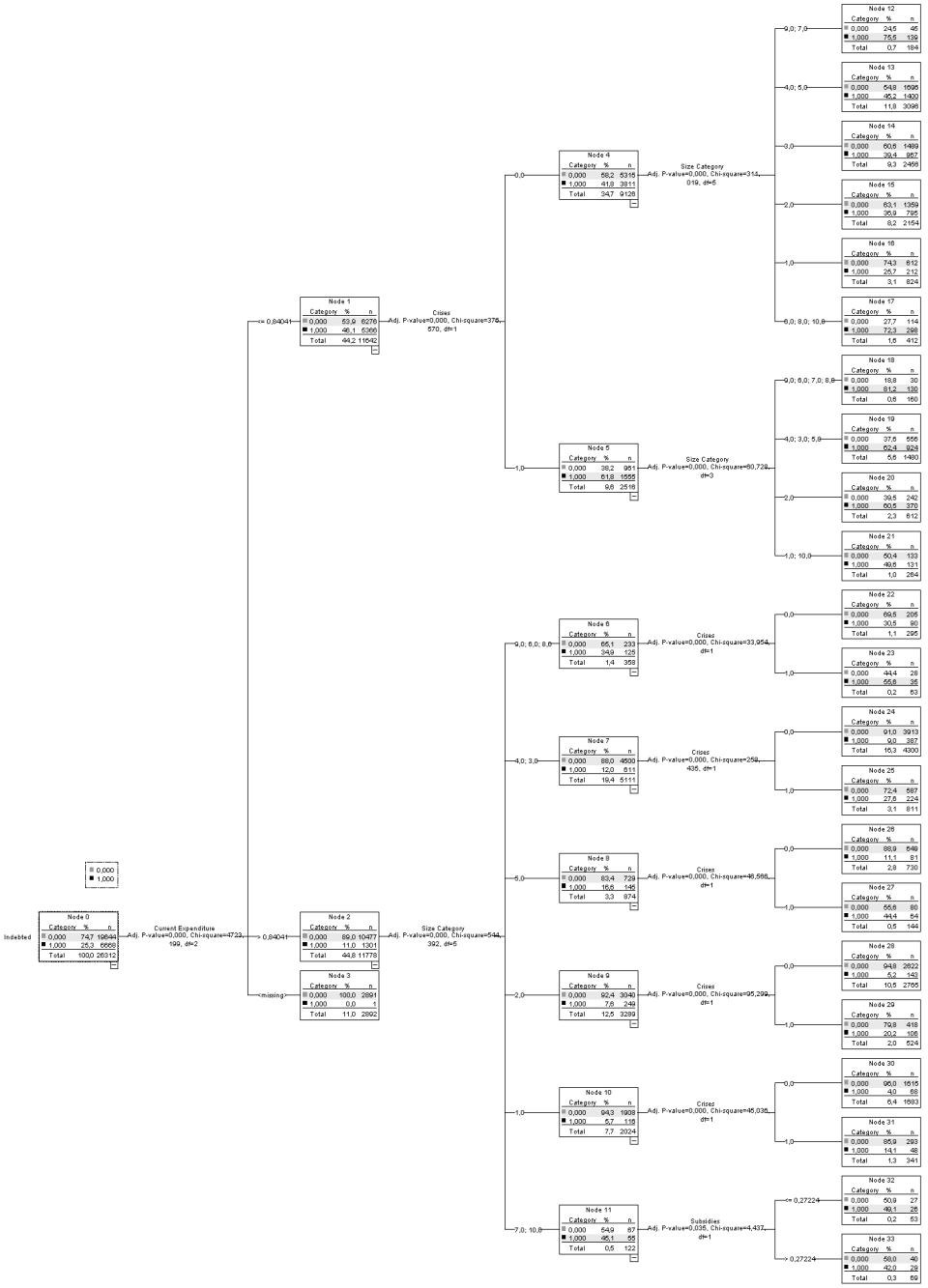
F i g u r e 3
CHAID Decision Tree



Source: Own processing.

F i g u r e 4

Exhaustive CHAID Decision Tree



Source: Own processing.

Starting with the results presented in the QUEST tree (Figure 1), the size category variable splits the nodes, and it is obvious, that in smaller sizes categories (1, 2, 3, 4, 5; up to 5,000 inhabitants), there are fewer indebted municipalities. We can interpret it in the way that smaller municipalities with a limited tax base can hardly enter the financial markets because they cannot provide the potential creditor with any future guarantees (based on their future income). Our findings are in line with the assumption of Bröthaler, Getzner and Haber (2015), Brusca, Rossi and Aversano (2015), and Galinski (2023a) that municipalities with smaller populations are less indebted.

The next split is based on the current expenditure variable, where results show, that municipalities with, e.g. higher shares of current expenditure on total local expenditure (above 54%) are less indebted. From the point of view of variable construction, the portion of current expenditure on total local expenditure decreases with an increase in capital expenditure. Capital expenditure is tied to financing the investments and thus is often supported using returnable financial resources that contribute to the indebtedness of the municipality. It is in line with the findings of Maličká (2019) and Galinski (2023a), who find a positive relationship between capital expenditure and local indebtedness. In the case of the variable on subsidies, lower shares of subsidies on total local revenue are connected to a higher number of indebted municipalities which could be explained by the lower amount of resources received into the local budget, thus a higher need for returnable financial resources. All municipalities in Slovakia receive current earmarked transfers from the central government level to cope with transferred competencies. Besides, the subsidies variable includes capital transfers, too, which often cover spending on investments. According to Kozera, Standar and Satoła (2020), the condition of co-funding the capital investments in the locality might impose serious pressure on the increase in local indebtedness.

In a similar spirit, we can interpret the results observed in the case of other decision trees too. The same splitting patterns regarding the current expenditure and the size categories are presented in CHAID and exhaustive CHAID trees confirming the results observed in the QUEST and CRT decision trees. Lower shares of current expenditure on total local expenditure are tied to higher local indebtedness, and municipalities smaller in size tend to be less indebted. Besides, the variable on crises tells us, that municipalities are less indebted in periods that are not connected to financial crises. In the case of CHAID, the moving-in variable is significant in larger size categories in municipalities. It corresponds to the higher migration of the population in towns and cities (size categories 6, 7, 8, 9 and 10) as reported by the SO SR (2023a). In the CHAID tree of depth set to 3, the variable on the mayor's party orientation is significant in greater size categories, but both left-wing and

right-wing mayors tend to be associated with local indebtedness at this level of splitting. To interpret the results on the effect of aging index and nontax revenues, again the further depth of the tree might provide us with more insights. Besides, the branch on missing values is visible in CHAID and exhaustive CHAID, contrary to the QUEST and CRT growing methods using the imputations, as mentioned in the methodological part. Another question is the use of continuous variables in these types of growing methods, while the QUEST can handle both categorical and continuous variables (Lin and Fan, 2011).

However, the results observed using the machine learning methods cannot be compared to other studies in this field of local public finance because of their lack of. We can confront them with other studies focusing on the same topic but using different methodologies, as done in the next part of the analysis (regression analysis based on logit and probit models).

In the next part of the analysis, we provide an examination of the effects of independent variables identified by the machine learning procedures to be the determinants of local indebtedness in Slovakia. Due to the binary character of the dependent variable, we conduct the logit estimations to catch the relationship between the determinants in the question and local indebtedness in Slovakia. As a robustness check, we perform the probit estimations, too. Considering the results of four types of decision trees (four types of growing methods) we run for each decision tree a logit and probit regression. The results of the estimations presented in Table 4 are in line with those of decision trees. All regressions were checked for multicollinearity using the Variance Inflation Factor test (vif test).

The estimation results show a stable effect of determinants identified by the decision trees on whether the locality is indebted or not across all the estimations conducted.

In the case of current expenditure, in the logit estimation with an increase in current expenditure by a unit, we can observe that the log odds of being the municipality indebted decreases. Interpreting the results of the probit estimation, in a very similar sense we can observe a decrease in the probability that the municipality is indebted. As already mentioned, when interpreting the results of decision trees, the portion of current expenditure on total local expenditure decreases with an increase in capital expenditure. Capital expenditure is tied to financing the investments and thus is often supported using returnable financial resources that contribute to the indebtedness of the municipality, in line with the findings of Veiga and Veiga (2014), Maličká (2019), and Galinski (2023a).

For the rest of the fiscal variables, with an increase in the immovable property tax revenue and other local tax revenues, the log odds of being indebted decrease. Revenues generated at the base of the local tax collection contribute to better local

financial performance and allow the municipalities to create surpluses or accumulate revenue in the budget reserve funds. Municipalities having the rescue cushion might tend to have a lower need for returnable financial resources. These results are in line with the findings of Ribeiro, Jorge and Nogueira (2019), Galinski (2023b), and Maličká (2021), while Maličká (2021) proceeds similarly when computing the financial autonomy of Slovak municipalities and its relationship to local indebtedness. Besides the observed negative effect of local tax revenues, the effect of subsidies and local non-tax revenues on the log odds of being indebted is the same. Subsidies and local non-tax revenues present revenue of a local budget, and their increase decreases the log odds of being the municipality indebted. However, Kozera, Standar and Satoła (2020) mention that local governments beneficiating from the European Union funds face a higher risk of indebtedness due to the requirements of co-funding.

With an increase in the municipalities' size category and area (which is in Slovakia positively correlated to the population size, thus to the size categories) the log odds of being the municipality indebted increases. It is in line with the findings of Bröthaler, Getzner and Haber (2015), Brusca, Rossi and Aversano (2015), and Galinski (2023a) who mention the positive relationship between population size and local indebtedness.

In the case of the variable on altitude, the higher the altitude, the lower the indebtedness from the point of the hypsometry, in Slovakia only one city bigger in the population is located in the mountainous area (Poprad). The population is concentrated in low-elevation municipalities, hence the rest of the bigger cities that tend to be more indebted are in the lowlands. Therefore, with an increase in the municipalities' altitude, the log odds of being the municipality indebted decreases.

With an increase in the share of municipalities' productive population the log odds of being the municipalities indebted increase, but when comparing with the decision trees' results, this variable is not statistically significant in both logit and probit estimations (using the results of QUEST and CRT). Just to mention the similarity of our findings with previous findings, e.g. Galinski (2023a) finds a negative relationship between the dependency ratio (the negative of the productive population) and local indebtedness.

With an increase in the share of municipalities' unemployed population on its total population the log odds of being the municipalities indebted increase in line with the findings of Veiga and Veiga (2014), Brusca, Rossi and Aversano (2015), Galinski (2023a and 2023b). Veiga and Veiga (2014) mention that an increase in unemployment causes higher local indebtedness because of the need for higher expenditure in social areas and lower revenues.

Table 4

Regressions Run at the Base of Decision Trees' Results

logit/probit								
Growing Method	**QUEST**		**CRT**		**CHAID**		**EXHAUSTIVE CHAID**	
Dependent Variable	Indebted		Indebted		Indebted		Indebted	
Independent Variables Included	Logit	Probit	Logit	Probit	Logit	Probit	Logit	Probit
Intercept	2.7378***	1.5899***	3.1808***	1.7423***	1.6911***	1.0081***	2.1580***	1.2496***
Current Expenditure	−6.1552***	−3.5816***	−6.2068***	−3.5893***	−5.3803***	−3.1661***	−5.7806***	−3.3669***
Subsidies	−2.0178***	−1.0696***	−2.0321***	−1.0686***			−1.2085***	−0.6258***
Size Category	0.4327***	0.2439***	0.4083***	0.2312***	0.3974***	0.2272***	0.4118***	0.2331***
Unemployment	2.1927***	1.2226***	1.6311***	0.9756***				
Non-Tax Revenues	−2.7265***	−1.4897***	−2.2490***	−1.2100***	−1.3644***	−0.7774***		
Shared Taxes	[A]	[A]	[A]	[A]				
Immovable Property Taxes	−1.8420***	−1.0096***	−2.2448***	−1.2002***				
Other Local Taxes	−0.7422***	−0.4522***	−1.0521***	−0.6245***				
Altitude	−0.0008***	−0.0004***	−0.0008***	−0.0004***				
Area km2	0.0038***	0.0022***	0.0068***	0.0065***				
Productive Population	0.5932	0.0426	0.2762	0.2215				
Ageing Index			0.0004***	0.0003***	0.0002*	0.0001*		
Moving In	−1.7661**	−0.9275**	−2.3774***	−1.2978***	−3.0580***	−1.6980***		
Crises					1.0165***	0.5962***	1.0606***	0.6179***
Mayor Party Orientation					0.1282***	0.0792***		
McFadden R^2	0.2323	0.2308	0.2325	0.2311	0.2376	0.2388	0.2410	0.2413
Cox & Snell R^2	0.2420		0.2430		0.2470		0.2500	
Nagelkerke R^2	0.3480		0.3480		0.3550		0.3590	
No. of obs.	46,634	46,634	46,368	46,368	46,392	46,392	46,657	46,657
Collinearity (vif test)	Yes[A]	Yes[A]	Yes[A]	Yes[A]	No	No	No	No

Note: * significant at 0.1, ** significant at 0.05, and *** significant at 0.01; [A] In initial model collinearity encountered for Shared Tax, Immovable Property Tax, and Other Local Taxes – Share tax variables are excluded from estimations; QML standard errors.

Source: Own processing.

With an increase in the aging index of the municipalities' population, the log odds of being the municipalities indebted increase. Ferreira, Caldas and Marques, (2021) mention the expectations that aging is detrimental to local performance, in line with Rodríguez et al. (2016), but e.g. findings of Galinski (2023b) and Veiga and Veiga (2014) do not support the statement.

With an increase in the population moving into the municipality, the log odds of being the municipality indebted decrease. This effect may originate in the additional tax collection (based on both income taxes and property taxes) generated by the additional population (Kozera, Standar and Satoła, 2020). On the other side, the same authors mention, that higher rates of net migration relate to a higher risk of indebtedness.

In the period of economic crises, the log odds of being the municipalities indebted increase. The periods of crises usually present the worsening of economic conditions and thus affect the local indebtedness positively. Our findings are in line with the findings of Malicka (2017) when time dummies during the period of the Global financial crisis have positive beta estimates (similar findings provided by Wichowska, 2019. Contrary, Ehalaiye, Botica-Redmayne and Laswad (2017) mention, that the Global financial crisis has not a serious impact on local indebtedness in New Zealand.

In the municipalities with right-wing mayors, the log odds of being the municipality indebted increase. Bröthaler, Getzner and Haber (2015) found out that in Austria, with the increase of the electorate of the right-wing party local indebtedness increased. Veiga and Veiga (2014) state, that left-wing mayors incur less debt, so our findings are in line with this empirical evidence. However, Basílio and Borralho (2022) make an opposite assumption in this question, they mention that the evidence offers only ambiguous results.

Conclusion

In this paper, machine learning methods based on decision trees are employed to search for local indebtedness determinants in the sample of Slovak municipalities, covering 2,926 municipalities in the period 2005 – 2022. As the use of decision trees in the field of local public finances is not common, thus, to check the results obtained by machine learning methods we conduct the conventional regression analysis, too.

Decision trees growing by QUEST, CRT, CHAID, and the exhaustive CHAID growing method point to the most significant association between local indebtedness and current expenditure, municipalities' size category, the share of subsidies,

and the period of crises. The rest of the statistically significant variables are present in the results of each decision tree at a different rate. By involving the determinants of local indebtedness in Slovakia detected by the data mining processes in the logit and probit estimations, we confirmed the results observed by using the decision trees.

The results obtained by the decision trees and regression models are comparable. However, the use of machine learning methods with a tree-like visualization of the results brings a certain contribution tied to different views of the problem. The results of regression analysis (logit and probit) provide us with a general pattern of the relationship between the dependent and independent variables, while decision trees allow us to gain further insight based on a branch case-by-case approach when performing the splits. Anyway, the machine learning methods offer new possibilities in terms of research methods in the field of local public finance, too.

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