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COGNITIVE MAPPING OF THE ECONOMY OF TRUST

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ABSTRACT. The concept of trust has been extensively explored by governments, researchers, and academic communities focusing on public authorities and the financial system, albeit in separate contexts. Trust plays a vital role in both sectors, influencing various aspects of governance, economic stability, and societal well-being. However, the relationship and interdependencies between trust in the government and trust in the financial system remain relatively unexplored. In addressing this gap, this study aims to improve the understanding of the role of trust in the socio-economic system and provide a framework for analysing the complex causal mechanisms between developments in the financial and public sectors using trust concepts. To achieve this, the study adopts the Fuzzy Cognitive Mapping (FCM) method in combination with the fuzzy Delphi method (FDM) as the methodological approach. The results highlight that even a small decline in trust can have severe repercussions on the stability of the financial system, deposit levels, exchange rate stability, and the prevalence of non-performing loans. Additionally, violations of trust in the financial sector also impact the development of the public sector, resulting in decreased trust in the government, fiscal stability, tax revenues, and government bond purchases. The study also demonstrated that when trust in both the financial sector and the government is eroded simultaneously, the complexities and the extent of negative consequences are amplified. These findings emphasize the interconnected nature of trust dynamics in both sectors and underscore the importance of a comprehensive approach to addressing trust-related challenges.

Keywords: trust, financial system, government, macroeconomic stability, fuzzy cognitive mapping

Introduction

The occurrence of significant events, such as the 2008 global financial crisis, the COVID-19 pandemic, and inflationary pressures, has ignited widespread debate on the relationship between government policies and public trust. These crises have highlighted how citizens' confidence in their governments can be severely undermined when government responses are perceived as insufficient or corrupt.

Following the 2008 financial crisis, public trust in both governments and financial institutions declined sharply, particularly in countries where governments were seen as prioritizing bank bailouts over addressing the financial struggles of ordinary citizens. In the United States, for example, the Troubled Asset Relief Program (TARP), which provided substantial bailouts to failing banks, provoked widespread discontent. Many citizens believed that the government was protecting the very financial institutions responsible for the crisis. A 2009 study by the Edelman Trust Barometer found that trust in banks among U.S. individuals aged 35 to 64 dropped dramatically from 69% to 36% post-crisis, with global trust in financial institutions also falling by more than 20%. Similarly, trust in governments plummeted, as the public perceived their responses to the crisis as unfair.

During the COVID-19 pandemic, while fiscal stimulus and central bank actions helped stabilize economies, trust eroded in countries where the responses were deemed inadequate or slow. An OECD survey (2021) reported a decline in public trust, particularly in nations affected by corruption or poor crisis management. In Brazil, for instance, trust in the government's handling of the pandemic fell to just 19%, with economic hardships further eroding confidence in the financial system (OECD, 2023).

Government interventions, such as stimulus packages, bailouts, and regulatory oversight, are crucial for maintaining public trust in both governmental and financial systems. The enactment of the Coronavirus Aid, Relief, and Economic Security (CARES) Act in 2020 by the U.S. government, which provided direct financial assistance to individuals, businesses, and state/local governments, was a substantial effort to stabilize the economy. Research, including from the Pew Research Center (Deane et al., 2021), has shown that these interventions positively impacted public trust, with an increase in trust in government programs due to these economic relief efforts.

Governments also play a critical role in establishing regulatory frameworks that build trust in the financial system. Following the 2008 crisis, the U.S. government's 2010 Dodd-Frank Act aimed to restore public trust through enhanced financial regulations, stricter bank oversight, and the creation of the Consumer Financial Protection Bureau (CFPB). As a result of these reforms, public trust in financial institutions increased from 21% in 2009 to 25% by 2012 (The Financial Brand, 2012). In contrast, Argentina's 2001 financial crisis, characterized by a lack of regulatory controls and poor governance, led directly to a debt default that severely eroded public trust and triggered long-term economic instability (IMF, 2004).

The rise of fintech, cryptocurrencies, and decentralized financial systems has further complicated the relationship between trust in governments and traditional financial systems. These innovations challenge government control and regulation, as many seek alternatives like Bitcoin to achieve financial independence from government oversight. For example, in Venezuela, economic mismanagement and hyperinflation led many citizens to adopt cryptocurrencies as a hedge against the devaluation of the Bolivar (Chainalysis, 2020). Conversely, China responded by banning all cryptocurrency transactions in 2021 to prevent decentralized currencies from undermining trust in the state-controlled financial system (Shin, 2022). These cases illustrate how governments are trying to balance innovation with the need to maintain control over financial stability.

The rise of social media and increased access to information has also influenced public trust. The rapid dissemination of both accurate and false information about government actions and financial systems has made public perception more volatile. For example, the surge in GameStop’s stock value in early 2021, driven by retail investors on Reddit’s "r/WallStreetBets," fuelled misinformation about hedge fund manipulation. This deepened distrust in traditional financial systems, as many believed that financial markets favoured large institutions over small investors. Casperson (2021) noted that the rapid escalation of this event on social media increased both market volatility and public distrust in Wall Street and its regulators.

Trust in government and the financial sector are deeply interconnected. Studies have shown that when trust in government is high, citizens are more likely to trust the financial system, as effective governance is essential for enforcing regulations and maintaining economic stability (Cruijsen et al., 2019). Countries with higher levels of government trust also tend to exhibit greater public trust in their financial institutions, demonstrating the mutual reinforcement between these sectors (Foster & Frieden, 2017). Conversely, financial scandals, banking collapses, and inadequate regulation can severely erode public trust. The OECD (2011) report on Iceland’s financial collapse in 2008 highlights this dynamic. Trust in the Icelandic government fell from nearly 40% in 2007 to just 15% by 2010, reflecting public outrage over the government's handling of the crisis.

The intricate interconnectedness between trust in the financial system and trust in government, along with the multifaceted "contagion effects" and their cumulative impact, presents significant risks to the development of both the financial sector and government institutions. Therefore, the application of system-based simulation models, such as cognitive mapping, may replicate the chain reactions between behavioural factors and their monetization across the financial and public sectors. This paper provides an opportunity to enhance the comprehension of novel mechanisms of regulatory intervention that would be more suitable for complex, heterogeneous, decentralized socio-economic systems, and modern non-stationary economic conditions.

By doing so, the research aims to advance the understanding of the role of trust in the socio-economic system and provide a framework for analysing the complex causal mechanism between financial and public sector developments through trust concepts. This research offers three distinct contributions compared to existing studies. Firstly, the study introduces a fuzzy cognitive model that explains the causal mechanism between financial and public sector developments through the lens of trust concepts. This model provides a comprehensive framework for understanding the interplay between trust, financial sector, and government development in socio-economic systems. Secondly, the research employs the Fuzzy Delphi Method (FDM) to identify valid attributes of trust, financial sector, and government development based on qualitative information. This approach enhances the robustness of the study by incorporating expert opinions and ensuring the inclusion of relevant variables. Thirdly, the implementation of Fuzzy Cognitive Mapping (FCM) enables the establishment of convergent causal relationships among behavioural concepts and indicators of financial sector and government development, specifically in terms of macroeconomic stability. This analysis goes beyond previous studies that often discuss trust in the financial system and trust in government separately, providing a comprehensive examination of the interconnectedness of these concepts. Lastly, the paper contributes to the field by simulating different macroeconomic stability scenarios based on the patterns of multi-channel cross-sectoral and multi-level diffusion of behavioural impulses associated with changes in the level of public trust in public institutions and the financial sector. This simulation provides valuable insights into the potential outcomes and impacts of trust dynamics on macroeconomic stability.

This paper starts with a comprehensive literature review on trust in the financial sector and government. It subsequently provides a detailed description of the applied methodologies, namely the Fuzzy Delphi Method (FDM) and Fuzzy Cognitive Mapping (FCM). The fourth chapter presents the research findings, which centre around three main themes: the identification of essential concepts and connections, steady state analysis, and dynamic analysis of FCM. This section is followed by a discussion of the main research findings. Lastly, the concluding section encompasses empirical implications, limitations, and suggestions for future research directions.

1. Literature review

The relationship between trust in government and financial systems is crucial for the stability, economic growth, and overall well-being of a society. A substantial body of research has explored the critical role of trust imbalances within both the financial sector and government, although often in separate contexts. Trust serves as a cornerstone for the proper functioning of the financial system and the broader economy. Studies in economics have established a strong correlation between trust in the financial sector and the onset of credit crunches (Feeney, 2010; Bachmann et al., 2011). When trust erodes among key stakeholders – such as investors, employees, and financial institutions – this, combined with breaches of psychological contracts, triggers a cascade of negative outcomes, including mass bankruptcies, budget cuts, unemployment, emigration, and credit crunches (Feeney, 2010; Abbas et al., 2021; Aliyev & Gasimov, 2023). As a result, society grows increasingly cynical, and governments face significant losses.

The consequences of declining trust in the financial sector have been well-documented, particularly concerning bank runs, liquidity crises, and bankruptcies. When trust in banking institutions diminishes, customers grow uncertain about the banks' solvency, prompting mass withdrawals that lead to bank runs. This withdrawal of funds heightens the risk of liquidity crises and eventual bankruptcy. The panic can spread to other solvent banks, creating a systemic crisis (Guiso, 2010; Iyer & Puri, 2012). In extreme cases, banks may find themselves lacking sufficient reserves to cover the withdrawals, causing a sudden demand for liquidity and a subsequent reduction in its availability (Van der Cruijsen et al., 2016; Levine et al., 2018). This situation can escalate, resulting in widespread defaults and bankruptcies across the financial system (Jetter & Kristoffersen, 2018).

Recent research has increasingly focused on the rise of digital technologies, fintech, and cryptocurrencies, and their connection to public trust in central and local governments as well as financial institutions. Information and communication technologies play a pivotal role in reinforcing public trust and fostering good governance, particularly by enhancing transparency and encouraging citizen engagement (Amrani et al., 2022; Fauzie et al., 2023). Pelau et al. (2024) provide key insights into the design of AI systems that build consumer trust through emotional engagement, thereby encouraging greater information-sharing behaviours. However, financial and technological innovations are also disrupting traditional frameworks regulated by the state, challenging governmental control over financial markets (Koziuk et al., 2024). Central bank digital currencies, while innovative, pose significant risks, such as security and privacy concerns, which could erode trust in both the financial system and government (Shafranova et al., 2024; Guley & Koldovskyi, 2023).

Declining trust has a direct and adverse effect on investment flows and trade volumes. When trust deteriorates, investors become more cautious and hesitant to engage in long-term investments or allocate capital to riskier assets (Charda & Pendaraki, 2023). The erosion of trust, often driven by behavioral biases and negative experiences, reduces both direct and portfolio investment (Gurun et al., 2017; Bottazzi et al., 2016). As a result, investment flows contract, slowing economic activity and curbing growth. A lack of trust between economic entities and financial institutions also hinders the intermediation process, creating further obstacles to investment (Guiso et al., 2004; Adamek & Solarz, 2023; Taujanskaitė & Kuizinaitė, 2022). The proliferation of social media has exacerbated this issue, providing easier access to and dissemination of information – both accurate and false – about government and financial institutions (Kuráth et al., 2023; Thi Huyen et al., 2024). Social media strongly influences public opinion (Phuong et al., 2024), often making it more volatile, as trust can be rapidly undermined by scandals, rumours, or government failures. However, institutions can mitigate this by enhancing their communication strategies on social media, focusing on specific trust dimensions (Mičík et al., 2022).

The loss of trust in both the financial sector and public authorities represents a significant threat to macroeconomic stability. This is often driven by lack of transparency, corruption, and unaddressed behavioural patterns, alongside shifting public expectations (Linhartova & Pucek, 2024; Djouadi et al., 2024; Horvath & Katuscakova, 2016; O'Neill & Bardrick, 2015). Dées & Zimic (2019) have shown that expected errors by economic agents account for nearly 50% of short-term cyclical fluctuations, while technological shocks account for around 20% of output variation.

Numerous studies have confirmed that a lack of trust triggers economic crises, halts interbank lending, reduces the effectiveness of regulatory measures, and increases the likelihood of crises in the real sector. Additionally, it leads to lower tax revenues and exacerbates inflationary pressures (Krause & Giansante, 2012; Kaya, 2023; Morrison & White, 2010; Steenbergen et al., 2023; Mazurenko et al., 2023). Trust in government is critical for the effective functioning of state governance and economic development (Calisto et al., 2023; El Gharbaoui et al., 2024; Vysochyna et al., 2024). The level of trust in government strongly influences the behaviour of economic actors, including their willingness to pay taxes. Research shows that citizens are more likely to comply with tax obligations when they trust the government and have confidence in tax authorities (Anderson, 2017; Godlewska, 2023; Yin & Li Y, 2023). Financial oversight plays a key role in reinforcing trust in governance, particularly in decentralized fiscal systems (Li et al., 2023). Public participation and trust can also be enhanced through the use of e-governance systems (Kuzior et al., 2023; Aswar et al., 2024).

The absence of trust fosters environments where illicit activities, such as money laundering, can flourish, undermining the stability and legitimacy of the global financial system (Cohn et al., 2014). When trust is lacking, individuals may turn to unregulated channels or offshore entities to conduct illegal transactions (Christensen, 2012). This creates a vicious cycle, where corruption further erodes trust and confidence. However, the application of blockchain technology in anti-money laundering and combating the financing of terrorism has the potential to improve transaction tracking and ensure greater accountability, thereby enhancing trust (Utkina, 2024). Similarly, the use of AI and machine learning can promote transparency and combat corruption (Lyeonov et al., 2024).

Recent research has highlighted the pivotal role of trust in government during the COVID-19 pandemic. Studies show that trust in government and public health experts directly influenced compliance with quarantine regulations and public confidence during the crisis. Countries with low levels of trust experienced higher dissatisfaction with coercive measures, which impeded efforts to control the virus. By contrast, countries with higher levels of trust were able to implement more effective, less contentious measures, yielding better public health outcomes (Cairney & Wellstead, 2021; Apeti, 2022; Gilani et al., 2024). Failure to manage healthcare effectively has been shown to significantly erode trust in both government and the healthcare system (Agustina et al., 2024; Vasylieva et al., 2023a).

Given the extensive body of research on trust in the public sector, it is clear that a decline in trust poses a serious threat to achieving the Sustainable Development Goals (SDGs). The success of these goals, from poverty eradication (SDG 1) to promoting innovation and fostering peaceful, inclusive societies (SDG 16), hinges on the trust that citizens and businesses place in all sectors of the economy. This leads to the concept of an "economy of trust," a socio-economic system in which interactions across sectors are based on trust. A decline in trust is not confined to the financial or public sectors but can spread across the entire economy, due to the contagious nature of trust (Laurence, 2015; Kroknes et al., 2015; Foster & Frieden, 2017). Yet, many uncertainties remain regarding the interaction between trust in government and trust in the financial sector. Questions remain about how trust in government would be affected if trust in the financial sector diminishes, and vice versa. Additionally, the consequences of a simultaneous decline in trust in both remain largely unexplored, highlighting the need for further investigation.

2. Methodological approach

Considering the behavioural component of trust, scientific literature employs both quantitative and qualitative methods to establish relationships between trust and socio-economic phenomena. Qualitative methods commonly involve surveys, which encompass the development of questionnaires, respondent selection, and response analysis. Surveys have been utilized to determine the influence of general or interpersonal trust on political trust, such as trust in the government and power (Schiffman et al., 2010), and to identify the impact of external socio-economic and political shocks on trust in the government (Chanley, 2002; Nye, 1997). Furthermore, surveys have been employed to analyse the effects of negative perceptions of the economy, government scandals, and increasing public concerns about crime on the decline of trust in the government (Chanley et al., 2000). While qualitative methods are also employed to study trust in the financial sector, quantitative methods are more commonly utilized due to their ability to investigate the situation through statistical financial statements. Nevertheless, surveys have been used in the financial sector to determine the impact of financial market turbulence on trust in the European Central Bank (Wälti, 2011), understand the effects of global shocks on trust in banks, businesses, and the US government (Betsey & Wolfers, 2011), and establish the relationship between systemic confidence in the financial sector and the financial crisis.

When studying trust in the financial sector and its connection with the development of various sectors and macroeconomic stability, quantitative methods such as structural equation modelling (SEM) have been commonly employed (Pozovna et al., 2023; Vasylieva et al. 2023b). SEM allows for the identification of structural relationships among the studied concepts through factor analysis and multiple regression analysis, considering both explicit and latent constructs. However, SEM has certain limitations, particularly when examining cognitive relationships.

Firstly, a well-fitting SEM model may not necessarily provide information about the causal relationships between the studied concepts. The direction of arrows in the model may be determined qualitatively, and the causal relationships can change over time (Raykov & Penev, 2002; Nachtigall et al., 2003; Juhászová et. al., 2023). Secondly, obtaining enough statistical information to construct a qualitative and adequate model can be challenging. The sample size needs to exceed the number of parameters by more than 25 times, which is particularly difficult when dealing with trust (Stelzl, 1983). Consequently, using qualitative indicators and survey results becomes nearly impossible since the implicitly specified variables must be explained using specific statistical indicators. Thirdly, the structural equation modelling method lacks the capability to simultaneously assess the impact of two concepts on the system and develop scenarios, unlike fuzzy cognitive modelling (FCM) (Nozari et al., 2021). FCM is an effective method for researching behavioural categories, decision-making features, and game theory, building upon the use of cognitive maps as a formal representation of social scientific knowledge and decision-making in social and political systems (Gray et al., 2015).

Therefore, considering the limitations of SEM in capturing cognitive relationships and the advantages of FCM in exploring simultaneous impacts and developing scenarios, FCM emerges as a suitable approach for studying trust and its implications in the financial sector and broader socio-economic systems. By employing FCM, researchers can overcome the challenges associated with the quantitative nature of SEM, incorporate qualitative indicators, and effectively analyse the interplay of various factors in decision-making processes. This alternative methodology offers new opportunities for understanding the complex dynamics of trust and its impact on economic stability and development.

The research identified several significant gaps in the existing literature and methodology analysis. Firstly, while some articles have explored trust in the state and trust in the financial sector independently, there is a dearth of research that examines the interrelated effects of these concepts. This gap hinders a comprehensive understanding of the complex dynamics between trust, the financial sector, and government institutions. Secondly, there is a lack of research that investigates the causal relationship between trust variables and fuzzy cognitive mapping. Understanding how trust influences the formation of cognitive maps is crucial for developing a nuanced understanding of the socio-economic system's behaviour. Lastly, the integration of quantitative and qualitative methods, particularly incorporating the judgments of interviewed respondents, is an area that has been overlooked in previous studies. This approach allows for a more comprehensive analysis that combines the strengths of both approaches.

To address these gaps, the study adopts the Fuzzy Cognitive Mapping (FCM) method, which will be combined with the fuzzy Delphi method (FDM). This combined approach aims to achieve the research objective and bridge the identified gaps. The research process and methodology are outlined in Figure 1, providing a clear roadmap for conducting the study.

By employing FCM and FDM, the research aims to provide a more holistic understanding of the interplay between trust, the financial sector, and government institutions. The integration of quantitative and qualitative methods will enhance the research's validity and enable a deeper exploration of the complex relationships involved. This approach has the potential to contribute valuable insights to the existing body of literature and advance our understanding of trust dynamics in socio-economic systems.

2.1. Fuzzy Delphi Method (FDM)

Fuzzy Delphi Method (FDM) was utilized by adapting the procedure used by Bouzon et al. (2016) and Tohidi et al. (2020). To identify research variables, a systematic literature review and theoretical frameworks of the recent studies were performed. Prior to gathering and consolidating expert opinions, expert subjective perspectives on the relevant substantive issues were gathered based on a survey developed by the researchers.

In the Fuzzy Delphi Method (FDM), the importance value of research variable *j* estimated by an expert *i*, where $A_{ij} = (a_{ij};\ b_{ij}; c_{ij})$ for *i* = 1, 2, 3, . . . , n; *j*= 1, 2, 3, . . . , m. In this case *n* represents the number of experts and *m* indicates the number of research variables. The weight of $A_j = (a_j;\ b_j; c_j)$, while $a_j = \min(a_{ij})$, $b_j = (\Pi_1^n b_{ij})^{1/n}$, and $c_j = \max(c_{ij})$. Linguistic variables used to assess the importance of each research variable (Table 1) were transformed into qualitative assessments or comparable values using the Triangular Fuzzy Number based on the Triangular Fuzzy Membership Function (Figure 2).

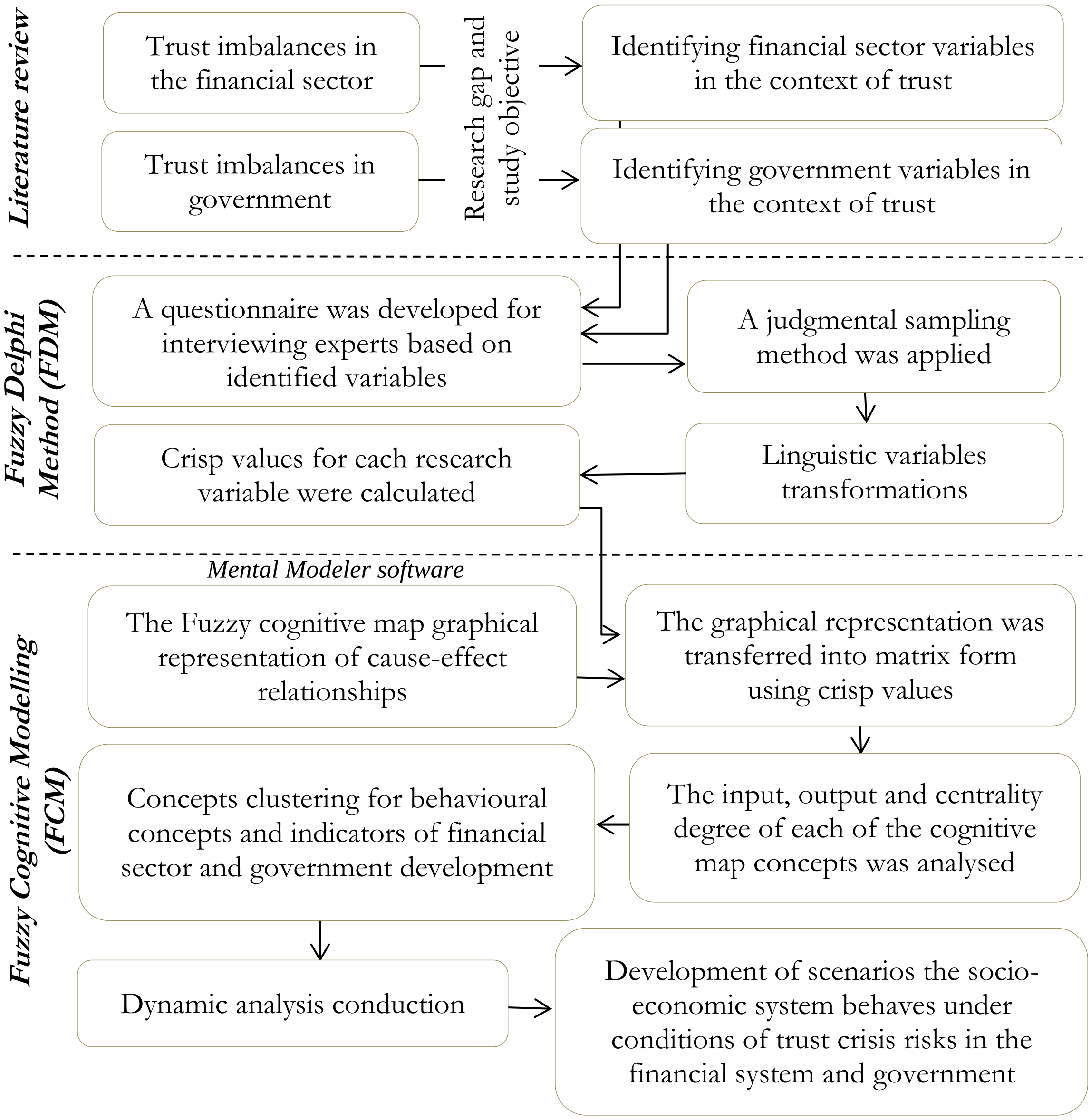

Figure 1. Research Process and Methodology
Source: *own compilation*

Table 1. Linguistic variables transformations

Linguistic Variables	Triangular Fuzzy Number (TFN)
High Important	(0.75; 1.0; 1.0)
Important	(0.5; 0.75; 1.0)
Moderate	(0.25; 0.5; 0.75)
Not important	(0; 0.25; 0.5)
Without any importance	(0; 0; 0.25)

Source: *own compilation*

It is important to note that the Fuzzy Delphi Method (FDM) allowed for the integration of expert opinions and the quantification of qualitative assessments, enhancing the rigor and reliability of the research findings. This methodology provides a systematic approach to determining the importance of research variables in a fuzzy cognitive model, considering the uncertainties and subjectivity inherent in the decision-making process. By utilizing the FDM, this study ensures a robust analysis of the identified variables and their significance within the proposed framework.

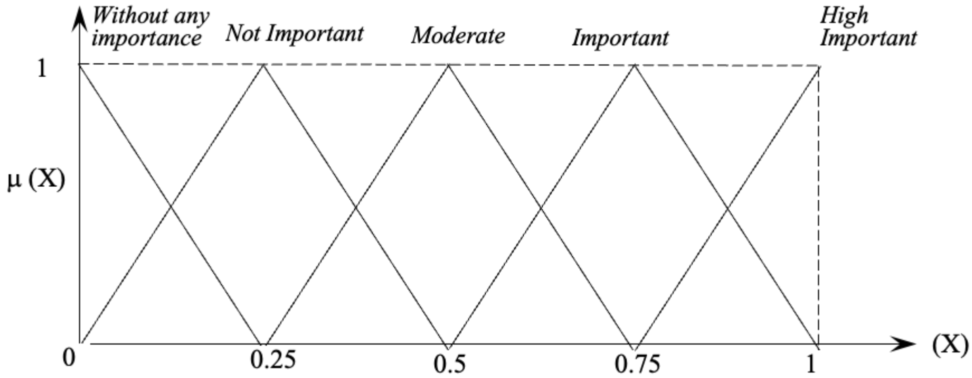

Figure 2. Triangular Fuzzy Membership Function
Source: *own compilation*

Given that expert panel opinions have been used, the average of their opinions for each research variable is applied in accordance with the following equation:

$$A_{average} = (a_j;\ b_j; c_j) = ({}^1\!/_n \textstyle\sum_{i=1}^{n} a_{ij}\,, {}^1\!/_n \sum_{i=1}^{n} b_{ij}\,, {}^1\!/_n \sum_{i=1}^{n} c_{ij})$$

Finally, each variable's acquired value was compared with the threshold value (Z) that was ascertained by the mental inference of experts and directly determined the number of research variables chosen for the study. In this research, the threshold value (Z) is presented by a crisp number. According to the procedure used by Nozari et al. (2021), to determine where each research variable has acquired a value within the acceptable threshold range, crisp values for each research variable were calculated from the following equation:

$$Crisp\ (A_{average}) = (\frac{a_j + 2b_j + c_j}{4})$$

Once defuzzification of each fuzzy number were completed, the final weight of each research variable ($\mathbf{A_j}$) was compared to the threshold value (Z). In the case when the threshold value is less than the research variable' weight ($\mathbf{A_j} \geq \mathbf{Z}$), the desired research variable has been accepted and incorporated into the cognitive model. In contrast, where the threshold is higher than the final weight of a variable ($\mathbf{A_j} < \mathbf{Z}$), the desired research variable was rejected. The threshold value was calculated as the simple average value of the opinions of experts based on the crisp values obtained.

2.2. Fuzzy Cognitive Modelling (FCM) construction and analysis

Fuzzy Cognitive Modelling (FCM) was developed through a combination of artificial neural networks and fuzzy logic (Nasirzadeh et al., 2019). FCM is a knowledge-based method allowing investigation of the research objects, which are complex decision-making systems, represented by dynamic elements (concepts) and cause-effect interconnections.

Cognitive mapping is an initial step in the simulation modelling of different scenarios for the functioning and development of the financial sector and public authorities in relation to the intensity of the increase in trust crisis risks. FCM method was chosen to simulate scenario planning, intervention strategies development and policy decision-making to ensure financial balance and manageability of the real sector of the economy. The application of FCM's technique in this study relies on constructing a cognitive map in sign-oriented graphic language to formalize convergent causal relationships among a set of behavioural concepts and indicators of financial sector and government development. Cognitive maps were used for simulation modelling, resulting in different scenarios for the financial and public sectors' development, by describing socio-economic system behaviour over time through cause-effect interrelations by introducing initial impulses into the specified vertices of the graph (concepts).

Cognitive map is a visualized graphical diagram that comprises selected concepts (variables, components, nodes) and directed edges (the cause-effect relationships). The simulation model concepts (C_i) that reflect the complex system-constituting variables, phenomena or factors are located at graph vertices (nodes). Each two concepts (C_i and C_j) are interconnected by arcs that reflect cause-and-effect relationships, with a weighted degree of influence. These directed edges are depicted by arrows or double arrows. The weights of directed edges (w_{ij}) indicate to what extent the concept *i* affects the concept *j*, i.e. the strength of the cause-effect relationships.

The formalization of convergent cause-and-effect relationships between vertices is carried out by determining the nature of the system concepts influence. According to the weights of directed edges, three types of cause-and-effect relationships is depicted in the cognitive map. Causality between the two concepts (C_i and C_j) is defined as a positive ($w_{ij} > 0$) in the case when the trends in concepts change characteristics coincide, i.e., increasing/decreasing the value of the one concept (C_i) results in increasing/decreasing the value of the other concept (C_j). Causality between the two concepts (C_i and C_j) is defined as a negative (inverse) ($w_{ij} < 0$) in the case when the trends in concepts change characteristics do not coincide, i.e., increasing the value of the one concept (C_i) results in decreasing the value of the other concept (C_j) and vice versa. A special case is the zero value of the weight ($w_{ij} = 0$), which occurs when there is no relationship between the considered concepts (zero causality).

The level of strength of the cause-effect relationships between concepts (w_{ij}) can be extracted by applying mathematical models (accurately describing the identified quantitative dependencies between the concepts) or experts' opinions of informal qualitative relationships between the concepts using linguistic variables. Linguistic assessments are aggregated into a fuzzy linguistic scale, which is represented by an ordered set of linguistic assessments of the probable consequences of the impact of one concept on another. Linguistic variables via fuzzy membership functions were then converted into fuzzy quantitative estimates (numbers), that, in turn, were converted into crisp numbers using the given defuzzification methods. Therefore, crisp numbers between 0 and +1 were assigned for positive causal relationships, and crisp numbers between –l and 0 to represent inverse causality.

FCM analysis is a useful tool that allows to transfer graphical representation of the complex model (depicted by components and directed edges) into mathematical form of adjacency matrix A (D) = $\{e_{ij}\}$, where e_{ij} is the weights of directed edges (w_{ij}) between concepts. The matrix presentation of the conceptual model helps to make algebraic calculations for the identification of different network structural characteristics as well as other concept-level parameters.

To analyse a fuzzy cognitive map, the number of (a) concepts (components (C)); (b) concept connections (N); (c) driver components; (d) receiver components; (e) ordinary components; along with (f) density (D); (g) connections per component; (h) complexity score.

The clustering coefficient also referred to as density is a measure of connectivity that shows to what extent concepts are connected or separated. For the density calculations, the number of concept connections (N) was divided by the maximum number of connections (C) among the number of concepts:

$$D = \frac{N}{C(C-1)}$$

When the cognitive map has a great number of cause-effect relationships between concepts, the density of a cognitive map is also high. A set of concepts that perceive more cause-effect relationships could be a catalyst for changes in macroeconomic stability, as they provide more options for changing things.

Mental Modeler through concept-level analysis provide with description of each variable used in the study, including (a) type of the component (concept); (b) indegree; (c) outdegree; (d) centrality along with (e) preferred state. The type of the concept defines the role of the component in the model by explaining how the concept behaves in relation to other concepts (cause-effect relationship). Mental Modeler determines three types of components namely driver (also referred to in the literature as transmitters, givens, tails), receiver (also referred to as ends, heads), and ordinary (also referred to as means) (Eden et al., 1992; Norman, 1965). A number of drivers, receivers and ordinary components contribute to a deeper understanding of the structure of the cognitive map. However, for identification the important concepts and relationships, all components are analysed from their indegree [id(v_i)] and outdegree [od(v_i)].

Indegree indicates the cumulative strength of the concepts coming into the concept. It could be calculated as a sum of absolute values of the concept from the column adjacency matrix.

$$\mathrm{id}(v_i) = \sum_{k=1}^{C} \overline{e_{ki}} ,$$

where e_{ki} is the strength of the cause-effect relationships, and C is the total number of concepts.

Outdegree denotes the cumulative strength of the connections coming out the concept. It could be calculated as a sum of absolute values of the concept from the row adjacency matrix.

$$\mathrm{od}(v_i) = \sum_{k=1}^{C} \overline{e_{ki}} ,$$

Driver components could be characterized by zero indegree and non-zero positive outdegree. In contrast, receiver components could be characterized by non-zero positive indegree and zero outdegree. A component is defined as ordinary when it has both a non-zero positive indegree and outdegree. However, based on the concept ratio of in- and outdegree, ordinary concepts could be considered as more or less driver or receiver.

The sum of indegree (in-arrows) and outdegree (out-arrows) indicates the importance of the concept in the cause-effect relationship and is called in the literature as the degree of centrality or total degree (td(v_i)) (Norman, 1965). That is, the higher the degree of centrality of the concept, the greater the number of interactions this concept has within a cognitive map. The following means a higher cumulative strength of the cause-effect relationship. Kosko (1986) pointed out that in contrast to binary cognitive maps, in fuzzy cognitive maps, concepts could have a high degree of centrality, even if cause-effect relationships are less numerous due to their higher weight.

A range of specialized dialogue complexes and publicly available software applications have been developed for fuzzy-logic cognitive modelling purposes. Applications such as Anylogic, Excel, Matlab, Vensim, FCM Modeler, FCM Tool, JFCM, and ISEMK, among others, have proven highly valuable in conducting complex simulation studies that mirror real-world scenarios. In addition, the utilization of Data Mining techniques has gained substantial popularity in recent years, enabling the identification of factors, and establishing cause-and-effect relationships through semi-automatic analysis of large datasets. For this study, the web-based software Mental Modeler developed by Gray et al. (2013) was employed.

The use of Mental Modeler software offers several advantages. Its user-friendly concept mapping, matrix, and scenario interfaces provide useful functions that allow for simulation modelling of complex systems under various conditions, without requiring specialized programming knowledge. The software facilitates multi-step FCM analysis, which can be easily performed even in data-poor situations, thereby limiting model complexity. However, it is important to acknowledge certain drawbacks associated with the application of fuzzy cognitive modelling. FCM analysis cannot serve as a substitute for statistical techniques, and in some instances, it may be insufficient in providing accurate estimations of real-value parameters and conducting inferential statistical tests.

The dynamic analysis of FCM offers a powerful approach for examining the complex causal mechanisms between financial and public sector developments through the lens of trust concepts. FCM enables the modelling and simulation of dynamic relationships, allowing researchers to explore the intricate interplay between these key elements over time. By incorporating the dynamic aspect, the analysis captures the evolving nature of trust and its impact on the financial and public sectors. This dynamic perspective provides a more comprehensive understanding of how changes in trust levels influence the interactions and outcomes within these sectors. Through the application of FCM, researchers can assess the long-term effects, feedback loops, and emergent behaviours that arise from the intricate relationships between trust, the financial sector, and government development. This approach enhances the ability to identify critical leverage points, potential vulnerabilities, and opportunities for policy interventions to promote trust and enhance the stability and performance of both sectors.

3. Conducting research and results

3.1. Fuzzy Delphi Method (FDM) application

To identify essential concepts for financial and governmental sector development in the context of trust among social-economic and behavioural variables gained from previous studies conducted by the authors and the literature review, a Fuzzy Delphi Method (FDM) was applied. The questionnaire was designed to gather experts' opinions. There is no common opinion in scientific literature regarding the number of experts required for the Fuzzy Delphi Method (Nozariet al., 2021). According to previous research, the number of experts to be involved in the Delphi survey could vary from at least seven to sixty professionals. It has been shown that to achieve valid and consistent judgements, it is not necessary to involve many experts. An increase in the size of a statistical sample by the addition of a greater number of experts who are limited in the field of expertise causes less accurate results.

For this study, 20 experts from the academic community (university researchers) and governmental authorities working with issues concerning the financial and public sectors were chosen. Experts were chosen according to their high-level academic education, background in financial and public sectors, professional skills and competencies, practical experience and knowledge of the subject being studied. The characteristics of the experts who answer for questionnaire are depicted in Table 2. For the academic community, the number of years of experience was determined from the first peer-reviewed publication in the respected field. For experts from government authorities, the number of years of experience was estimated from the moment they got a position.

Table 2. Characteristics of experts

	Characteristic	Percentage
Gender	Male	0.49
	Female	0.60
Academic qualification	Master	0.10
	Candidate of Sciences*	0.50
	Doctor of Sciences**	0.40
Affiliation	Academia	0.50
	Government authority	0.50
Experience (number of years)	More than 10 years	0.55
	Between 5 and 7 years	0.25
	Less than 5 years	0.20

** Candidate of Sciences According to the International Standard Classification of Education (ISCED) 2011, Candidate of Sciences belongs to ISCED level 8 – "doctoral or equivalent", together with PhD, DPhil, D.Lit, Doctorate or similar. Candidate of Sciences allows its holders to reach the level of the Associate Professor.*
*** Doctor of Sciences is the degree higher than Ph.D. and similar to the equivalent habilitation degree in Poland, Germany and Austria. Candidate of Sciences allows its holders to reach the level of the Professor*

Source: *own compilation*

A judgmental sampling method was applied to gather the opinions of experts. For this purpose, the questionnaire was developed to identify essential concepts and the cause-effect relationships among concepts.

To identify the cause-effect relationships among essential components of FCM, participants were asked to rate how one research variable affects another. A sample questionnaire question is provided below.

Trust in government has	(1) no (2) positive/ negative	(2.1) very low (2.2) low (2.3) medium (2.4) high (2.5) very high	effect on amount of **government bonds purchased**

To identify the most essential components of FCM, participants were asked to rate concepts (high important, important, moderate, not important, without any importance) for financial and governmental sector development in the context of trust among social-economic and behavioural variables gained from previous studies conducted by the authors and the literature review. Based on the methodology and research plan described, the linguistic variables identified in Table 1 were applied in this study. The selection of essential concepts for financial and governmental sector development in the context of trust among social-economic and behavioural variables was made by comparing the final weight of each research variable with the threshold value considered in this study. As a result of the Fuzzy Delphi Method (FDM) application 21 of the 33 original concepts were selected (Table 3) based on a threshold value equal to 0.73.

Table 3. The result of Fuzzy Delphi Method (FDM) application

Concept	Crisp value	A/R
Trust in the financial system	0.938	Accept
Central bank policy	0.919	Accept
Stability of the financial system	0.837	Accept
Deposits volume	0.856	Accept
Exchange rate stability	0.919	Accept
Amount of non-performing loans	0.713	Accept
Number of contracts on voluntary insurance	0.589	Reject
Investments in gold	0.249	Reject
Investments in pension funds	0.274	Reject
Investments in Institutes of Joint Investments	0.274	Reject
Number of failed banks	0.499	Reject
Destructive media	0.888	Accept
Trust in government	0.863	Accept
Fiscal stability	0.881	Accept
Tax revenues	0.869	Accept
Government policy	0.925	Accept
Government bonds purchased	0.794	Accept
Lack of payment discipline	0.742	Accept
Revenue from central government activities	0.364	Reject
Regulatory charges and license fees	0.165	Reject
Financial literacy	0.919	Accept
Perceived economic inequality	0.794	Accept
Corruption perception	0.844	Accept
Level of social tension	0.881	Accept
Panic proneness	0.818	Accept
Positive previous experience	0.838	Accept
Failure in service delivering	0.730	Accept
Time saving spent on service delivery	0.692	Accept
Deposit Guarantee System efficiency	0.499	Reject
Unemployment level	0.364	Reject
Risk aversion	0.230	Reject
Uncertainty	0.563	Reject
Crime rate	0.499	Reject

Source: *own compilation*

Following the same procedure, the final weight of each research variable was compared to the threshold value of 0.677 after defuzzification of each fuzzy number. As a result of the application of the Fuzzy Delphi Method (FDM), 21 essential concepts for the development of the financial and governmental sectors, in the context of trust among socio-economic and behavioural variables, were recognized and incorporated into the cognitive model. Among the 21 accepted concepts, the level of social tension (IN4), followed by corruption perception (IN2), emerged as the most important concepts of trust in the government. Additionally, financial literacy (AT1), panic proneness (IN3), and positive previous experience (AT2) were also ranked among the top three important concepts of trust in the financial system.

3.2. Fuzzy Cognitive Modelling (FCM) application and analysis

3.2.1. Steady-state analysis

Figure 3 represents the system that is being modelled as a cognitive map in sign-oriented graphic language by adding the most important behavioural concepts and indicators of financial sector and government development (dynamic elements) and establishing cause-effect interconnections. The graphical representation of cause-effect relationships according to the weights of the directed edges was transferred into matrix form (Appendix A) using crisp values obtained from aggregated expert opinions. Each number in the table represents the cause-effect relationship and is used for analysis of the power and direction of the impact of row variables on column variables.

As shown in Figure 3, some of the concepts represented by the nodes in the cognitive map have arrows ranging only from these to other concepts. No arrows are inserted in these nodes; therefore, these concepts are not affected by other concepts. In total, the cognitive map consists of ten driving concepts. Since all concepts influence at least one other concept, the cognitive map does not incorporate any receiver node. Other eleven components of the cognitive map are ordinary concepts, that are both influenced by and influence on others. According to figures 2-3, 21 research concepts constitute 56 connections (the cause-effect relationship). The density of the cognitive map is 0.133, which indicates the existence of different cause-effect relationships that can catalyse changes in macroeconomic stability. Moreover, the connection by component is equal to 2.667.

Figure 4 describes the input, output and centrality degree of each of the cognitive map concepts. According to Figure 4 trust in the financial system (TFS) and trust in government (TG) have the highest indegree among other concepts. These concepts of the system are the most influenced by other behavioural concepts and indicators of financial sector and government development. Also, the stability of the financial system (S1) and fiscal stability (S2) have the highest indegree that denotes the cumulative strength of the concepts coming into these concepts. Ten concepts are not affected by other concepts of the system, that affirmed by have zero indegree. Based on the level of outdegree, Government policy (P2), Central bank policy (P1) and trust in the financial system (TFS) have the highest influence on other system concepts. These concepts are followed by trust in government (TG) and exchange rate stability (FSD3) that indicated by the cumulative strength of the connections coming out of these concepts. The degree of centrality demonstrates that trust in the financial system (TFS) and trust in government (TG) have the greatest importance in the cause-effect relationship within the system. Besides these concepts, the stability of the financial system (S1), fiscal stability (S2) and exchange rate stability (FSD3) have numerous interactions within a cognitive map.

To identify the relevant behavioural concepts and indicators of the financial sector and government development that should be taking into consideration by policymakers and decision-makers to formulate sound financial and budgetary policies that promote macroeconomic stability and sustainable development Figure 5 was drawn. Figure 5 has been drawn with respect to the input and output degrees of a whole set of concepts. While Figures B1 and B2 (Appendix B) have been developed according to the input and output degrees of two distinct sets of decision variables which separately influence the development of monetary and fiscal policies.

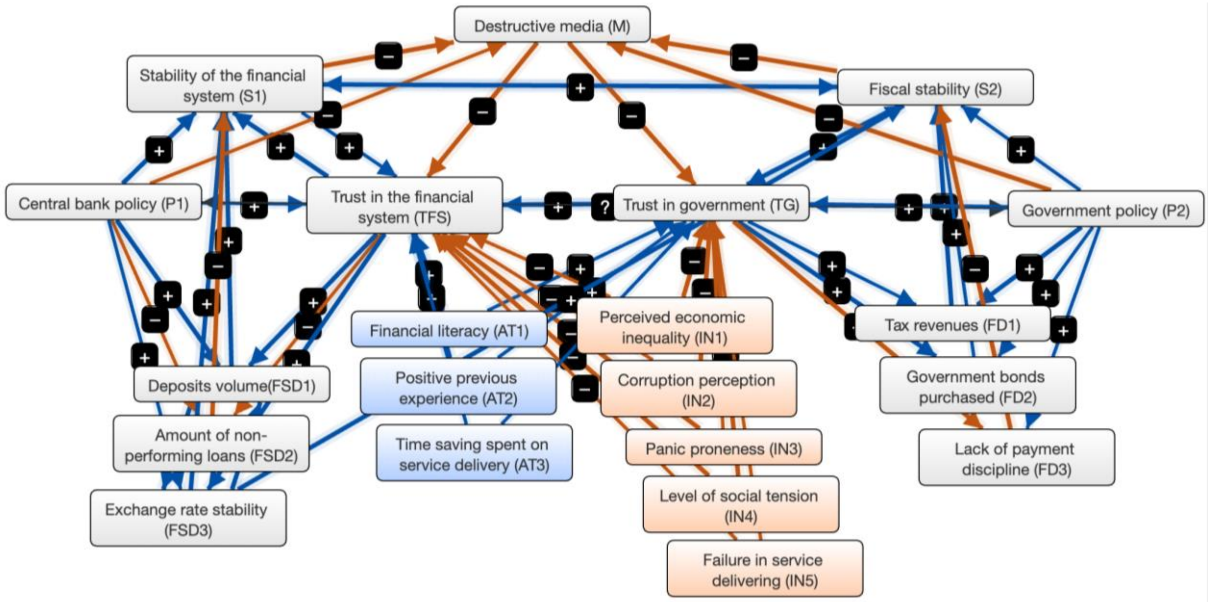

Figure 3. Fuzzy cognitive map of cause-effect relationships
Source: *own compilation*

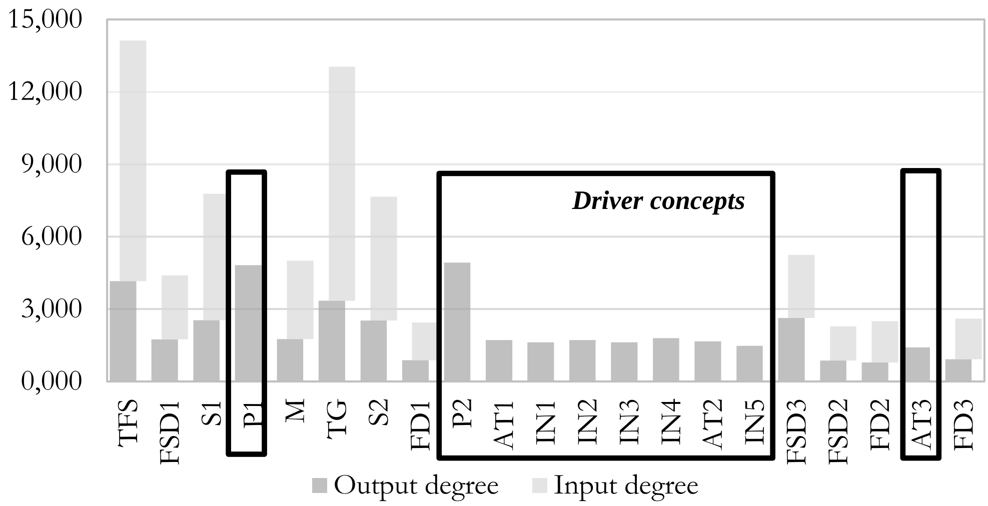

Figure 4. Concept metrics
Source: *own compilation*

Concepts are considered crucial in understanding the behaviour of socio-economic systems as they exert strong influences on macroeconomic stability through cause-effect interrelations. Consequently, when developing policies, it is important to consider concepts that are significantly impacted by other concepts. These highly affected concepts can complicate the transmission mechanism of policymaking. In Figure 5, the axes have been constructed based on the minimum and maximum values of the output and input degrees of all variables. Trust in the financial system (TFS) has the highest indegree, which is 9.89, placing it at the highest point on the X axis. Government policy (P2) has the highest outdegree, which is 4.93, determining its position at the highest point on the Y axis. In Figure 5, all concepts have been divided into four clusters (I-IV) based on the level of input and output degrees.

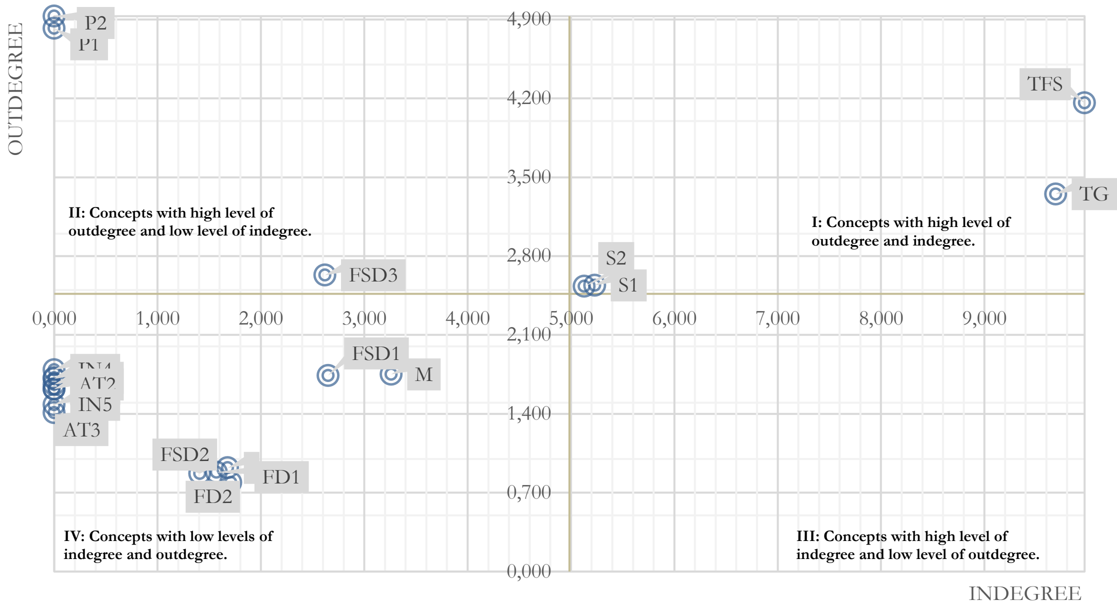

Figure 5. Concepts clustering
Source: *own compilation*

The first cluster (I) consists of trust concepts, specifically trust in the financial system (TFS) and trust in government (TG), as well as stability concepts, including stability of the financial system (S1) and fiscal stability (S2). These concepts exhibit high levels of influence both within and outside the cluster, making them crucial for the development of the financial and governmental sectors, as well as other socio-economic factors. However, their high indegree indicates that they are complex and challenging to handle.

The second cluster (II) comprises concepts with a high level of outdegree and a low level of indegree. These concepts, namely government policy (P2), central bank policy (P1), and exchange rate stability (FSD3), demand special attention due to their significant potential for improving the socio-economic system and enhancing macroeconomic stability. Their high outdegree suggests that effectively managing these concepts can have substantial positive impacts on macroeconomic stability.

In contrast, the third cluster (III) consists of concepts with a high level of indegree and a low level of outdegree. These concepts are heavily influenced by other factors, making them challenging to manipulate and control. Consequently, they have limited effects on macroeconomic stability. None of the cognitive map concepts fit into this cluster, indicating that the examined concepts do not fall into this category.

The fourth cluster (IV) comprises concepts with low levels of both indegree and outdegree. While these concepts are relatively easy to manage and control, they have minimal impact on macroeconomic stability. Examples of concepts within this cluster include financial literacy (AT1), positive previous experience (AT2), timesaving spent on service delivery (AT3), and failure in service delivery (IN5), among others.

Understanding the distribution of concepts across these clusters provides valuable insights for policymakers and researchers. It highlights the critical role of trust, stability, and key policy areas in driving macroeconomic stability. Moreover, it underscores the need to prioritize and allocate resources effectively, focusing on concepts within clusters I and II to achieve desired improvements in the socio-economic system and ensure long-term macroeconomic stability.

3.2.2. Dynamic analysis

In contrast to other domains, conducting experiments on an entire country's economy is not feasible. Therefore, simulation modelling serves as a valuable tool for exploring hypothetical "what-if" scenarios. The dynamic analysis of Fuzzy Cognitive Mapping (FCM) allows for the examination of how the socio-economic system would behave under different conditions of trust crisis risks in the financial system and government. These simulations enable the implementation of various scenarios for the functioning and development of the financial sector and public authorities, considering different levels of trust crisis risks. Consequently, they provide an opportunity for scenario planning and the development of diverse policy options prior to implementing macroeconomic intervention strategies.

The baseline scenario is represented by the steady state of the socio-economic system, as described in Figure 2 and Appendix A. In comparison to this steady state, simulations have been conducted to stimulate trust concepts both individually and in their synergistic interaction. In all simulations, impulses of different strengths were given to the concepts of trust in the financial system (TFS) and trust in government (TG). Specifically, a value of -0.25 was assigned to indicate an erosion of trust, -0.50 represented a shortage of trust, -0.75 denoted a trust crisis, and the worst-case scenario was assigned a value of -1, indicating a widespread distrust of the entire society towards the financial system and/or government. It should be noted that violations of synergies between trust in the financial system and trust in government do not simply equate to the sum of separate trust shifts on other concepts within the socio-economic system.

The utilization of simulation modelling and the consideration of various trust crisis risk scenarios provide valuable insights into the potential outcomes and impacts of trust dynamics on the socio-economic system. By examining the interconnectedness of trust, the financial sector, and government, policymakers and stakeholders can gain a deeper understanding of the complex relationships and make informed decisions to foster macroeconomic stability and address trust-related challenges.

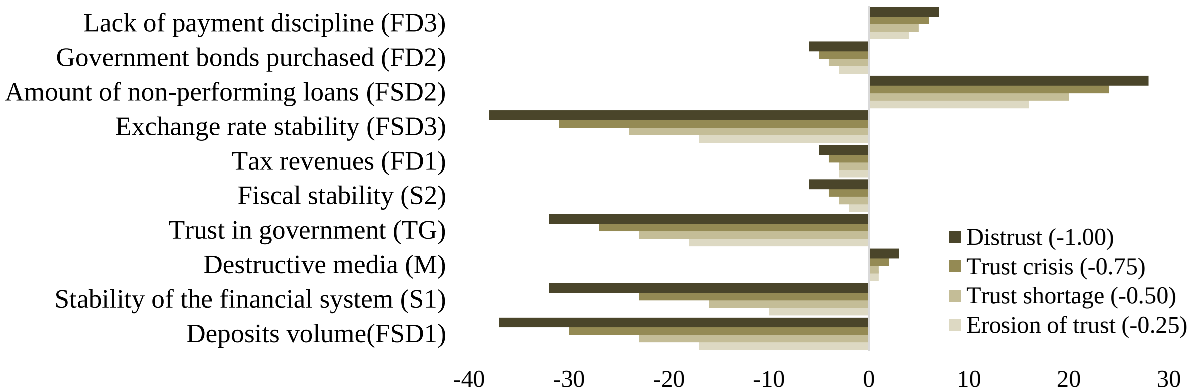

Figure 6. The effect of trust violations in the financial sector to other concepts of the system
Source: *own compilation*

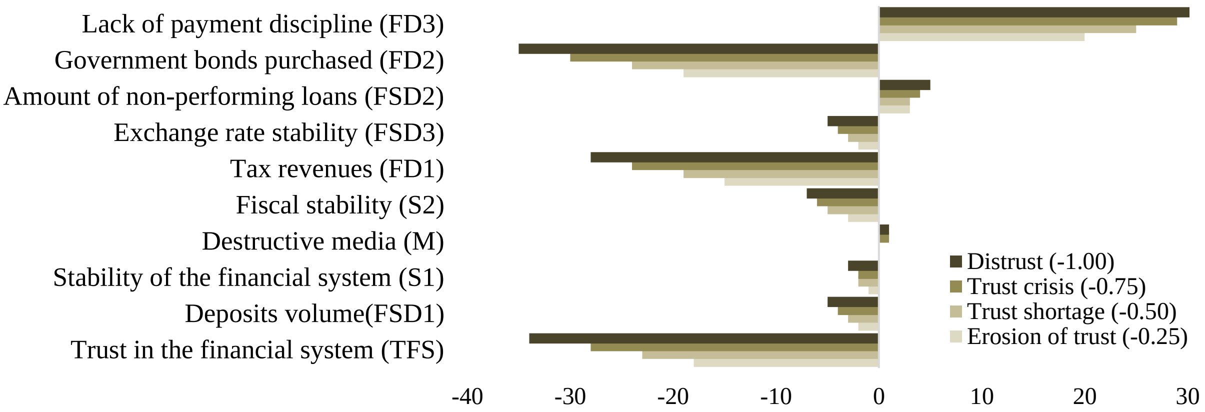

Figure 7. The effect of trust violations in government to other concepts of the system
Source: *own compilation*

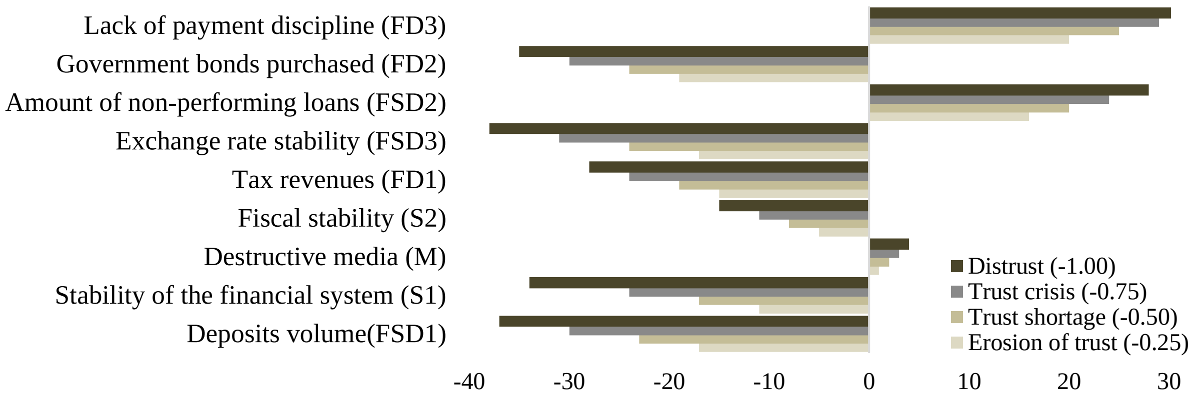

Figure 8. The effect of trust violations in the financial sector and government to other concepts of the system
Source: *own compilation*

Based on the findings presented in Figures 6 to 8, the fragility of the socio-economic model becomes evident when trust in the financial sector is violated. Specifically, when the initial value of trust in the financial sector (see Figure 6) is set at -0.25, representing an erosion of trust, the stability of the financial system (S1) deteriorates by 10%. Additionally, there is a simultaneous decline of 17% in deposit volumes (FSD1) and exchange rate stability (FSD3), while the amount of non-performing loans (FSD2) increases by 16%. It is important to note that the intensity of the trust crisis risks in the financial sector also impacts the development of the public sector. Consequently, the violation of trust in the financial sector results in a decrease of 18% in trust towards the government (TG), accompanied by slight deteriorations in fiscal stability (S2) by 2%, tax revenues (FD1) by 3%, and government bonds purchased (FD2) by 3%. Furthermore, there is an increase in the lack of payment discipline (FD3) by 4%.

In the worst-case scenario of complete distrust, when the initial value of trust in the financial sector is set at -1.00, the stability of the financial sector collapses by 32%. This catastrophic event led to a dramatic reduction in deposit volumes (by 37%) and exchange rate stability (by 38%), while the amount of non-performing loans (FSD2) continues to climb by 16%. The distrust towards the financial system also has a substantial impact on trust in the government, causing a decline of 32% in public trust. However, the subsequent changes in the public sector development concepts were not as significant, with impacts ranging from 3% to 7%.

When examining the impact of trust in government within the socio-economic model, it becomes apparent that certain aspects of financial system development are less affected (see

Figure 7). Specifically, deviations from the initial steady state are observed in various indicators, ranging from -1% (erosion of trust) to -5% (distrust). The stability of the financial system (S1), exchange rate stability (FSD3), and deposits volume (FSD1) experience deviations due to fluctuations in trust in government. Additionally, the initial impulses towards trust in government result in deviations in the amount of non-performing loans (FSD2) ranging from 3% (erosion of trust) to 5% (distrust). However, indicators such as tax revenues (FD1), government bonds purchased (FD2), lack of payment discipline (FD3), and trust in the financial system (TFS) are significantly more affected by a breach of trust in the national government. These concepts suffer notable losses, ranging from -15% to -35%, depending on the trust crisis risks scenario. It is worth noting that lack of payment discipline (FD3) exhibits a particularly worrisome trend, as it can be worsened by 20% (erosion of trust), 25% (trust shortage), 29% (trust crisis), or even 34% (distrust). This indicates the strong impact of trust dynamics on payment discipline within the socio-economic system.

The simultaneous violation of trust in both the financial system and the government leads to complications and negative consequences for the functioning and development of these sectors (see Figure 8). The impact of trust crisis risks can be observed in various indicators related to the financial sector and public authorities. For instance, government bonds purchased (FD2), exchange rate stability (FSD3), and deposit volume (FSD1) are particularly affected. The data reveals that the decline in these concepts ranges from 17 to 20% in cases of eroded trust, and from 34 to 38% in cases of distrust. These findings highlight the significant detrimental effects caused by a lack of trust. Notably, one striking observation that emerges from the data comparison, as depicted in Figure 8, is the relative resistance of fiscal stability (S2) to trust violations. Despite the erosion of trust or the presence of distrust, fiscal stability appears to exhibit a certain level of resilience. This finding suggests that fiscal stability may be influenced by factors beyond trust alone, indicating the presence of other contributing elements that help maintain its relative stability even in times of trust crises.

4. Discussion

The empirical findings of this study contribute to the understanding of the role of trust in the socio-economic system, specifically in the context of the financial and public sectors. The study introduces a comprehensive framework that explores the complex causal mechanism between financial and public sector developments through trust concepts. By employing the Fuzzy Delphi Method (FDM) to identify valid attributes of trust and utilizing Fuzzy Cognitive Mapping (FCM) to establish causal relationships, the study provides valuable insights into the interplay between trust, financial sector, and government development in socio-economic systems.

The study highlights the importance of trust in the financial system and trust in government as key drivers of macroeconomic stability. It reveals that erosion or violation of trust in these areas can have significant negative consequences for various indicators of the socio-economic system. Consistent with the literature (Feeney, 2010; Guiso, 2010; Bachmann et al., 2011; Van der Cruijsen et al., 2016 among others), this research found that a decrease in trust in the financial system leads to a deterioration of the stability of the financial system, reduced deposit volumes, and increased non-performing loans. Similarly, a decline in trust in government results in decreased fiscal stability, tax revenues, and government bond purchases. These results match those observed in earlier studies (Levi & Stoker, 2000; Torgler et al., 2011; Elgin & Garcia, 2011 among others).

One significant contribution of this research is the utilization of the Fuzzy Delphi Method (FDM) to identify valid attributes of trust, financial sector, and government development. This approach enhances the robustness of the study by incorporating expert opinions and ensuring the inclusion of relevant variables. By employing Fuzzy Cognitive Mapping (FCM), the study establishes convergent causal relationships among behavioural concepts and indicators of financial sector and government development, specifically in terms of macroeconomic stability. This analysis goes beyond previous studies that often examine trust in the financial system and trust in government separately, providing a comprehensive examination of the interconnectedness of these concepts.

The findings emphasize the interconnectedness of trust, the financial sector, and government. Trust dynamics in one area can have ripple effects on the other, highlighting the need for a holistic approach to understanding and addressing trust-related challenges. Policymakers and decision-makers should consider the complex relationships between trust, stability, and key policy areas when formulating financial and budgetary policies. Based on the level of in and outdegree, the study suggests that when developing policies, it is essential to consider concepts that are strongly influenced by other concepts. These highly affected concepts can complicate the transmission mechanism of policymaking.

The simulation modelling approach adopted in this study proves to be a valuable tool for examining hypothetical scenarios and conducting dynamic analyses. Conducting experiments on an entire country's economy is not feasible, making simulation modelling an effective alternative. This approach provides a proactive approach to addressing potential trust-related issues, enhancing the resilience of the socio-economic system.

The findings from the simulation modelling provide valuable insights into the fragility of the socio-economic model when trust in the financial sector is violated. The results demonstrate that even an erosion of trust can lead to significant negative impacts on the stability of the financial system, deposit volumes, exchange rate stability, and non-performing loans. Furthermore, the violation of trust in the financial sector also affects the development of the public sector, leading to a decline in trust towards the government, fiscal stability, tax revenues, and government bonds purchased. These findings emphasize the interconnectedness of trust dynamics in both sectors and the need for a holistic approach in addressing trust-related challenges. Similarly, trust violations in the government also have significant repercussions on the socio-economic system. When both the financial sector and government experience trust violations simultaneously, the complications and negative consequences are magnified. These findings underscore the importance of building and maintaining trust in both sectors to mitigate adverse impacts on the socio-economic system.

Conclusion

This paper has sought to make significant contributions to the understanding of the role of trust in the socio-economic system and provide a comprehensive framework for analysing the intricate causal mechanism between financial and public sector developments through trust concepts. The added value of this research compared with existing studies is three-fold.

Firstly, this research utilizes the Fuzzy Delphi Method (FDM) to identify valid attributes of trust, financial sector, and government development. By employing qualitative information, this method helps recognize essential concepts related to trust within social-economic and behavioural variables in the context of financial and governmental sector development.

Secondly, the research implements Fuzzy Cognitive Mapping (FCM) to establish convergent causal relationships among a set of behavioural concepts and indicators of financial sector and government development in terms of macroeconomic stability. While existing literature separately discusses the role of trust in the financial system and trust in government, this research seeks to analyse the interrelationship between these concepts, which has not been explored extensively before.

Thirdly, the research simulates different macroeconomic stability scenarios based on the patterns of multi-channel cross-sectoral and multi-level diffusion of behavioural impulses associated with changes in the level of public trust in public institutions and the financial sector. By examining the simulated scenarios, this study offers insights into the potential effects of trust fluctuations on various sectors and levels within the economy.

There are, however, some shortcomings to this study, which should be considered. First, the findings and conclusions of this study may have limited generalizability due to the specific context and scope of the research. The study's focus on a particular set of behavioural concepts and indicators may not capture the full complexity and diversity of trust, financial sector, and government development across different regions or countries. Second, while Fuzzy Cognitive Mapping (FCM) is a useful technique to represent causal relationships, but it may overlook nuances or nonlinear dynamics that exist within the relationships between behavioural concepts, indicators, and macroeconomic stability. In addition, the study is based on the available data and research up until the time of its completion. However, economic and political dynamics can evolve, and new developments may influence the relationships and conclusions presented in the study.

Further research work is recommended to overcome the limitations of the current study and deepen our understanding of the relationships between trust, the financial sector, and government development. This can be achieved through replication and extension studies in different contexts, adopting a mixed-methods approach to combine qualitative and quantitative data, conducting longitudinal analyses to capture dynamic changes over time, and comparing different countries or regions to identify contextual factors and policy lessons. Additionally, exploring multi-level dynamics, incorporating additional variables such as cultural dimensions and technological advancements, conducting experimental studies, and fostering cross-disciplinary collaborations would provide valuable insights into the complex interactions and mechanisms at play.

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Annex A. Matrix representation of cognitive model

	TFC	FCD1	S1	P1	M	TG	S2	FD1	P2	AT1	IN1	IN2	IN3	IN4	AT2	IN5	FCD3	FCD2	FD2	AT3	FD3	SUM
TFC		0,89	0,94			0,73											0,91	-0,69				2,780
FCD1			0,84														0,9					1,740
S1	0,82				-0,84		0,88															0,860
P1	0,83	0,86	0,88		-0,72				0								0,81	-0,72				1,940
M	-0,89					-0,86																1,750
TG	0,84							0,71											0,9		-0,9	1,550
S2			0,83		-0,86	0,84																0,810
FD1							0,88															0,880
P2					-0,84	0,84	0,8	0,86											0,81		0,78	3,250
AT1	0,93					0,79																1,720
IN1	-0,74					-0,88																1,620
IN2	-0,79					-0,92																1,710
IN3	-0,91					-0,71																1,620
IN4	-0,85					-0,94																1,790
AT2	0,91					0,75																1,660
IN5	-0,72					-0,76																1,480
FCD3		0,9	0,87				0,86															2,630
FCD2			-0,87																			0,870
FD2							0,79															0,790
AT3	0,74					0,67																1,410
FD3							-0,92															0,920
SUM	0,170	2,650	3,490	0,000	3,260	0,450	3,290	1,570	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	2,620	1,410	1,710	0,000	0,120	

Source: *own compilation*

Annex B. Concepts clustering

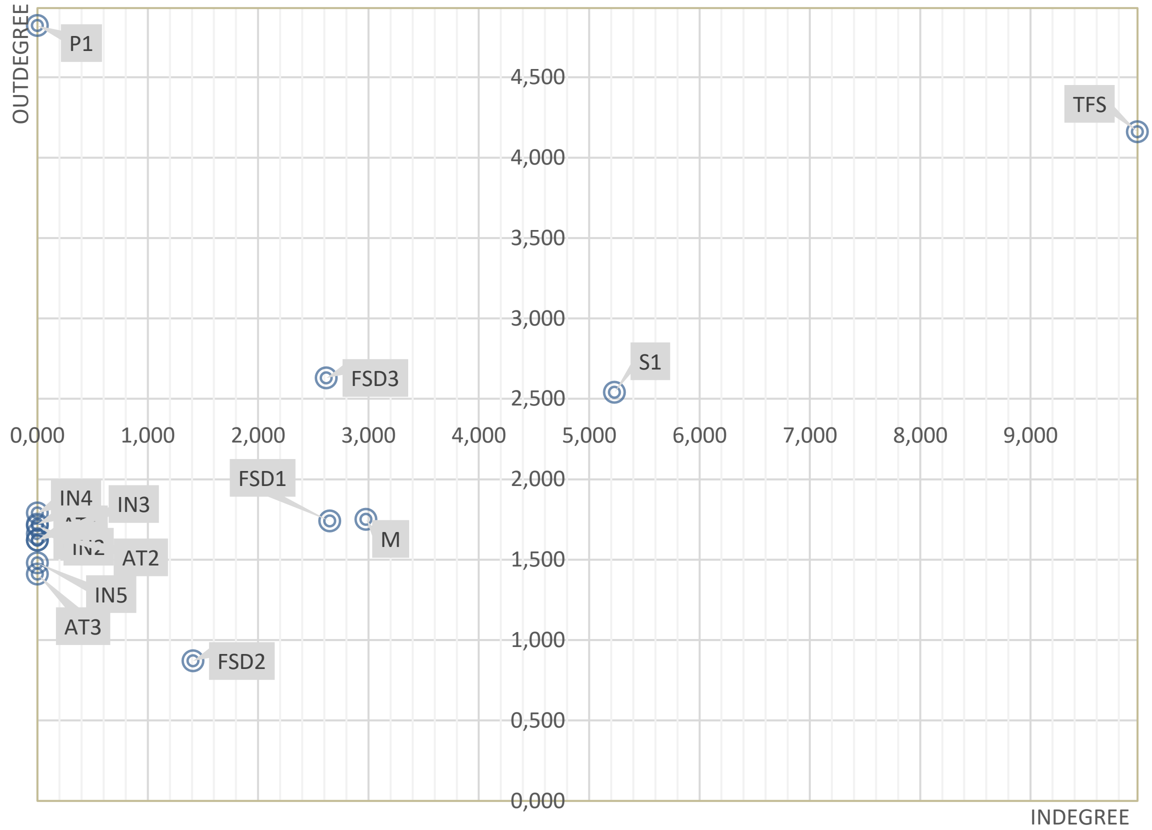

Figure B1. For monetary policymakers.
Source: *own compilation*

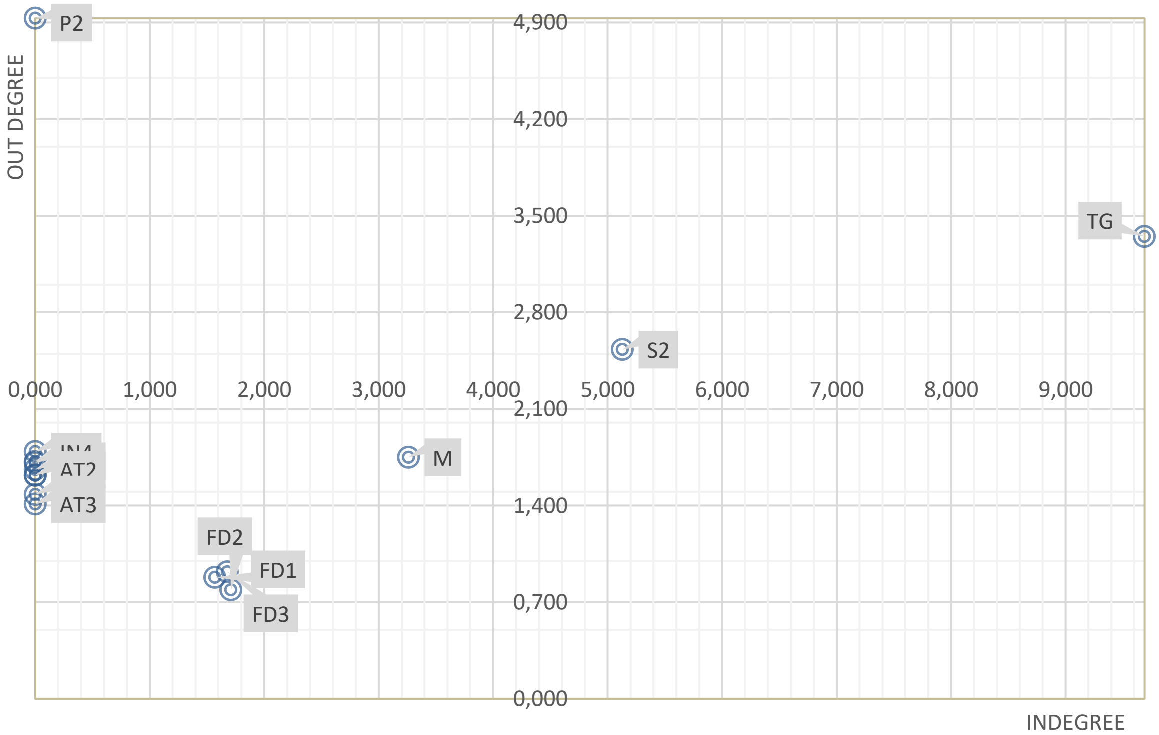

Figure B2. For fiscal policy-makers
Source: *own compilation*