Applied Decision Analytics

Journal homepage: www.ada-journal.org
ISSN: 3104-2945

A Decision Analytics Approach to Apartment Affordability Analysis Using Power BI

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ARTICLE INFO

Article history:
Received 29 December 2025
Received in revised form 1 March 2026
Accepted 30 March 2026
Available online 10 April 2026

Keywords:
Residential real estate market, Decision Analytics, Microsoft Power BI, Stata/MP statistical software, Housing affordability

ABSTRACT

In the contemporary real estate market, the ability of citizens to meet their housing needs represents a significant economic and social challenge. This paper focuses on analyzing the purchasing power of the population in Serbia in the context of buying residential property, using modern tools for data processing and visualization. The research relies on data covering average prices of newly built apartments, average net salaries, interest rates, and credit conditions. The aim of this study is to provide an objective insight into the financial affordability of housing for an individual with an average income in Serbia, based on the available data. The Stata software package was used for data preparation and processing, while analysis, metric calculations, and result visualization were carried out in Microsoft Power BI. The analysis reveals pronounced regional differences, with particularly noticeable challenges in urban areas such as Belgrade and Novi Sad. Furthermore, while both average salaries and apartment prices have shown steady growth over the years, the increase in property prices significantly outpaces salary growth, further reducing housing affordability. Ultimately, the results of this study may serve as a basis for designing housing policy measures and for the further application of BI tools in economic analysis.

1. Introduction

The purchasing power of the population in the context of acquiring real estate represents one of the central issues in contemporary society. This topic is particularly prominent in the Republic of Serbia, where significant challenges exist regarding the availability of housing for broad segments of the population. The real estate market - characterized by rising apartment prices - has increasingly become an area of unequal accessibility, especially for young people and individuals in the process of establishing independence.

The motivation for selecting this topic stems from personal circumstances that encouraged a deeper understanding of the difficulties faced by a growing number of citizens attempting to secure their own living space [1-4]. In this context, the importance of this analysis lies not only in its academic contribution but also in its relevance to everyday life and future planning.

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https://doi.org/10.66972/ada21202616

In this paper, data on average net salaries, average prices of newly built apartments, and average surface areas of newly built apartments in the territory of the Republic of Serbia are analyzed. The analysis is based on the principles of descriptive statistics, and Chapter 2 – Descriptive Statistics presents key statistical concepts.

Chapter 3 – Tools for Data Processing and Visualization is dedicated to the software tools used in this research, such as Stata MP for data processing and database preparation, and Microsoft Power BI for data visualization. The process of data collection and preparation is described in detail in Chapter 4 – Data Acquisition and Processing, which outlines the data sources, processing procedures, and the datasets generated through Stata.

The central part of the analysis is presented in Chapter 5 – Visual Analysis and Data Interpretation. Using Microsoft Power BI, the data was visualized to enable a comprehensive presentation of results. The chapter provides an interpretation of the relationship between average salaries and apartment prices, an overview of the real estate market situation, an assessment of creditworthiness conditions, comparisons across datasets based on user-defined criteria, and a housing affordability calculator.

The objective of this paper is to determine the extent to which average net salaries make it possible to purchase residential property, to contribute to a better understanding of housing affordability challenges, and to encourage further research and initiatives aimed at improving housing policy in Serbia.

2. Methodology

Statistics is the art and science of collecting, analyzing, presenting, and interpreting data [5, 6].

In academic literature, statistics is commonly divided into two main branches [6, 7]: descriptive and inferential statistics. Descriptive statistics include methods for graphical and numerical data processing, such as table and chart presentation, calculation of the arithmetic mean, median, mode, and measures of dispersion such as variance and standard deviation. Inferential statistics allow drawing conclusions about an entire population based on data obtained from a representative sample. It includes methods of statistical inference, such as parameter estimation, hypothesis testing, and analysis of relationships between variables, including regression analysis.

Measurement scales in statistics define the way data are classified and analyzed. There are four basic scales [8]:

i. Nominal scale – uses names or labels to classify data with no inherent order (e.g., colors, gender, countries). Mathematical operations do not apply.
ii. Ordinal scale – allows not only classification but also ranking (e.g., satisfaction ratings: poor, good, excellent). Differences between ranks are not necessarily uniform.
iii. Interval scale – has order and equal intervals between values but lacks an absolute zero point (e.g., temperature in Celsius). Addition and subtraction are valid operations.
iv. Ratio scale – contains all properties of the interval scale but also has an absolute zero point (e.g., height, weight, income). All mathematical operations are allowed, including ratios (e.g., “twice as much”).

Data in statistics are generally divided into [9]:

i. categorical data,
ii. quantitative data.

The type of statistical analysis that can be applied depends on whether the variables are categorical or quantitative. For categorical variables, analysis typically involves frequencies and

percentages, while quantitative variables allow for more extensive and complex statistical procedures.

In this research, the following quantitative variables were used: average net salaries, average prices of newly built apartments, and average surface areas of newly built apartments expressed in square meters. All three variables are measured on the ratio scale, as they possess a natural zero point and allow expression of proportional relationships.

The data are structured along spatial and temporal dimensions, where the variables "city/municipality" and "year" represent identifying categorical variables. Additionally, the dataset includes a categorical variable [10] that classifies apartments based on size (small, medium, large, extra-large). This variable is measured on an ordinal scale because, although expressed verbally, the categories follow a natural order that enables ranking but not quantification of the differences between them.

3. Tools For Data Processing and Visualization

To ensure efficient data processing, analysis, and visual representation, this research relies on software tools that enable comprehensive statistical and analytical insight into the collected information. Specifically, the Stata/MP software package was used for preliminary data processing and structuring, providing reliable and precise manipulation of numerical datasets. Subsequently, Microsoft Power BI was applied for further analysis, calculation of key indicators, and visual interpretation, offering a platform for creating interactive and dynamic reports. The combined use of these tools made it possible to observe the data from multiple perspectives and extract relevant conclusions forming the analytical core of this paper.

3.1 Stata Software

Stata is a data analysis software package that enables the execution of a wide range of statistical procedures [11]. Stata is a specialized statistical software developed in 1985 by StataCorp, a company based in the United States. Since its introduction, Stata has become widely used among researchers - particularly in the social sciences, economics, epidemiology, and biostatistics - because of its flexibility and ability to handle large datasets. The program is designed to support data processing, statistical analysis, graphical visualization, and process automation through commands and scripts.

One of the main advantages of Stata is its efficiency in working with large datasets. Additionally, it offers users the option to switch between command-line operations and a graphical user interface (GUI), accommodating both beginner and advanced users.

Stata is available in several versions, tailored to different levels of analytical complexity and data size. All versions offer the same statistical command set but differ in data capacity, processing speed, and scalability. Versions of Stata software [12]:

i. Stata/IC (Intercooled) – The standard version, capable of handling up to 2,047 variables in a dataset. Suitable for users working with moderately sized datasets and standard statistical analyses. In newer versions, the term Stata/BE is used instead of Stata/IC.
ii. Stata/SE (Special Edition) – An expanded version supporting up to 32,766 variables. Intended for more complex research, large databases, and multidimensional analyses.
iii. Stata/MP (Multiprocessing) – The most advanced version, optimized for processing across multiple CPU cores, making it the fastest and most powerful option. It is ideal for large-scale data and computationally intensive analyses such as time series, panel data, and simulations.

Table 1 illustrates the maximum number of variables, independent variables, and observations that can be processed in each Stata version. In addition to defined performance limits, the total number of observations is also dependent on available system RAM.

Table 1
Stata performance [12]

	Max. no. of Variables	Max. no. of independent variables	Max. no. of observations
Stata/MP	120.000	65.532	20 bilion*
Stata/SE	32.676	10.998	2,14 bilion
Stata/BE	2.048	798	2,14 bilion

For the data processing in this research, Stata/MP was used due to its superior speed and processing capacity. Within this study, Stata was used to prepare the data, which included handling missing values, forming new variables, and preparing datasets for visual analysis in Power BI. This ensured a valid and well-structured foundation for reliable interpretation of results.

3.2 POWER BI

Power BI is a tool developed by Microsoft in 2013 with the aim of creating a simple yet powerful platform for business analytics, enabling organizations to integrate data and create interactive reports [13]. Power BI is an advanced visualization and analysis tool that supports connection to various data sources, data transformation, and display through interactive visuals. Although it began as an Excel add-in, it quickly evolved into an independent solution capable of supporting complex analytics and aiding business decision-making. Power BI uses the M language for data transformation and DAX (Data Analysis Expressions) for calculations. This combination makes Power BI highly flexible and powerful for data analysis at all levels.

Power BI has two primary components:

i. Power BI Desktop – a local application installed on a computer; used for data modeling and report creation.
ii. Power BI Service – a web platform used for publishing and sharing reports, real-time data refresh, and access management.

There is also a Power BI mobile application for report viewing on portable devices. Reports in Power BI can be shared through Apps (Figure 1) on the Power BI Service.

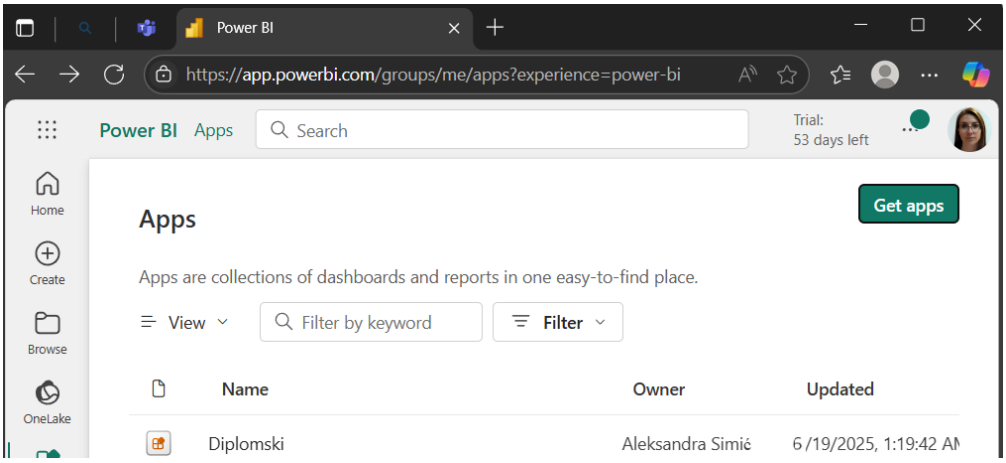


Fig. 1. Power BI Apps

An App represents an organized unit that brings together related reports, dashboards, semantic models, and other content in one place. It is created within a workspace and shared with end users - individuals, groups, or entire organizations. Apps allow independent access management, separate from workspace permissions, facilitating controlled content distribution.

4. Data Acquisition and Processing

This chapter covers the activities related to collecting and preparing data used in this research. Data was obtained from relevant official sources and then processed to meet the requirements of Microsoft Power BI, which was used for visualization and analysis. The processing involved data organization, validation, and restructuring to enable smooth input and further analysis within the software.

4.1 Data Acquisition

The data used in this analysis were obtained from publicly available sources: the Statistical Office of the Republic of Serbia and the National Bank of Serbia (NBS). Since these are official institutions that regularly publish verified and reliable data, the quality and trustworthiness of the data are considered high. This step is crucial, as the validity and accuracy of all subsequent interpretations and conclusions depend on the integrity of the data sources.

4.1.1 Statistical office of the Republic of Serbia

The Statistical Office maintains and publishes a centralized database on its official website, containing data from various social, economic, and demographic areas. This database serves as an official source of statistical information, available to the public for analysis, research, and decision-making.

Figure 2 shows the structure of the database on the website, along with one of the data sets used in this study. This dataset contains data on average gross and net salaries in Serbia from 2018 to 2024. In addition, datasets covering the period 2011–2017 were also retrieved from the website [14].

Fig. 2. RZS database structure [14]

Figure 3 shows the databases related to newly built apartments, allowing the selection of desired territorial units, time periods, and value indicators marked as "Data Type." Before downloading, the first modification was performed to reduce the set of indicators to retain only the average price and average area of newly sold apartments. Two datasets were downloaded: one covering 2011–2018 and another covering 2019–2024 [14].

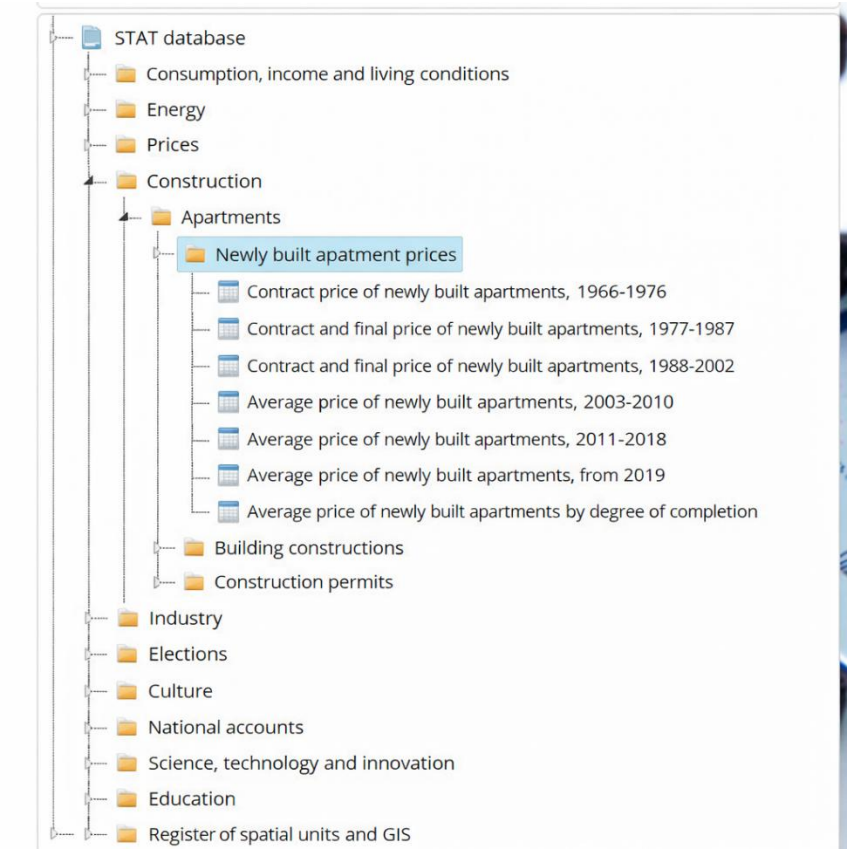


Fig. 3. RZS database structure [14]

The territory of Serbia is administratively classified according to the NUTS (Nomenclature of Territorial Units for Statistics). NUTS is the official classification used by the Statistical Office to group the country into statistical units (regions, districts, and municipalities) according to analytical needs and reporting.

NUTS facilitates:

i. Easier comparison of data between regions,
ii. Monitoring regional development,
iii. Harmonization of domestic statistics with international practices.

Within municipalities, there is a further subdivision into municipalities, cities, and cities with city municipalities.

Two codebooks were downloaded from the website [14] (Figure 4 and Figure 5).

Register of spatial units			Publication standards		
New municipality/ city code	City registr.	**Municipality/city** municipality registration number	**Region**, area, city, city, municipality	**Region** Area	**Region** City - Municipali
New municipality/city code	City registrat number	Region, area, city, municipality	REPUBLIC OF SERBIA	Region Area	Region City - Municipali
		REPUBLIC OF SERBIA	REPUBLIC OF SERBIA		
10	79014	Belgrade-Barajevo	Belgrade-Barajevo	Belgrade	Belgrade region
20	79014	Belgrade-Voždovac	Belgrade-Voždovac	Belgrade	Belgrade region
30	79014	Belgrade-Vračar	Belgrade-Vračar	Belgrade	Belgrade region
40	79014	Belgrade-Grocka	Belgrade-Grocka	Belgrade	Belgrade region
50	79014	Belgrade-Zvezdara	Belgrade-Zvezdara	Belgrade	Belgrade region
60	79014	Belgrade-Zemun	Belgrade-Zemun	Belgrade	Belgrade region
70	79114	Belgrade-Lazarevac	Belgrade-Lazarevac	Belgrade	Belgrade region
80	79114	Belgrade-Mladenovac	Belgrade-Mladenovac	Belgrade	Belgrade region
90	79114	Belgrade-Novi Beograd	Belgrade-Novi Beograd	Belgrade	Belgrade region
90	70114	Belgrade-Obrenovac	Belgrade-Obrenovac	Belgrade	Belgrade region
40	70114	70114	70114	70114	Belgrade region
40	70114	70114	70114	70114	Belgrade region

Fig. 4. Statistical codebook

	A	B	C	D	E	F	G
1	CODEBOOK OF MUNICIPALITIES/CITIES BY ADMINISTRATIVE DISTRICTS IN THE REPUBLIC OF SERBIA						
2	current status						
3	District code	District name	City/municipality ID number	City/municipality name	Type city/municipality	Municipality/city ID number	Municipality/city name
4	00	City of Belgrade	79014	City of Belgrade	city	70092	Barajevo
5	00	City of Belgrade	79014	City of Belgrade	city	70106	Voždovac
6	00	City of Belgrade	79014	City of Belgrade	city	70114	Vračar
7	00	City of Belgrade	79014	City of Belgrade	city	70122	Grocka
8	00	City of Belgrade	79014	City of Belgrade	city	70149	Zvezdara
9	00	City of Belgrade	79014	City of Belgrade	city	70157	Zemun
10	00	City of Belgrade	79014	City of Belgrade	city	70165	Lazarevac
11	00	City of Belgrade	79014	City of Belgrade	city	70173	Mladenovac
12	00	City of Belgrade	79014	City of Belgrade	city	70181	Novi Beograd
12	00	City of Belgrade	79014	City of Belgrade	city	70190	Obrenovac
13	00	City of Belgrade	79014	City of Belgrade	city	70203	Palilula (Belgrade)
14	00	City of Belgrade	79014	City of Belgrade	city	70211	Rakovica
16	00	City of Belgrade	79014	City of Belgrade	city	70220	Savski venac
17	00	City of Belgrade	79014	City of Belgrade	city	70238	Sopot
18	00	City of Belgrade	79014	City of Belgrade	city	70246	Stari grad
19	00	City of Belgrade	79014	City of Belgrade	city	70254	Cukarica
20	00	City of Belgrade	79014	City of Belgrade	city	71293	Surcin
21	01	Severnobački upravni okrug	80071	Bačka Topola	municipality		
22	01	Severnobački upravni okrug	80241	Mali Idoš	municipality		

Fig. 5. Municipalities and cities codebook

4.1.2 National Bank of Serbia (NBS)

An analysis of the data revealed that some values were expressed in RSD while others were in EUR. Therefore, it was necessary to convert all values to a single currency for meaningful comparison. The average annual euro exchange rates from 2011 onward were retrieved from the NBS website.

For assessing housing creditworthiness, data on mortgage interest rates were also obtained. Figure 6 shows a portion of the raw data, which was later processed in Stata for further analysis.

	A	B	C	D	E	F	G	H	I	J	K	L	M
1		Date of reporting:	27/June 2025										
2		Tables 1.3.2 and 1.3.2a											
3		**Interest rates of banks on loans approved for households and the non-financial sector, by loan types**											
4		(in % annually)											
5													
6						Housing loans					Total		
7	Year	Revolving loans	Credit card debt	Overdraft	Total (1, 2 and 3)	Dinar	Dinar loans	Foreign currency–indexed loans and foreign currency loans	Total	Up to 1 year	Over 5 years	Total	
8													
9		1	2	3	4	5	6	7	I	J	K	L	
10	2010.	19.42	24.97	37.18	28.46	11.18	5.38	11.18	5.38	32.25	22.62	22.74	
11	2011.	18.42	22.96	31.83	25.73	11.11	5.38	13.85	5.38	23.35	22.10	22.71	
12	2012.	18.04	22.26	28.22	27.27	11.85	4.65	13.20	4.05	32.35	21.92	22.83	
13	2013.	18.77	22.72	28.90	22.17	11.94	5.28	13.20	5.28	32.35	21.92	20.83	
14	2014.	18.32	22.96	22.68	37.11	11.18	4.68	13.91	4.83	30.16	22.11	21.92	
15	2015.	18.12	24.97	24.97	28.96	11.18	5.98	11.18	5.99	32.35	22.70	22.74	
16	2016.	19.12	24.97	24.97	28.96	11.18	5.98	11.18	5.99	32.35	22.70	22.74	

Fig. 6. Interest rates [15]

4.2 Data Processing

The goal of data processing is to obtain a structured dataset that allows efficient visualization, analysis, and interpretation in Power BI. The raw data from the selected sources were not initially organized in a format suitable for analytical work in Power BI (more on this in Chapter 5.2 – Data Model). Stata was used for data transformation, cleaning, and modeling. The processing was organized through scripts combined into a main script.

4.2.1 Creation of codebooks

To enable analysis by municipalities, cities, districts, and regions, a dedicated codebook was created. Input tables are shown in Figure 5 and Figure 6.

According to NUTS classification, the terms Belgrade District and City of Belgrade cover the same territory. To compare the district with other districts and the city with other cities, column renaming, table merging, and data corrections for the Belgrade District were applied.

An additional column, “indication”, was created to allow further filtering and multi-level analysis. It contains the following values:

i. City – cities not divided into urban municipalities
ii. City with Municipality – cities divided into urban municipalities
iii. Municipality – all municipalities

After processing the input data, a table at the municipality/city code level, titled “0_CODEBOOK_OF_MUNICIPALITIES_AND_CITIES” was created. It contains the following columns:

i. code – primary key
ii. municipality_city
iii. NUTS3_district_code
iv. NUTS3_ district _name
v. NUTS2_region_code
vi. NUTS2_region_name
vii. NUTS1_region_code
viii. NUTS1_region_name

4.2.2 Processing net salary data

As part of preparing the net salary data, two datasets covering different time periods were merged. Using shared identifiers, information from both periods was combined.

The merged data was then joined with the territorial unit's codebook to filter and retain only observations related to municipalities and cities. Since the dataset also contained higher administrative levels - such as regions and districts - these were removed to ensure analytical consistency and accuracy at the local unit level.

Finally, the dataset was supplemented with euro exchange rate data, enabling the conversion of all amounts expressed in RSD.

After processing, the " 1_NET_SALARY_BY_DISTRICT " dataset was created with the following columns:

i. code
ii. municipality_city
iii. year
iv. net salary
v. exchange rate

Columns „code" and „year" form a composite primary key.

4.2.3 Processing data on prices and sizes of newly built apartments

Two datasets covering different periods were also used for the preparation of average prices and sizes of newly built apartments. As with earnings, they were merged using shared identifiers.

Before merging, the data structure was transformed so that price and size information would be stored in two separate columns. This transformation made the analysis more straightforward by clearly separating key variables.

At the time of data preparation, data were available up to the first half of 2024, so those values were used as the values for the year 2024.

The final dataset was then joined with the territorial codebook to remove all aggregated administrative levels, leaving only data for municipalities and cities.

The resulting database "2_PRICES_AND_APARTMENT_SIZES_BY_DISTRICT" contains:

i. code
ii. municipality_city
iii. size
iv. price
v. year

Columns „code" and „year" form a composite primary key.

4.2.4 Merging the databases

At the end of data processing, the tables containing average earnings and real estate indicators (prices and sizes of newly built apartments) were merged into a single main table. This enables comparison of earnings and housing prices over time at the municipality and city level.

Interest rate data for housing loans was also added to provide a fuller picture of housing affordability in different periods and locations.

The merged table, "1_DATABASE" includes:

i. primary key
ii. municipality_city
iii. year
iv. net_salary_RSD
v. price_EUR
vi. size
vii. exchange_rate
viii. interest_rate

Columns „code" and „year" form a composite primary key.

5. Visual Analysis and Data Interpretation

In chapter 4., the data was processed and prepared for analysis using the Stata software package, which enabled structuring and basic statistical treatment. This section focuses on visual data analysis and interpretation through the creation of interactive displays in Power BI. By defining relevant metrics, designing visualizations, and comparing key indicators, it becomes possible to gain deeper insight into relationships among variables and draw conclusions that may not be immediately visible from raw data, which is essential for effective data-driven decision-making and accurate interpretation of complex datasets [16].

Special attention is given to comparisons between territorial units, differences in economic indicators, and assessments of the population's credit capability.

5.1 Power Query

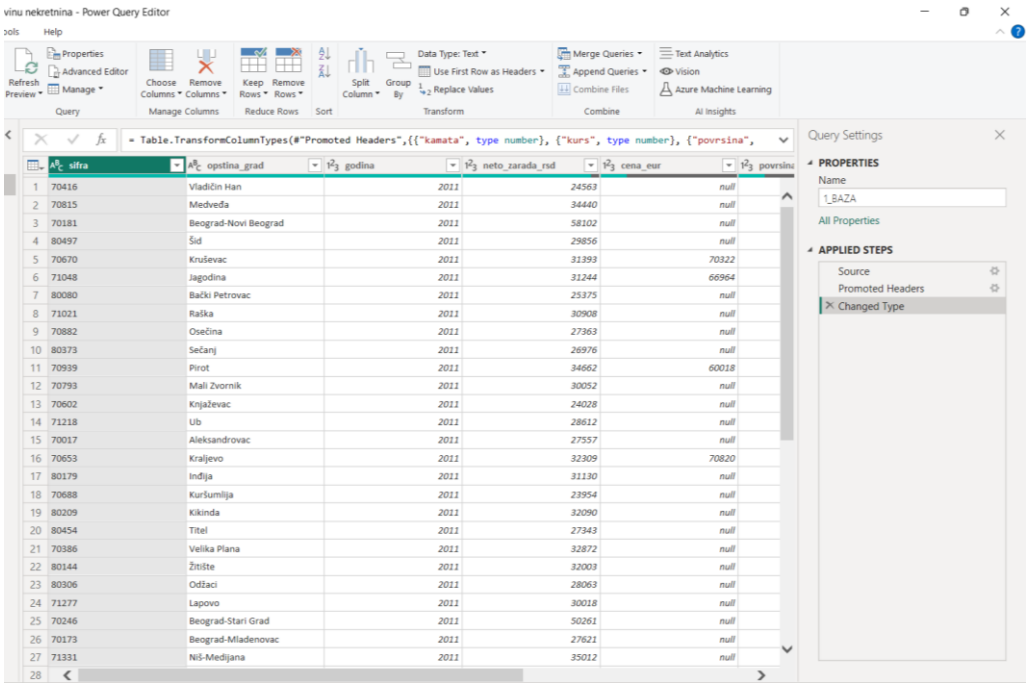
Power Query is a data connection and preparation technology that enables end users to easily load and transform data from various Microsoft products, including Excel, Power BI, Analysis Services, Dataverse, and others [17].

Once data is loaded into Power Query, it often requires various transformations to ensure consistency and readiness for further use. One of the key operations in this process is changing the data type of specific columns. This step is essential because an incorrect data type can make visualization and analysis more difficult.

For example, numeric data may be imported as text, or dates may be recognized as plain strings. Power Query allows simple data type adjustments, ensuring that each column is correctly classified as a number, text, date, or another appropriate format. This guarantees accurate calculations, filtering, and reporting in Power BI.

In addition to data type transformations, Power Query provides a wide range of functions, including table merging, filtering, grouping, and the creation of calculated columns. These capabilities allow the data to be prepared in a way that best suits the analysis' needs.

Power Query's intuitive interface and advanced features make it an essential component of the data preparation workflow in Power BI. Figure 7 shows the layout of Power Query - tables are listed on the left, the selected table is displayed in the main section, and transformation steps are shown in the "APPLIED STEPS" pane on the right.



	sifra	opstina_grad	godina	neto_zarada_rsd	cena_eur	povrsina
1	70416	Vladičin Han	2011	24563	null	
2	70815	Medveđa	2011	34440	null	
3	70181	Beograd-Novi Beograd	2011	58102	null	
4	80497	Šid	2011	29856	null	
5	70670	Kruševac	2011	31393	70322	
6	71048	Jagodina	2011	31244	66964	
7	80080	Bački Petrovac	2011	25375	null	
8	71021	Raška	2011	30908	null	
9	70882	Osečina	2011	27363	null	
10	80373	Sečanj	2011	26976	null	
11	70939	Pirot	2011	34662	60018	
12	70793	Mali Zvornik	2011	30052	null	
13	70602	Knjaževac	2011	24028	null	
14	71218	Ub	2011	28612	null	
15	70017	Aleksandrovac	2011	27557	null	
16	70653	Kraljevo	2011	32309	70820	
17	80179	Indija	2011	31130	null	
18	70688	Kuršumlija	2011	23954	null	
19	80209	Kikinda	2011	32090	null	
20	80454	Titel	2011	27343	null	
21	70386	Velika Plana	2011	32872	null	
22	80144	Žitište	2011	32003	null	
23	80306	Odžaci	2011	28063	null	
24	71277	Lapovo	2011	30018	null	
25	70246	Beograd-Stari Grad	2011	50261	null	
26	70173	Beograd-Mladenovac	2011	27621	null	
27	71331	Niš-Medijana	2011	35012	null	

Fig. 7. Power Query

5.2 Data Model

A data model is a set of tables connected through relationships. Even a single table can be considered a model, though it is not particularly insightful. When multiple tables are used, relationships between them make the model significantly more powerful and analytically relevant [18].

Different business activities generate different types of data, and interactions among these data elements typically form a distinction between core entities and events. This structure is common across industries. The distinction between entities and events leads to the star schema modeling technique, where tables are divided into:

i. Dimensions – entities that store descriptive information (e.g., products, customers, employees, patients).
ii. Facts – event tables that store measurable numerical data (e.g., sales transactions), usually containing metrics that can be aggregated.

5.2.1 Basic data model

The data model in this project (Figure 8) contains two related tables with a clearly defined one-to-many (1:*) relationship.

The dimensional table “0_CODEBOOK_OF _MUNICIPALITIES_AND_CITIES” stores information about geographic units, including codes and names of regions, areas, and municipalities/cities. It serves as the reference table for categorizing and linking other data. The fact table “1_DATABASE” contains quantitative and descriptive variables relevant for the analysis - average real estate prices (EUR), year, interest rate, apartment size classification, exchange rate, net earnings (RSD and EUR), and apartment size. The column „code“ is used to connect it to the dimensional table.

The relationship between the tables is established through „code“, with the dimensions table on the “one” side and the fact table on the “many” side. This enables data filtering and aggregation by geographic categories.

Such a model allows efficient analysis and creation of complex Power BI visualizations, especially when working with geographic and time-based parameters. The model is available in Power BI Desktop under the Model view.

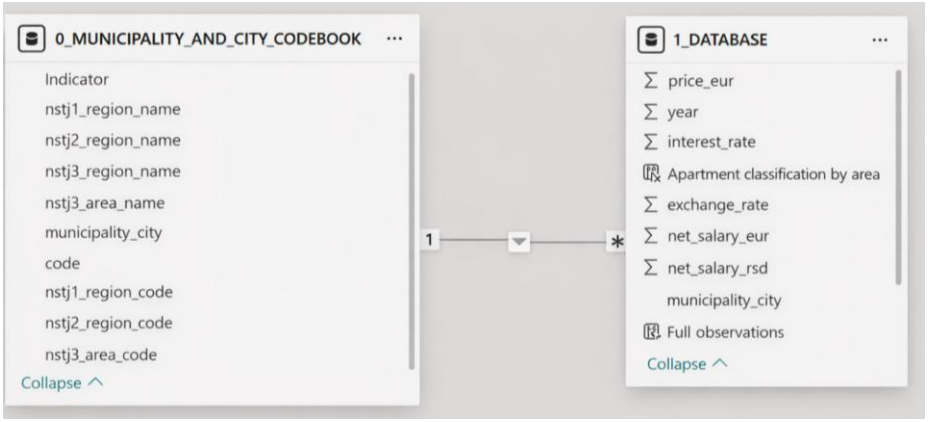


Fig. 8. Basic Data Model

5.2.2 Extended data model

For the “Comparison” tab, the model was extended (Figure 9) by adding duplicate tables for the left and right selection panels (discussed in section 5.3.5). These additional tables are connected to the main fact table through inactive relationships. This approach allows independent filtering and analysis for the left and right sections. Relationships are activated explicitly through DAX calculations, enabling parallel comparisons without cross-interference - an advanced model design commonly used for comparative analytical scenarios in Power BI.

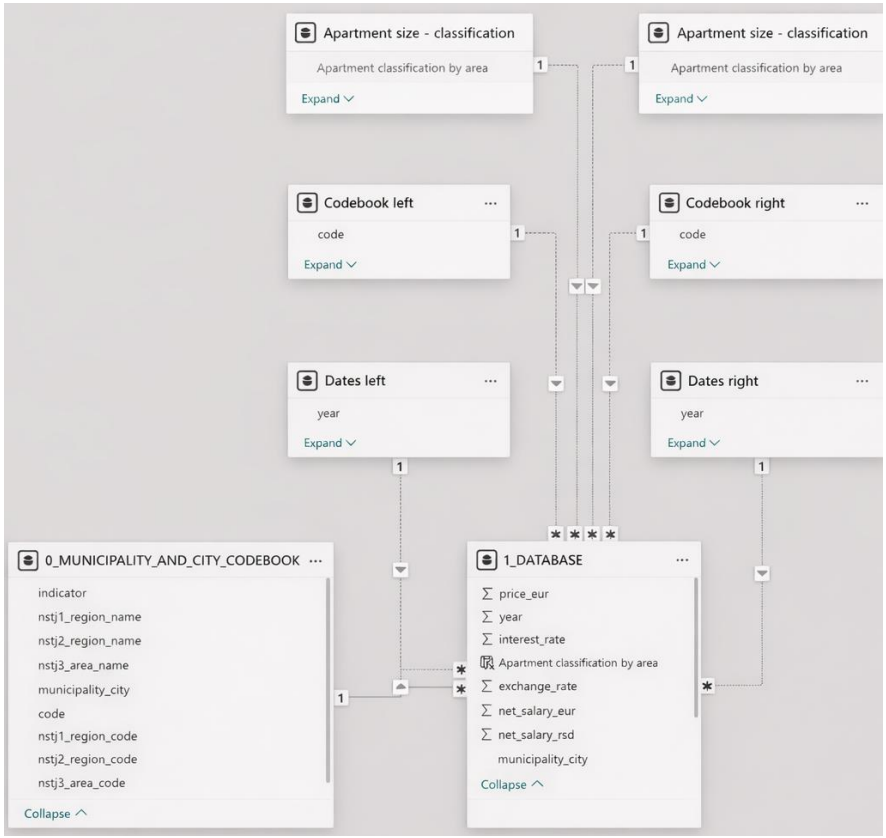


Fig. 9. Extended data model

5.3 Structure and Analytics in Power BI

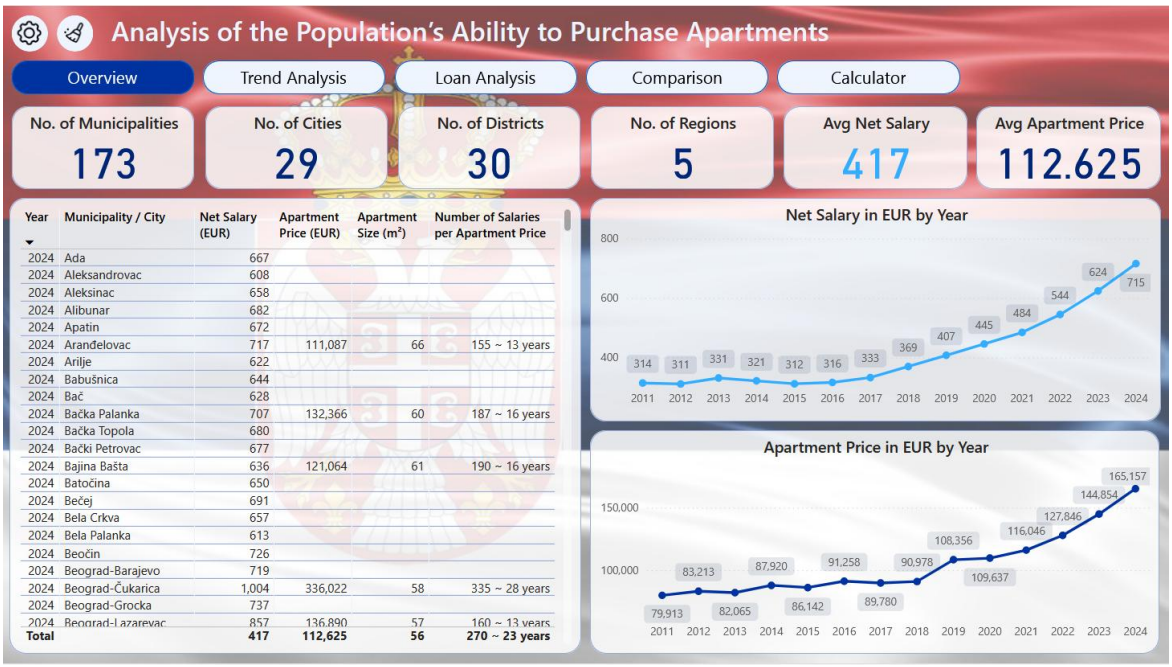
The Power BI report uses bookmarks to create an application-like interface. Each section (tab) represents a separate analytical unit with its own display logic and metrics. This ensures organized, intuitive navigation - from basic overviews to detailed breakdowns.

5.3.1 Overview

The “Overview” tab (Figure 10) contains a table showing:

i. • average net earnings
ii. • average price of newly built apartments
iii. • average size of newly built apartments
iv. • number of average salaries required to purchase an apartment

Data is displayed by year and for each municipality/city in the current selection. Above the table, cards show aggregated values for the number of municipalities, cities, districts, regions, as well as average net salaries and average apartment price. These dynamically update according to the applied filters or visual interactions. Line charts on the right illustrate trends over time for net salaries and apartment prices.



Year	Municipality / City	Net Salary (EUR)	Apartment Price (EUR)	Apartment Size (m²)	Number of Salaries per Apartment Price
2024	Ada	667			
2024	Aleksandrovac	608			
2024	Aleksinac	658			
2024	Alibunar	682			
2024	Apatin	672			
2024	Aranđelovac	717	111,087	66	155 ~ 13 years
2024	Arilje	622			
2024	Babušnica	644			
2024	Bač	628			
2024	Bačka Palanka	707	132,366	60	187 ~ 16 years
2024	Bačka Topola	680			
2024	Bački Petrovac	677			
2024	Bajina Bašta	636	121,064	61	190 ~ 16 years
2024	Batočina	650			
2024	Bečej	691			
2024	Bela Crkva	657			
2024	Bela Palanka	613			
2024	Beočin	726			
2024	Beograd-Barajevo	719			
2024	Beograd-Čukarica	1,004	336,022	58	335 ~ 28 years
2024	Beograd-Grocka	737			
2024	Beograd-Lazarevac	857	136,890	57	160 ~ 13 years
Total		**417**	**112,625**	**56**	**270 ~ 23 years**

Fig. 10. Tab "Overview"

From 2011 to 2024, the average net salary increased from 314 € to 715 €, with continuous growth after 2015. Sorting the table (Figure 11) reveals the lowest salaries - Trgovište (209 € in 2017), Malo Crniće (210 € in 2015), Gadžin Han (210 € in 2011) - and the highest salaries (Figure 12) in Belgrade: Stari Grad (1,505 €), Vračar (1,437 €), Savski Venac (1,373 €) in 2024.

Year	Municipality / City	Net Salary (EUR)	Apartment Price (EUR)	Apartment Size (m^2)	Number of Salaries per Apartment Price
2011	Grad Vranje		69,784	39	~ years
2011	Novi Sad		106,913	60	~ years
2017	Trgovište	209			
2015	Malo Crniće	210			
2011	Gadžin Han	212			
2012	Arilje	212			

Fig. 11. Lowest average net salaries

Year	Municipality / City	Net Salary (EUR)	Apartment Price (EUR)	Apartment Size (m^2)	Number of Salaries per Apartment Price
2024	Beograd-Stari Grad	1,505	480,351	66	319 ~ 27 years
2024	Beograd-Vračar	1,437	339,370	78	236 ~ 20 years
2024	Beograd-Savski Venac	1,373	520,616	78	379 ~ 32 years
2024	Beograd-Novi Beograd	1,358	360,447	63	265 ~ 22 years
2023	Beograd-Stari Grad	1,317	414,427	67	315 ~ 26 years

Fig. 12. Highest average net salaries

During the same period, the average price of newly built apartments increased from 79,913 € to 165,157 €. Growth was not constant, with declines in 2013, 2015, and 2017. A sharp increase occurred in 2019, from 90,978 € to 108,356 €, followed by continuous growth afterward. The highest prices are in Belgrade municipalities (Figure 13), led by Savski Venac (520,616 €) and Stari Grad (480,351 €).

Year	Municipality / City	Net Salary (EUR)	Apartment Price (EUR)	Apartment Size (m^2)	Number of Salaries per Apartment Price
2024	Beograd-Savski Venac	1,373	520,616	78	379 ~ 32 years
2023	Beograd-Savski Venac	1,198	491,596	71	410 ~ 34 years
2024	Beograd-Stari Grad	1,505	480,351	66	319 ~ 27 years
2022	Beograd-Savski Venac	981	459,049	74	468 ~ 39 years
2023	Beograd-Stari Grad	1,317	414,427	67	315 ~ 26 years

Fig. 13. Highest average prices of newly built apartments

The “Number of salaries in the price of an apartment” indicator (Figure 14) shows how many average annual salaries are required to buy a typical apartment. In Savski Venac (2024), this value is around 379 salaries (~32 years), while Bujanovac requires 102 salaries (~8 years).

Year	Municipality / City	Net Salary (EUR)	Apartment Price (EUR)	Apartment Size (m^2)	Number of Salaries per Apartment Price
2024	Bujanovac	599	61,013	75	102 ~ 08 years
2022	Kučevo	510	55,467	62	109 ~ 09 years
2024	Petrovac na Mlavi	619	71,995	72	116 ~ 10 years
2022	Bujanovac	446	52,000	75	117 ~ 10 years
2024	Ćuprija	680	79,406	53	117 ~ 10 years

Fig. 14. Lowest values of the "Number of Salaries per Apartment Price" indicator

5.3.2 Settings

In the upper left corner of the interface, two icons are available:

i. a gear icon, which opens the settings panel (Figure 15),
ii. a broom icon, which clears all selections and resets the report.

Filters include:

i. time period
ii. municipality/city
iii. district
iv. NUTS regions
v. indicator (municipality, city, city-with-municipalities)
vi. apartment variables (price, size, net salaries, apartment size classification)

The size classification filter is computed in Power BI and groups apartments into:

i. small (up to 40 m²)
ii. medium (41–70 m²)
iii. large (70–100 m²)
iv. extra large (100+ m²)

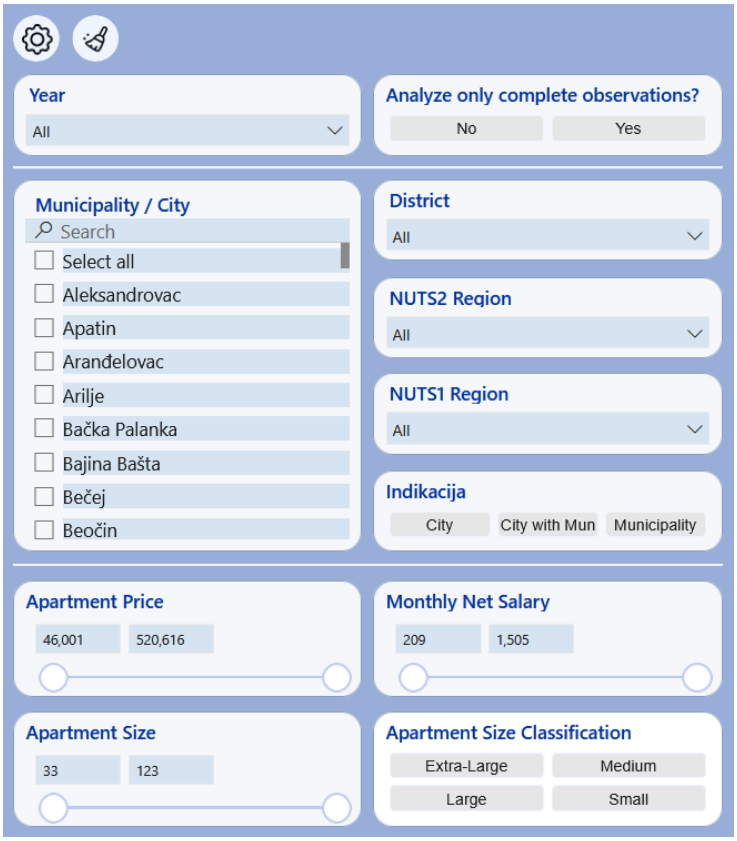


Fig. 15. Settings

5.3.3 Trend analysis

The "Trend Analysis" tab (Figure 16) enables year-to-year comparison of net salaries, apartment prices, apartment size, and number of salaries needed to buy an apartment. Percentage changes can be tracked through both nominal and cumulative charts, providing insight into the direction and intensity of change.

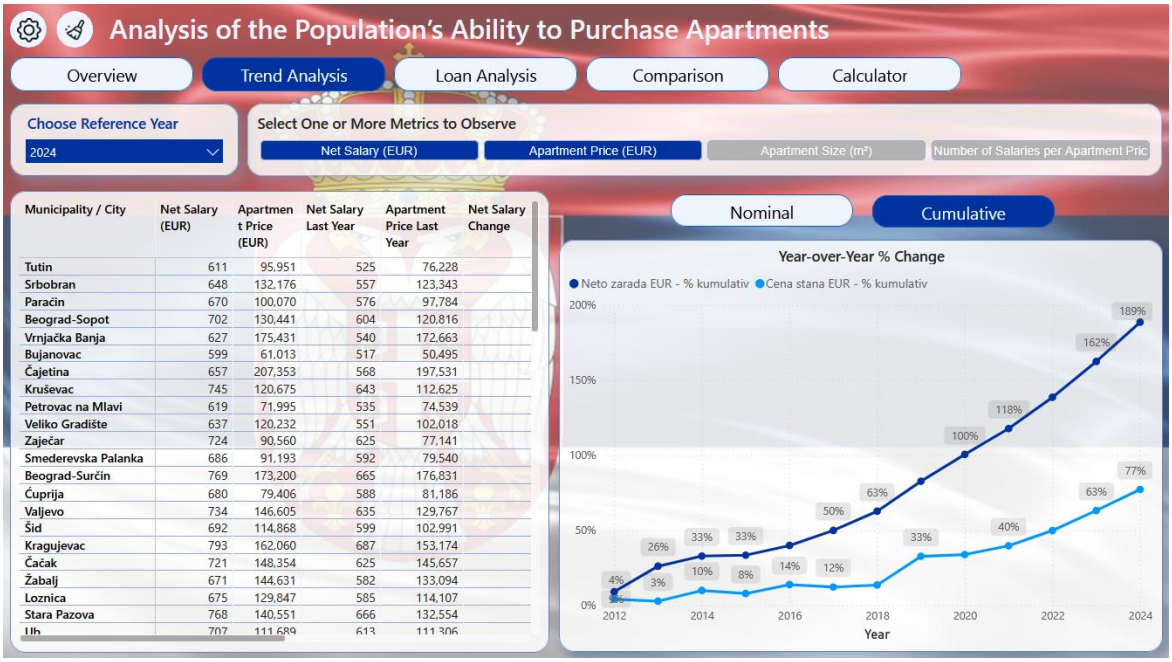


Fig. 16. Tab "Trend Analysis"

Figure 17 shows proportional changes in earnings and housing prices from 2011 to 2024. Both increased, but earnings grew twice as fast.

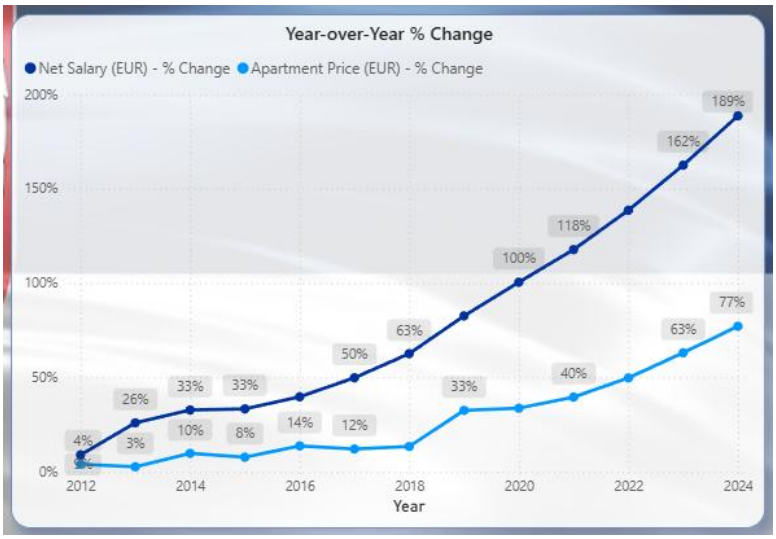


Fig. 17. Percentage change in average net salaries and average apartment prices

5.3.4 Loan analysis

The "Loan Analysis" tab (Figure 18) assesses the population's ability to meet credit eligibility requirements. Banks typically limit monthly loan payments to 60% of net salary. Eligibility is analyzed for down payments of 10% (first property) and 20% (standard mortgage) over 20-, 30-, and 40-year repayment periods.

A table shows which municipalities meet or fail to meet eligibility conditions, while summary cards display the percentage of municipalities that satisfy these requirements. This percentage refers to the share of municipalities where the average salary is sufficient to obtain a housing loan large enough to purchase a newly built apartment at the average market price.

The graph on the left shows the percentage of eligible municipalities/cities/areas/regions for selected repayment periods. From 2011 to 2024, Toplica District had the highest eligibility rate, while South Bačka District had the lowest (2%).

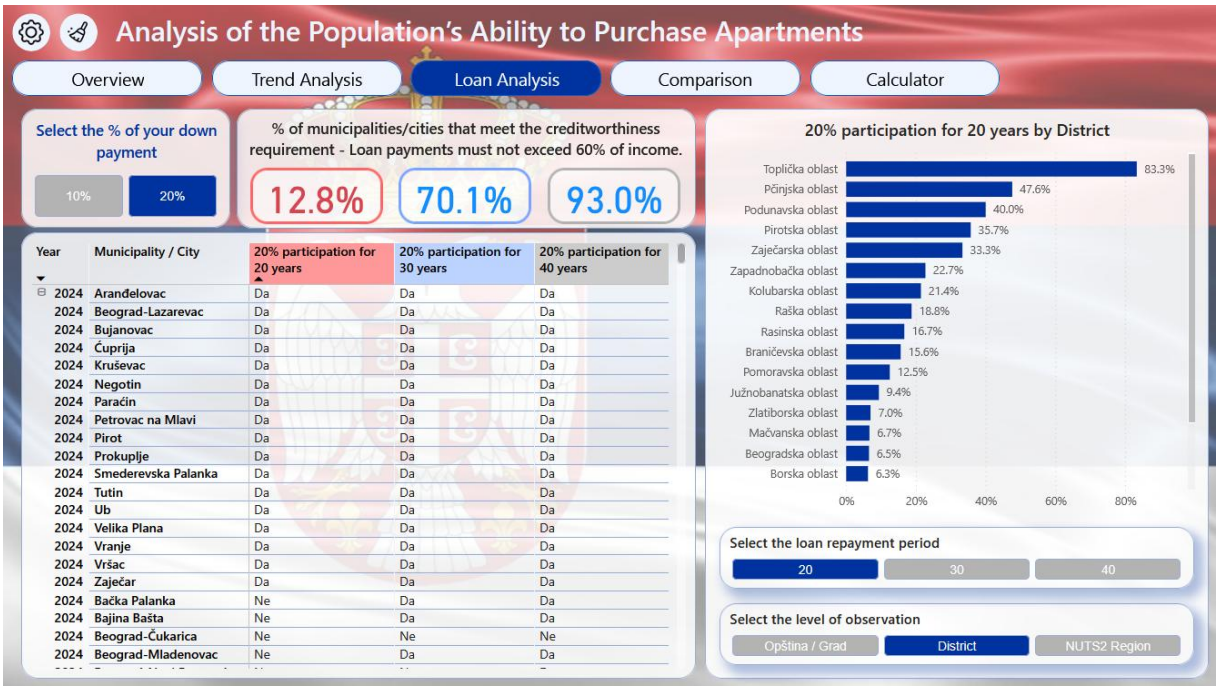


Fig. 18. Tab "Loan Analysis"

Hovering over a table entry displays a detailed tooltip (Figure 19), showing the payment amount and its percentage of salary. For example, in 2024, the average salary in Belgrade's Zvezdara municipality (1,089 €) does not meet eligibility for a 20% down payment (DP) and a 20-year mortgage, because the monthly payment would be 889 € = 81.7% of income.

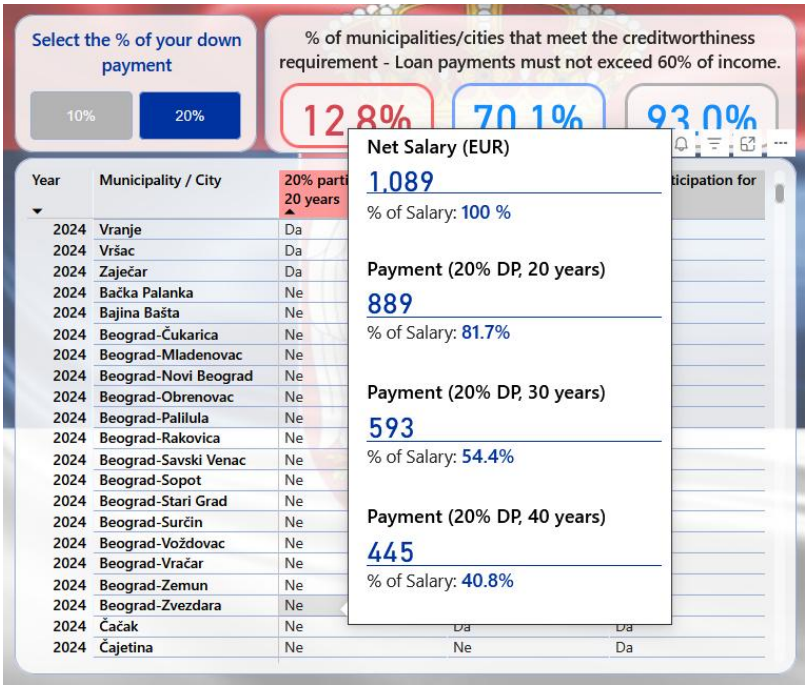


Fig. 19. Tooltip – Details

5.3.5 Comparison

The “Comparison” tab (Figure 20) enables parallel analysis of two independent selections - left and right panels. Each side includes identical filters (year, municipality/city, area, NUTS regions, size class). The center displays percentage differences between the left and right selections for key indicators: net earnings, apartment price, size, price per square meter, and number of salaries needed for purchase.

Fig. 20. Tab "Comparison"

Figure 21 shows an example comparing Niš (left) and Leskovac (right). Key insights:

i. net earnings in Leskovac are 16% lower
ii. average apartment price is 4% lower
iii. apartments are 21% larger on average
iv. buying an apartment requires 228 salaries in Leskovac vs. 198 in Niš (approx. 3 additional years)

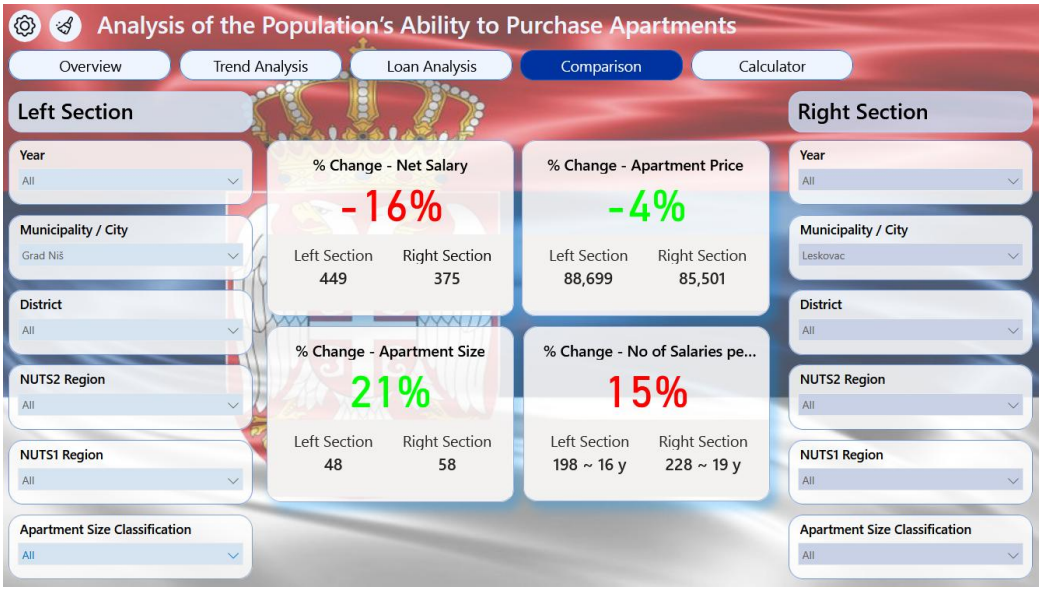


Fig. 21. Comparison of the Cities of Niš and Leskovac

5.3.6 Calculator

The calculator presented in this part of the tool (Figure 22) enables simulation of an individual's credit eligibility in the context of purchasing real estate. On the left side of the interface, users can enter the key parameters relevant for calculating the monthly loan payment and assessing creditworthiness. It is possible to input the total apartment price, the amount of the down payment, the person's age, the planned repayment period (in years), the value of the six-month EURIBOR, and the fixed interest rate.

On the right side, the calculation results are displayed, including the computed monthly loan payment and the minimum monthly income required to meet the credit eligibility criteria. In the example shown, based on the entered parameters, the monthly installment amounts to 806 euros. Credit eligibility is assessed according to the rule that the monthly installment must not exceed 60% of the borrower's monthly income. Accordingly, the minimum salary that satisfies this condition would need to be 1,343 euros.

If the income is below this amount, the borrower is considered ineligible, meaning that obtaining a housing loan under such conditions would not be possible. This display format allows for a preliminary assessment of borrowing conditions through a simple simulation, without the need for direct contact with a financial institution.

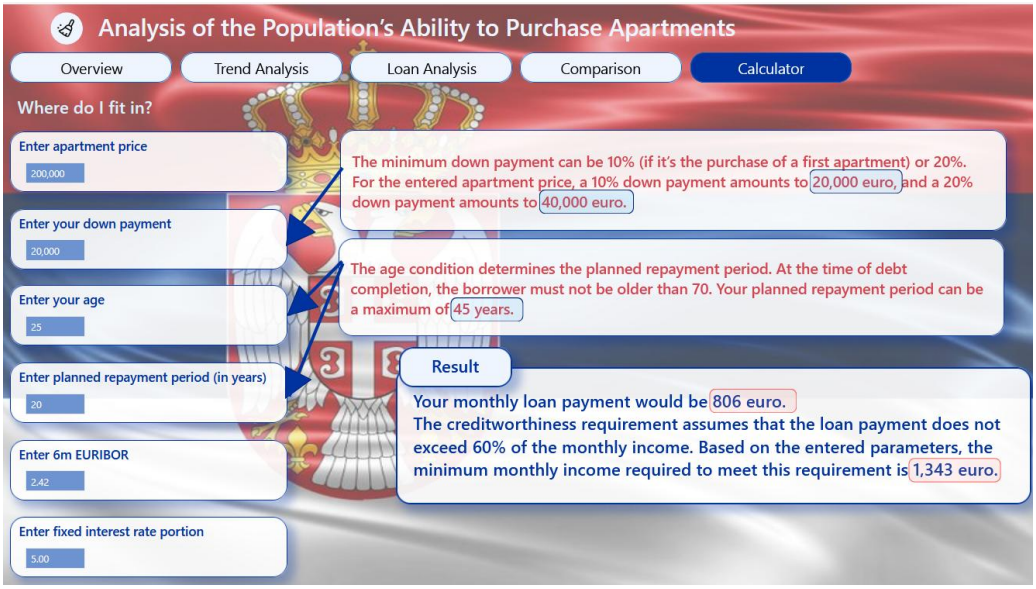


Fig. 22. Tab "Calculator"

6. Conclusion

Based on the conducted analysis, it can be concluded that the population's ability to purchase apartments in the Republic of Serbia primarily depends on two key variables - average net salaries and apartment prices. The values of these factors, however, vary depending on a range of other circumstances, such as the level of urban development, the prestige of the location and similar socio-economic conditions.

By analyzing data on apartment prices and sizes, as well as net salaries, areas have been identified where purchasing an apartment is practically unattainable, even with a loan, due to high monthly payments exceeding 60% of average salaries.

The study could be further improved by incorporating income data at the individual level rather than relying solely on average earnings. When using average values, the analysis is limited because an average salary does not always reflect the actual financial capabilities of all individuals, particularly those with significantly lower or higher incomes. As a result, the average may differ from true purchasing power, as it does not account for income distribution within the population.

The developed credit eligibility calculator provides an additional tool for assessing the ability to obtain a apartment loan, which can assist individuals in making apartment purchase decisions. The results of the analysis indicate the need for further research and for developing policies that could improve access to apartments.

The analysis of the population's purchasing power for apartments offers insight into the complexity of the housing market and the financial challenges faced by citizens. This study may serve as a foundation for future research and for the enhancement of housing policies, with the potential for further improvement through access to more detailed data.

Acknowledgement
This research was not funded by any grant.

Conflicts of Interest
The authors declare no conflicts of interest.

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