Revista Electrónica de Comunicaciones y Trabajos de ASEPUMA. **Rect@**
Volumen 25(2024). Páginas 37 a 65
DOI:

CITIZEN PROFILES BASED ON SOCIAL CAPITAL IN THE SPANISH FISCAL CONTEXT: PROFILE DEVELOPMENT AND MULTIVARIATE CONSISTENCY ANALYSIS

FRANCISCO RABADÁN PÉREZ

francisco.rabadan@urjc.es
Universidad Rey Juan Carlos, Departamento Economía Aplicada I e Historia e Instituciones Económicas
Pº de los Artilleros 38, 28032 Madrid. Spain

MARÍA VICTORIA RAMÍREZ-MUÑOZ

mramirezñuco.fr
Université d'Angers et Université Catholique de l'Ouest, Faculté DEGS
3 place André Leroy, | BP 10808 49008 Angers cedex 01, France

Recibido (30/04/2024)
Revisado (23/06/2024)
Aceptado (11/07/2024)

RESUMEN: Estudios previos han establecido que el capital social desempeña un papel significativo en los comportamientos individuales relacionados con los impuestos, incluyendo las inclinaciones hacia la evasión fiscal y el cumplimiento tributario. Este estudio busca ampliar la comprensión de la moral fiscal en España utilizando datos de la Encuesta de Opinión Pública y Política Fiscal (CIS, Estudio 3332). Utilizamos el análisis factorial con extracción de máxima verosimilitud y rotación Varimax para identificar variables clave de capital social y actitudes fiscales. Mediante análisis de conglomerados, identificamos perfiles en base a su capital social y cumplimiento tributario. Aplicaremos el clúster jerárquico con encadenamiento de Ward y el clúster de k medias. La robustez de los perfiles resultantes se confirmará mediante análisis discriminante y red neuronal perceptrón multicapa, buscando mayores tasas de clasificación correcta como indicador de mejora en la consistencia de los perfiles. Nuestros hallazgos sugieren que la identificación de perfiles de ciudadanos fiscales españoles es útil para el análisis del capital social en la política fiscal. Concluimos que un aumento en la acumulación de variables de capital social mejora colectivamente la adherencia fiscal.

Palabras Clave: capital social, evasión fiscal, presión fiscal, análisis factorial, clúster, consistencia de perfiles.

ABSTRACT: Previous studies have established that social capital plays a significant role in individual tax-related behaviors, including inclinations toward tax evasion and compliance. This study seeks to extend the understanding of tax morale in Spain using data from the Public Opinion and Fiscal Policy Survey (CIS, Study 3332). We use factor analysis with maximum likelihood extraction and Varimax rotation to identify key social capital variables and tax attitudes. We identify profiles based on their social capital and tax compliance using cluster analysis. We will apply hierarchical clustering with Ward's chaining and k-means clustering. The robustness of the resulting profiles will be confirmed by discriminant analysis and a multilayer perceptron neural network, which will look for higher rates of correct classification as an indicator of improved profile consistency. Our findings suggest that identifying Spanish tax citizens' profiles helps analyze social capital in tax policy. After our analysis, we have determined that enhancing the accumulation of social capital variables leads to better tax adherence.

Keywords: social capital, tax evasion, tax burden, factor analysis, cluster analysis, profile consistency.

1. Introduction

Fiscal policy plays a significant role in shaping the socio-economic fabric of a country, impacting areas such as public investment, income distribution, and overall economic stability (de Castro, 2006). Understanding public opinion on fiscal policy is crucial for establishing effective tax systems that promote compliance and social trust (Jimenez & Iyer, 2016). In the case of Spain, ensuring tax compliance is essential for maintaining public services (Núnez-Barriopedro et al., 2023) and infrastructure (Almunia & Lopez Rodriguez, 2014; Cantero-Galiano, 2022; Enciso de Yzaguirre, 2006).

Research has shown that cultural differences and attitudes towards taxation can influence tax morale, which in turn affects tax compliance (Cummings et al., 2009). Factors such as values, social norms, and attitudes vary across countries and can have measurable effects on economic behavior. Additionally, government governance and the effectiveness of information technology can also impact taxpayers' compliance with tax regulations (Torgler & Schneider, 2004).

Furthermore, economic factors can also influence political attitudes and movements. Economic decline, for example, has been found to provoke secessionist sentiments, with the belief that an independent state could handle economic policy better (Alm & Torgler, 2006).

From taxpayers' perspective, the perception of tax obligations can significantly vary based on numerous factors, including economic circumstances, social values, understanding of fiscal policies, and overall trust in government (Alm & Torgler, 2006). Taxpayers might view their tax obligations as a collective responsibility to support public utilities, infrastructure, and essential societal functions such as education, healthcare, and public security. However, some may face the perceived inequity in tax systems, feeling disproportionately burdened, or others are not paying their fair share.

Even though tax evasion is generally associated with developing economies, it remains a significant threat to the Organization for Economic Cooperation and Development countries "OECD" (Kemme et al., 2017). For instance, large corporations and wealthy individuals may exploit intricate tax loopholes, engage in aggressive tax planning, or use offshore tax havens to minimize their tax liabilities, constituting a form of tax evasion (Kemme et al., 2017; Maffini, 2009; Zucman, 2014). This results in a significant loss of revenue for the State and can create socio-economic inequality and undermine public trust in tax systems. Thus, tax evasion poses a danger to economies at all levels of development, including those within the OECD.

Previous studies suggest that social capital significantly shapes tax compliance behaviors (Bobek et al., 2007; Jimenez & Iyer, 2016). Nonetheless, a research gap exists when exploring specific social commitments, including tax compliance and various fiscal behaviors. This research will help identify groups of individuals who share similar profiles regarding individualized trust, individual expectations about social relationships, and the accessibility of opportunities for social mobility within the population. Other aspects, such as personal happiness and quality of life, will also be considered.

Based on the Public Opinion and Fiscal Policy Survey data (CIS, Study 3332) from 2022. We perform three statistical methods: Maximum likelihood factor analysis (MLFA), clustering (hierarchical and k-means), and supervised classification techniques like linear discriminant analysis (LDA) and multilayer perceptron neural network (MLP). Despite the difficulties associated with implementing neural networks in social science research, they have demonstrated their utility in predicting economic phenomena (González et al., 2000; Herbrich et al., 1999; Pukelis & Stančiauskas, 2019). Our study encompassed a range of factors, including attitudes towards tax evasion, happiness levels, perceptions of public services, social elevator positions, and taxation pressures (Alvarez-Garcia et al., 2024).

In addition, the study delves into personal attributes such as confidence and reliance on others to gain a deeper comprehension of social capital's function.

Citizens' profiles can be significantly influenced by various and complex cultural, economic, social, and employment conditions that shape distinct characteristics. This is evident in Spain, where regional differences can lead to variations in how these profiles interact with the fiscal system and access to social capital.

There are alternative ways of defining economic actors that are not based on preconceived notions, as explained by Rabadán Pérez (2009, 2015). This approach involves identifying characteristics shared by a group of actors, which sets them apart from others. This theory is particularly relevant when studying social capital, as it can help better understand the dynamics of networking and trust building. In this particular research, study participants identified themselves using this approach.

There are ways of defining economic actors in a non-aprioristic way, that is, by the characteristics they have in common and that differentiate them from other actors. This research is particularly interesting from a social capital perspective, helping to understand networking and trust flows. Citizens self-identify with this methodology.

Individuals in different socio-economic positions and cultural contexts may have varied perspectives on tax evasion. Their attitudes toward evading taxes can be influenced by societal roles, economic status, and adherence to specific cultural norms (Brink & Porcano, 2016; Jimenez & Iyer, 2016). Similarly, people's beliefs can influence how they perceive tax fairness and the value of public services. This impact can affect their willingness to participate in tax evasion and their overall sense of wellbeing. These factors also affect whether they engage in tax evasion activities and how they view their general wellbeing.

The following sections of this study will analyze empirical research, focusing on tax compliance and socio-economic satisfaction from the social capital perspective. Usually, the actors are predefined, but there is no empirical evidence of how citizens' profiles work, and the idea is to see if the variables of social capital affect and how and if there are profiles of citizens that can be defined based on social capital.

The paper is organized in the following manner: The first section presents a comprehensive review of pertinent literature. The subsequent section describes the methodology deployed and explains the selection of the sample population. The third section presents the findings from the empirical analysis. The final section highlights key takeaways from the paper and discusses any limitations encountered in the research process.

2. Exploring the Nexus Between Tax Evasion, Tax Compliance, and Social Capital

Tax evasion and tax compliance are two different approaches to handling taxes. Tax evasion involves illegal actions aimed at reducing one's tax liabilities, while tax compliance ensures that the fiscal system of a country functions smoothly. However, the decision to evade or comply with tax laws isn't solely determined by individual characteristics and situational factors but by diverse social aspects as well, and this is where social capital comes in (Alm et al., 2011; Bobek et al., 2013; Christoforou, 2011; Jimenez & Iyer, 2016; Torgler & Schneider, 2009).

Previous research suggests that factors such as cultural impact, religiosity, social norms, trust in government, and social capital play a significant role in determining individual tax-related behaviors (Bobek et al., 2013; Jimenez & Iyer, 2016). Among these factors, attitudes toward government spending and the tax system are particularly influential (Akçomak & Weel, 2007; Batinti et al., 2019; Knack, 1999). Additionally, regional differences have been observed in attitudes towards cheating on tax payments, with higher corporate tax avoidance seen in countries with stronger institutional characteristics like investor protection and disclosure requirements (Atwood et al., 2012; Lin et al., 2017).

Social capital refers to societal norms, networks, and trust promoting community collaboration (Christoforou, 2011; Fukuyama, 2001; Woolcock & Narayan, 2000). It is assumed to be an important deterrent against tax evasion and is associated with higher compliance rates. It affects tax compliance in two ways: indirectly, by affecting tax morale, and directly, by affecting voluntary compliance. (Alm & Gomez, 2008; Cummings et al., 2009). Social capital can foster a sense of civic duty and cooperation among individuals, leading to higher tax morale and a greater willingness to comply with tax laws voluntarily.

Moreover, social capital plays a crucial role in fostering accountability and social control (Bonatti & Lorenzetti, 2018; Nannicini et al., 2010). It encourages individuals to monitor and report tax evasion activities within their community, leading to higher levels of tax compliance and reduced prevalence of such practices. Furthermore, strong social capital enhances the effectiveness of enforcement mechanisms by promoting cooperation with tax authorities, accurate information sharing, and identification of tax evaders (Fukuyama, 2001).

The belief in the power of social capital to enhance tax morale is grounded in the understanding that individuals are more inclined to fulfill their tax obligations when they perceive trust, reciprocity, and effective cooperation within their community. Research by Alm and Gomez (2008) shows a positive correlation between an individual's tax morale in Spain and their belief in receiving benefits from public goods and services. In communities with a high level of trust in government, the court and the legal system positively affect tax morale among taxpayers and foster shared norms that discourage tax evasion (Torgler, 2003).

Tax morale thrives in communities where there is high trust in government institutions, courts, and legal systems, fostering collective norms that discourage tax evasion. Factors such as social norms, fairness, equality, trust in government, and tax authority play significant roles in shaping tax morale (P et al., 2017). Age, religion, gender, employment status, and educational level may enhance tax morale (Cascavilla et al., 2024; Ciziceno, 2024). Additionally, satisfaction with democracy governance, trust in government institutions, and contentment with the quality of public services also contribute to this enhancement (Daude et al., 2013).

Previous studies conducted by Chircop et al. (2018) and Gao et al. (2019) have revealed that organizations operating in areas with significant social capital are less inclined to participate in tax evasion practices, as they may perceive tax payments as acts of social responsibility. This highlights the importance of considering social capital elements when making fiscal decisions.

In addition, Wahl et al. (2010) conducted a study to investigate the impact of trust in authorities and their effectiveness in encouraging tax compliance. Their findings revealed a positive correlation between trust in authorities and tax payments, highlighting the significance of these factors in the realm of taxation. Similarly, Torgler and Schneider (2009) suggested that social capital, as depicted by individuals' willingness to contribute towards taxes voluntarily, can lead to cost reduction for governments while promoting an equitable distribution of these expenses.

In contrast, it is important to note that the dynamics can vary in different societies. These networks may facilitate tax evasion in less cooperative environments and ultimately undermine broader compliance efforts (Chang & Lai, 2004; Rothengatter, 2005).

Some studies suggest a positive correlation between social capital and the willingness to pay taxes, but other research challenges this assumption. Kondelaji et al. (2016) find that conditional cooperation and economic situation have the most significant effects on tax morale in Iran, while social capital variables like the importance of politics and religion do not significantly impact. Fostering norms against tax evasion cannot rely solely on community interactions, but requires strong enforcement mechanisms and institutional governance (Williams & Krasniqi, 2017). Therefore, relying solely on social capital to promote voluntary tax payment might overlook important factors contributing to overall tax compliance rates.

3. The Case of Spanish Population

Prior studies in Spain have examined the development of tax morale and its determinants, explicitly focusing on political and fiscal changes between 1981 and 1999/2000 (Martinez-Vazquez & Torgler, 2009). These changes have significantly influenced taxpayers' fiscal behavior. Llacer (2014) has used different data sources and suggests a correlation between the evolution of tax morale among wage earners in Catalonia and the observed trends in tax rates over time.

Llacer (2014) introduces the concept of "tax resentment" based on the results obtained. This concept considers taxpayers' various opportunities to evade taxes and addresses various emotional and adaptive aspects. The mechanism offers a more comprehensive explanation of tax morale than previous research in this field.

Tax morale in Spain has been extensively researched, considering sociological, behavioral, psychological, political, and socio-economic factors. The perception of social capital and the prevalence of tax fraud are also considered in these studies. Sá et al. (2017) compared tax morale influences in Portugal and Spain and highlighted the significance of sociological, behavioral, psychological, and political aspects on taxpayer behavior. Bilgin (2014), meanwhile, focused on determining factors affecting tax morale in

Turkey and Spain; social capital variables, demographic factors, and trust in political entities were found to be key factors for Turkey, whereas differences emerged for Spain's case.

María-Dolores et al. (2010) highlighted socio-economic variables such as age, gender, filing of income tax returns, and beliefs about immigrants' contributions as determinants of tax morale in Spain. Alm and Gomez (2008) also emphasized the role of social capital in this phenomenon. They concluded that perceptions of social benefits derived from public goods positively influenced tax morale, while perceived tax fraud decreased intrinsic motivation to pay taxes. Therefore, individual perceptions can be influenced by both social and economic factors.

Strengthening communities and creating support and collaboration networks are primarily supported by three categories of social capital: cognitive, relational, and structural (Nahapiet & Ghoshal, 1998). Some studies support the idea that social capital, encompassing cognitive, relational, and structural aspects, is crucial for strengthening communities and fostering collaboration networks in Spain. Díez-Vial and Montoro-Sanchez (2014) found that all three dimensions of social capital (structural, relational, and cognitive) contribute to improving knowledge exchange between organizations. Social capital encompasses a set of resources embedded in social networks (Valdaliso & Etxabe, 2016). It is worth noting that each of these dimensions can have different effects depending on the specific group of people to which they refer.

The cognitive aspect of social capital refers to the collective understanding, knowledge, and norms within a social network that impact resource accessibility and collaboration (Nahapiet & Ghoshal, 1998). In certain populations, this cognitive dimension can boost individual creativity (Oussi & Chtourou, 2020). It is especially relevant in industries reliant on extensive expertise where intellectual capital is crucial (Nahapiet & Ghoshal, 1998).

The structural aspect of social capital refers to the arrangement and interconnectedness within a social network, including both "strong" and "weak" ties (Nahapiet & Ghoshal, 1998). This factor directly impacts accessibility, underscoring the significance of promoting collaboration and interconnectedness (Granovetter, 1977). Hatala (2009) argues that having access to networks is essential for leveraging resources from social capital and attaining career progression. Meanwhile, Morales and Ramiro (2011) explore how social capital can facilitate the integration of communities with immigrant backgrounds. Such integration efforts have the potential to address deep-rooted poverty levels as well as geographical segregation. Lastly, Muñoz-Goy (2013) explores gender inequalities in social capital in Spain. The study reveals variations in access, utilization, and types of social networks, which are diminished for individuals from more privileged backgrounds. Fol and Gallez (2014) propose a broader understanding of access disparities beyond mere network connections. They emphasize the importance of considering socio-spatial factors and their implications for public policies.

The relational aspect of social capital focuses on the strength of connections, trust, and interpersonal interactions within particular communities (Nahapiet & Ghoshal, 1998). This dimension affects both trust levels and the creation of a shared vision (Prieto-Pastor et al., 2018). Piñeira Mantiñán et al. (2019) investigate new models of urban governance in Spain that emphasize collaborative and network-based approaches to addressing vulnerability. In the context of specific groups, such as young people experiencing urban challenges in medium-sized Spanish cities during the post-crisis period, this relational approach can offer assistance and essential resources to address difficulties and encourage collaboration (Piñeira-Mantiñán et al., 2018).

According to several studies, research findings suggest that various factors such as social connections, positive relationships, and support networks can significantly impact individual happiness (Fowler & Christakis, 2008; Majeed & Samreen, 2020; Mochón Morcillo & de Juan Díaz, 2016; Zhao et al., 2022). Sharing joy within social networks impacts mental health and underscores social capital's position in fostering happiness. Active participation in community activities, contributions through donations, and volunteer work have been found to positively affect overall happiness levels. Moreover, studies have also shown a strong link between high social capital levels and enhanced happiness, in particular under challenging circumstances (López-Ruiz et al., 2021; Maset-Llaudes & Fuertes Fuertes, 2015; Portela Maseda & Neira Gómez, 2012; Somarriba Arechavala et al., 2022).

Mutual trust among individuals and confidence in their abilities can motivate people to pursue educational and professional goals (Sanzo et al., 2012). This motivating factor can significantly improve their emotional wellbeing and strengthen their participation in social activities. Thus, the potential for economic benefits can be increased (Fredricks et al., 2004).

In a study by Vázquez et al. (2013), life satisfaction in a group of Spanish adults was examined. The study revealed that individuals with higher education and better jobs reported greater life satisfaction. Furthermore, the study found strong links between life satisfaction, subjective happiness, and social support, indicating that social support plays a significant role in individual wellbeing and satisfaction.

Studies point towards a fundamental role of social capital in shaping economic and social position, as well as satisfaction in the lives of citizens. Musson and Rousselière (2020) analyzed the impact of social capital on subjective wellbeing, concluding that trust and voluntary participation in associations have specific effects on emotional wellbeing. Active involvement, networking, and trust positively influenced life satisfaction. Sanzon et al. (2012) found that higher levels of social capital were directly related to higher satisfaction levels and a better quality of life in the workplace.

Furthermore, Andrews (2012) supports the notion that social capital is closely linked to the performance of public services. This factor influences how people utilize public health services, their willingness to participate in public service investment, and the outcomes achieved by providers of such services (Birdi et al., 2012; Fujiwara & Kawachi, 2008). Social capital can stimulate the flow of information, influence health-related behaviors and attitudes, empower citizens to demand public goods, and foster trust and civic participation (Andrews & Wankhade, 2015; Elgar et al., 2011; Hoogerbrugge & Burger, 2018).

Ponzetto's (2018) work demonstrates how social capital augments economic growth by enhancing government investment in human capital, thus contributing to long-term development and prosperity. Jottier's (2012) study bolsters this viewpoint by showing that a higher degree of social capital improves political accountability, as evidenced by stronger connections between perceived government quality and electoral outcomes in municipalities with robust social networks and trust among citizens. On the other hand, Tavits' (2006) research found evidence supporting the relationship between social capital and policy activism, suggesting that communities with strong ties are more likely to engage in collective action for change. However, it did not find a significant association with administrative efficiency. These findings highlight the complex nature of social capital's impact on various aspects of socio-political dynamics and demonstrate its potential role in shaping effective governance structures for sustainable development.

4. Research Methodology

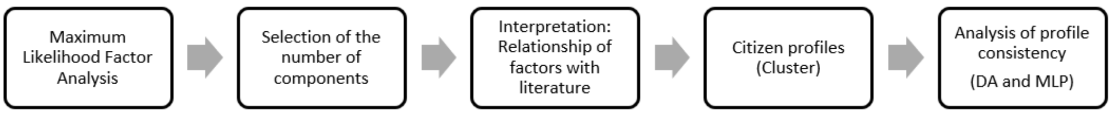

Figure 1. Conceptual framework. Source: Own elaboration

In Figure 1, we illustrate the methodology process applied in this paper using data from the Public Opinion and Fiscal Policy Survey conducted by the Center for Sociological Research in Spain (CIS, 2022).

Initially, we performed exploratory studies using the principal component analysis to reduce the dimensionality of correlated variables and transform them into uncorrelated principal components to begin developing a factorial model. This approach simplifies complex data (Hotelling, 1933; I. Jolliffe, 2016). However, for our final model, we incorporated maximum likelihood (ML) extraction as it assumes that the collected data is a linear combination of underlying factors and aims to maximize likelihood (Bentler, 1990). We then performed a Varimax rotation (Kaiser, 1958) to simplify the factorial design by maximizing variable loadings on one factor and creating an orthogonal structure.

Different criteria are used to determine if dimension reduction is appropriate for the data (Watkins, 2018). These criteria typically include assessing the determinant value of the correlation matrix, the Kaiser-

Meyer-Olkin (KMO) index (Kaiser, 1970, 1974), and Bartlett's test of sphericity (Bartlett, 1950; Fabrigar et al., 1999; Kaiser, 1974; Stevens, 1996).

Determining the appropriate number of components to retain is a complex process that involves evaluating multiple criteria and drawing on the researcher's expertise (Costello & Osborne, 2005; I. Jolliffe, 2016; Tabachnick & Fidell, 2013). This iterative process takes into account factors such as the proportion of total variance explained by the factorial model (Cattell, 1966; Horn, 1965), the Kaiser-Guttman criterion (Yeomans & Golder, 1982), and the interpretability principle (Arabie, 1991). Additionally, a loading matrix is required for analysis to determine which components to retain (Costello & Osborne, 2005).

The hierarchical cluster is a multivariate statistical technique that creates profiles by grouping individuals based on multivariate distances from smallest to largest, moving up the hierarchy by pairing data points with others. On the other hand, in the K-means cluster, the number of profiles is determined at the beginning, and an algorithm is used to iteratively refine the assignment of cases to profiles along with the centroids (average vectors) representing them.

We apply the Ward linkage method to connect conglomerates, aiming to reduce variability within each cluster (Everitt et al., 2001). This creates a hierarchical structure that can be visualized with a dendrogram, illustrating the merging of clusters throughout the analysis (Nielsen, 2016). Adjusting the cutting point on the dendrogram allows us to attain different levels of grouping, from broader and less detailed clusters to more specific and smaller ones. The widely used Ward linkage technique focuses on minimizing variance within clusters, leading to more coherent and meaningful groupings.

To determine the optimal number of profiles, we conducted a step-by-step analysis that aimed to identify distinct groups with cohesive characteristics. We examined the linkage process through the dendrogram to obtain an appropriate number of clusters. In parallel, we employed k-means clustering using the same number of profiles to calculate centroids (mean vectors) obtained from both methods. These centroids will define each profile statistically and enable subsequent interpretation based on social capital theory.

Two supervised statistical learning techniques, linear discriminant analysis (LDA) (Fisher, 1936; McLachlan, 2004) and multilayer perceptron neural network (MLP) (Minsky, 1974; Minsky & Papert, 1969; Rosenblatt, 1958) with backpropagation algorithm (Rumelhart et al., 1986), are used to analyze the consistency of the profiles. The better the classification capability, the greater the consistency of the identity of the profiles. MLP can pick up the influence of nonlinear correlations and contingency relationships by improving their predictions as they receive information (network training).

Neural networks have displayed potential in predicting various phenomena in the field of Economics, such as international conflicts (Beck et al., 2000; de Marchi et al., 2004), country default risk (Cooper, 1999), and poverty (Jean et al., 2016). Despite their growing application in social sciences (Bagautdinov et al., 2017; Davidson, 2019; Gambäck & Sikdar, 2017; Liao et al., 2019; Salganik et al., 2020; Waldfogel et al., 2010), there is some hesitancy to employ neural networks due to interpretational challenges. As a result, their usage has been mainly limited to specific subfields within the economic discipline (Falat & Pancikova, 2015; Li & Ma, 2010).

Applying this methodology in the social sciences presents challenges due to several factors. Firstly, there is a limited ability to interpret the impact of predictor variables on dependent variables because of their nonlinear relationships. Secondly, a large sample size is required to train the network effectively. Lastly, network results can be unpredictable since coefficient calculation relies on random case assignments for training and testing sets. Therefore, network quality is evaluated by measures like area under the receiver operating characteristic (ROC) curve, cross-entropy error coefficient, and model train time.

We postulate that if the area under the ROC curve is close to unity concerning the independent variables, and the expected classification ratio exceeds the discriminant analysis model, this difference reflects the importance of the nonlinear relationships between predictor variables and their linear relationships.

MLP is an artificial feedforward neural network. It comprises at least three layers of nodes: an input layer, one or more hidden layers, and an output layer. Each node, or neuron, in one layer, is connected to each node in the next layer, usually with an associated weight for each connection (Goodfellow et al., 2016; Haykin, 1998).

The activation function used in MLP neurons is typically nonlinear. Common activation functions include the sigmoid, hyperbolic tangent (tanh), and rectified linear unit functions (ReLU). By introducing non-linearity, the MLP can effectively model complex relationships between inputs and outputs (Aggarwal, 2018; Bishop, 2006; Goodfellow et al., 2016; G. James & al, 2022). Our model will utilize the hyperbolic tangent function (tanh), which maps input values to a range between -1 and 1. Unlike the sigmoid function, it has its center at zero, which helps address issues such as vanishing gradients and enables neurons to saturate in different regions.

We will use the Softmax function as an activation function in the output layer, suitable for multi-class classification problems. It transforms the outputs of the neurons into normalized probabilities that sum to 1, which allows us to assign a class to each output. The cross-entropy error function that measures the discrepancy between model predictions and actual outputs in classification problems is critical for evaluating the network's quality. The smaller the cross-entropy, the better the model's ability to fit the data (Bishop, 2006; Goodfellow et al., 2016).

The stopping criterion, the "Training Error Ratio Criterion Achieved," determines when to stop training a neural network. This criterion involves halting the training process once the error on the training set drops below a specific threshold. By doing so, overfitting can be avoided, which occurs when the network becomes too tightly fitted to the training data and fails to perform well on new unseen data.

When using predictor variables in a neural network, it is important to consider using factors derived from dimensionality reduction (I. T. Jolliffe, 2002). These factors allow for a reduction in dimensionality by selecting components that capture the most variability in the data. This can result in faster training and reduced risk of overfitting (Bishop, 2006). Principal components are orthogonal, which aids in improving efficiency and stability during training by decorrelated features (Golub & Van Loan, 2012). Additionally, selecting only a limited number of principal components may help eliminate some noise present in the data (Hyvärinen et al., 2001). However, if there are nonlinear relationships within the data set, Principal Component Analysis might not be the optimal choice (Hinton & Salakhutdinov, 2006; Van Der Maaten & Hinton, 2008).

4.1. *Application of the Methodology*

4.1.1. *Data*

We used the Public Opinion and Fiscal Policy Survey by the Center for Sociological Research in Spain in July 2022 for data analysis. The survey employed a comprehensive sampling procedure outlined in the technical specifications provided by CIS (2022). It was conducted from July 21 to 30, specifically targeting individuals above the age of 18 from various gender identities within the Spanish population.

The sampling design aimed for a total of 3300 interviews, out of which 2543 were completed. For factorial extraction, we worked with complete cases, totaling 1439 respondents, ensuring enough sample size for the analysis. The aim of this survey was to investigate Spanish citizens' attitudes, opinions, and perceptions towards trust, fiscal compliance, and personal beliefs. For computing, we use IBM SPSS Statistics v29 software (IBM Corp., 2021).

4.1.2. *Evaluation of the Factorial Model*

The factorial model, once interpreted, is presented in Table 1.

The determinant of the correlation matrix validates the model because it is close to zero ($|R| = 0'001$), allowing for the inversion of the correlation matrix.

The KMO statistic is excellent (0.819), and we reject the null hypothesis that the observed variables are independent (Bartlett's test of sphericity). See Table 14 in annexes. In the anti-image correlation matrix, we observe that the measures of sampling adequacy (MSA) are greater than 0.7, which supports the selection of the variables involved in the extraction. We selected 6 factors that verify the Kaiser criteria (Yeomans & Golder, 1982) and the interpretability principle. Due to the importance of the interpretability principle in social sciences, we do not take into account Cattell's criteria (Figure 5 in annexes) or the percentage of total variance explained (Hair et al., 2019) because when these criteria are met, factors higher than the sixth are not interpretable.

Table 1. Variance explained (VE) by the ML factor analysis. Source: Own elaboration

Factors	Eigenvalue	VE%	Total VE%
F1. Intolerance towards tax evasion (IRPF & IVA)	4.273	13.783	13.783
F2. Dissatisfaction with Public Services	3.508	11.316	25.099
F3. Happiness.	2.486	8.020	33.119
F4. Perceived tax pressure.	1.874	6.045	39.164
F5. Social elevator.	1.595	5.145	44.309
F6. Moral demand.	1.452	4.685	48.994

We performed maximum likelihood varimax extraction. The MSAs are adequate, the commonalities improve in the extraction in general, and the matrix of rotated factor loadings allows a good interpretation. For relevance in the literature and maintaining a certain linear independence for the factors, the following typed variables are included: "P3. Trust (0-10) in people" and Assessment scale (0 to 10) for factors contributing to a particular economic position (ESCAPOSICION).

The factorial interpretation can be found in the annexes (Table 8 to Table 13) and the component plot in the rotated space in Figure 6.

4.2. ***Hierarchical Cluster and K-means Profiling***

Through a segmentation process, we divide the population into four distinct profiles. To determine these profiles, we use both hierarchical clustering and k-means clustering approaches during an exploratory selection phase. The number of groups is determined based on the effectiveness of classification models, which allows us to accurately assign individuals to profiles with a low misclassification rate.

After analyzing the profiles generated by hierarchical clustering and k-means, the k-means method provides a clearer separation of groups through discriminant analysis.

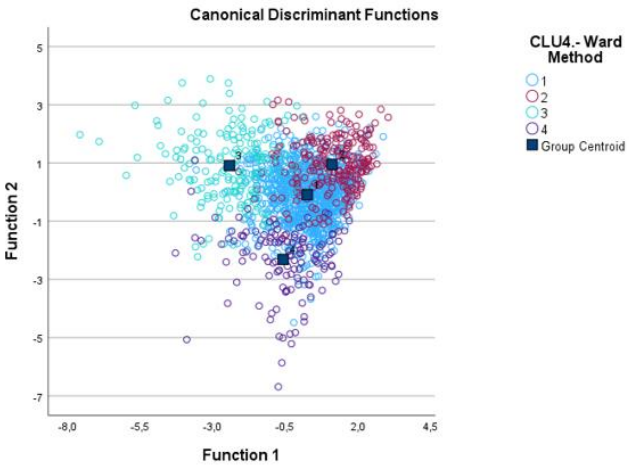

Figure 2. Discriminant map concerning the hierarchical cluster.
Source: Own elaboration

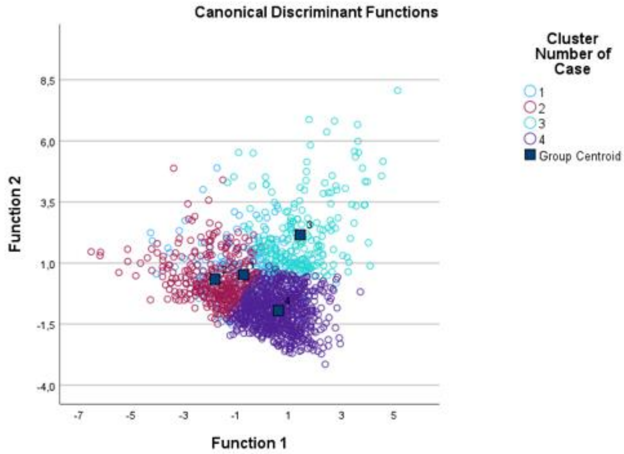

Figure 3. Discriminant map concerning the k-means cluster.
Source: Own elaboration

Table 2. Confusion matrix of LDA over k-means clustering. Source: Own elaboration

			Classification Results[a,c]				
		Cluster Number of Case	**Predicted Group Membership**				**Total**
			1	**2**	**3**	**4**	
Original	Count	1	172	1	3	11	187
		2	2	338	4	1	345
		3	2	3	213	9	227
		4	13	13	10	705	741
	%	1	92.0	.5	1.6	5.9	100.0
		2	.6	98.0	1.2	.3	100.0
		3	.9	1.3	93.8	4.0	100.0
		4	1.8	1.8	1.3	95.1	100.0
Cross-validated[b]	Count	1	171	2	3	11	187
		2	2	337	4	2	345
		3	2	3	213	9	227
		4	13	14	10	704	741
	%	1	91.4	1.1	1.6	5.9	100.0
		2	.6	97.7	1.2	.6	100.0
		3	.9	1.3	93.8	4.0	100.0
		4	1.8	1.9	1.3	95.0	100.0

a. 95.2% of original grouped cases correctly classified.

b. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

c. 95.0% of cross-validated grouped cases correctly classified.

Nevertheless, there is some difficulty in differentiating profile 4 based on the discriminant map of k-means. The cross-validated hit ratio for hierarchical clustering is 80.9%, and for k-means, it is 95.0% (See Table 2). As a result, we proceeded to analyze the profiles generated by k-means.

The obtained centroids are described in Table 7, and the average values are measured in z scores (deviations from the mean in terms of standard deviations).

The confusion matrix shows the classification hits and the errors. We can see how the predictions in the classification of LDA profile 4 could be more accurate in the original estimation and cross-validation.

We propose employing a multilayer neural network model to classify profiles using a nonlinear methodology and compare the accuracy in classification concerning the discriminant model. As mentioned in the methodology, if there is an improvement in prediction accuracy, we will attribute it to the existence of nonlinear differences among the profiles. The network model we propose is shown in Figure 4.

In Figures 2 and 3, we can observe that the profiles generated by K-means are better separated on the territorial map of discriminant analysis than those generated by hierarchical clustering. Profiles 1 and 2 are not well separated using the linear methodology shown in Figure 3. We are optimistic that employing the MLP methodology will enhance the precision of this classification.

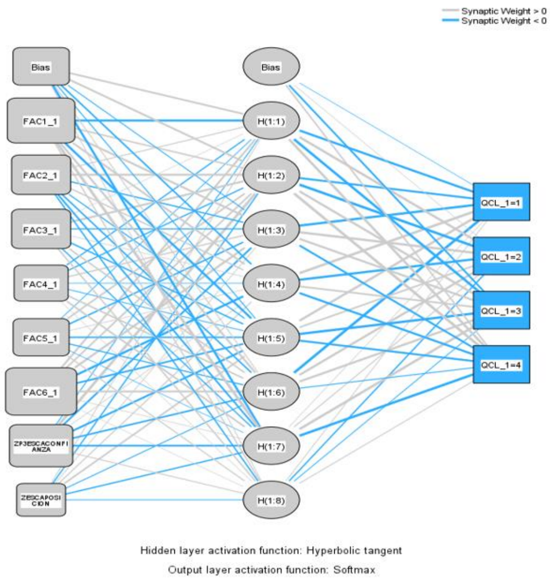

Figure 4. Artificial neural network (ANN) model. Hidden layer activation function: hyperbolic tangent; output. Source: Own elaboration

Table 3. Model summary. Source: Own elaboration

Model Summary		
Training	Cross Entropy Error	51.775
	Percent Incorrect Predictions	1.6%
	Stopping Rule Used	1 consecutive step(s) with no decrease in errora
	Training Time	0:00:00.03
Testing	Cross Entropy Error	31.631
	Percent Incorrect Predictions	3.6%
Hold-out	Percent Incorrect Predictions	2.9%
Dependent Variable: Cluster Number of Case		
a. Error computations are based on the testing sample.		

The values of the area under the ROC curves are very close to unity (Table 15), which supports the validity of the MLP model.

The summary of the model is described in Table 3.

The predictive capacity is assessed by calculating the complement of the prediction error in the reserve partition, resulting in a 97.1% probability of accurate classification. Table 4 presents the importance of variables concerning their predictive capability in the network.

Table 4. The importance of predictor variables in the MLP network for profiles segregated by k-means methodology. Source: Own elaboration

Independent Variable Importance	**Importance**	**Normalized Importance**
F6. Moral demand	.201	100.0%
F1. Intolerant towards tax evasion (IRPF e IVA)	.177	87.8%
Zscore: P3ESCACONFIANZA—Trust in people	.148	73.5%
F3. Happiness (Life Satisfaction)	.120	59.4%
F2. Dissatisfaction with Public Services	.119	59.3%
F5. Social Elevator	.099	49.0%
F4. Perceived tax pressure	.085	42.4%
ZESCAPOSICION—Assessment scale for factors contributing to a particular economic position	.051	25.3%

Table 5. Confusion matrix of MLP neural network over k-Means clustering. Source: Own elaboration

		Classification				
Sample	**Observed**			**Predicted**		
		1	**2**	**3**	**4**	**Percent Correct**
Training	1	103	0	2	2	96.3%
	2	2	222	0	2	98.2%
	3	2	2	131	1	96.3%
	4	0	0	2	449	99.6%
	Overall Percent	11.6%	24.3%	14.7%	49.3%	98.4%
Testing	1	40	1	2	2	88.9%
	2	0	64	0	1	98.5%
	3	0	0	40	1	97.6%
	4	2	1	1	150	97.4%
	Overall Percent	13.8%	21.6%	14.1%	50.5%	96.4%
Hold-out	1	34	0	0	1	97.1%
	2	1	49	0	4	90.7%
	3	0	0	50	0	100.0%
	4	1	0	1	134	98.5%
	Overall Percent	13.1%	17.8%	18.5%	50.5%	97.1%

Dependent Variable: Cluster Number of Case

Table 5 shows the confusion matrix of the MLP network. We observe how the nonlinear classification model has improved not only the joint classification capacity (Hit Ratio) but also better classifies the citizens of profile 4 with a probability of correct classification in this category in the hold-out partition of 98.5%, compared to LDA, which gave a probability of 95 in cross-validation.

As the classification ratios are close to unity, 95% in the LDA in cross-validation, and 97.1% in the Hold-out partition, we conclude that the profiles are consistent, i.e., that they have a high statistical identity that allows them to be differentiated between groups and to classify citizens adequately in statistical terms.

4.3. *Interpretation of the profiles according to the perspective of social capital*

After interpreting the profiles concerning the literature, we show the frequency distribution in Table 6.

Table 6. Distribution frequencies of citizen profiles concerning social capital in the context of fiscal opinion. Source: Own elaboration

Profiles	**Frequency**	**%**
CLU4_1. NetPower beneficiaries	187	12.47%
CLU4_2. Welfare recipients	345	23.00%
CLU4_3. Resilient citizens	227	15.13%
CLU4_4. Trustees	741	49.40%

Table 7 displays the centroids of the profiles determined by k-means. The variables in the table have been arranged based on their importance order in predicting outcomes according to the MLP network.

Table 7. Determination of centroids for citizen profiles based on social capital variables within the fiscal realm. Source: Own elaboration

Variables (MLP)	**NetPower beneficiaries**	**Welfare recipients**	**Resilient citizens**	**Trustees**
F6. Moral Demand	-1.44	0.32	0.04	0.20
F1. Intolerance towards tax evasion (IRPF e IVA)	-0.01	-0.31	1.46	-0.35
Zscore: P3ESCACONFIANZA—Trust in people	-0.26	-0.91	0.09	0.52
F3. Happiness (Life Satisfaction)	-0.41	-0.45	0.16	0.24
ZESCAPOSICION—Assessment scale for factors contributing to a particular economic position	0.30	0.17	-0.29	-0.05
F2. Dissatisfaction with Public Services	-0.06	-0.61	-0.10	0.34
F5. Social Elevator	-0.01	-0.42	0.17	0.23
F4. Perceived tax pressure	-0.09	0.21	0.39	-0.25

We interpret the profiles according to the literature as follows:

- Cluster 1—NetPower beneficiaries (González-Martel et al., 2021; Oney & Oksuzoglu-Guven, 2015). This group focuses on leveraging networks for power. They have very low moral demands and are slightly distrustful. Despite being unhappy, they exhibit high trust in networking (12.47%).
- Cluster 2— Welfare recipients (Parry & Bento, 2001). These individuals are welfare recipients who rely on social assistance. They have the highest level of moral demands and tolerance towards tax evasion. They are also the most distrustful and least happy among all clusters; however, they express higher satisfaction with public services but lower social mobility (23.00%).
- Cluster 3— Resilient citizens (Oney & Oksuzoglu-Guven, 2015). This group is characterized by self-reliance and self-confidence. They strongly oppose tax evasion and place great trust in personal efforts to achieve their goals. Additionally, they perceive higher levels of tax pressure but demonstrate above-average social elevator compared to other clusters (15.13%).
- Cluster 4— Trustees (Delgado-Rodríguez & De Lucas-Santos, 2021; Liang et al., 2020; Oney & Oksuzoglu-Guven, 2015). Ethically strict, highly trusting of others, most content, least satisfied with public services, and in the best position for upward social elevator. They tend to perceive a lower tax burden on the population (49.40%).

5. Discussions

It is important to note some methodological limitations. The assumption that the MLP network model is better at explaining the difference between profiles compared to the methodology of linear discriminant analysis is somewhat risky due to how the neural network is constructed. It involves an iterative process with random assignment to training, testing, and hold-out sets. Additionally, the importance of predictor variables in the MLP model depends on randomness. For future research, it would be beneficial to conduct cross-validation statistics and replicate the MLP model in successive stages to study the order of importance of variables as ranked statistics.

We assume that there is a direct relationship between moral demand and compliance with tax obligations. Previous research has highlighted the prevalent issue of tax evasion, fraudulent activities, and calculation mistakes among small and medium-sized business practices in Spain that may have contributed to a loss in VAT revenue in 2021 (Almunia & Lopez-Rodriguez, 2012; González-Martel et al., 2021).

For instance, with this classification, Resilient citizens (15.13%) in Spain are more likely to oppose tax evasion, which could be for a few reasons. Firstly, they might think everyone should contribute their fair share for the societal benefits everyone receives. This includes public services like healthcare, education, and infrastructure development funded by tax revenues (Oney & Oksuzoglu-Guven, 2015). Secondly, highly self-reliant individuals often value transparency, accountability, and lawfulness, contrary to tax evasion. They will likely pay their taxes diligently and expect others to do the same. Lastly, they might view tax payment as a responsibility accompanying their economic success. Despite this fiscal pressure, self-reliance tends to be above average regarding the social elevator, encouraged by their self-confidence to seek out and capitalize on opportunities that favor their personal and professional growth.

Thinking about the trustee group (49.40%) with a strong sense of trust in others perceives relatively less tax pressure (the lowest value in our analysis). Firstly, their deep trust in others could extend to their trust in the government and public institutions (Oney & Oksuzoglu-Guven, 2015), resulting in their belief that their taxes are being used appropriately. Secondly, moral stringency often aligns with law-abiding behavior, including tax compliance. Their emphasis on trust could also feed their sense of happiness, as trust promotes positive social interactions and a sense of community (Delgado-Rodríguez & De Lucas-Santos, 2021). Their dissatisfaction with public services (highest value) might be linked to their high governance and public accountability standards rather than dissatisfaction leading to tax evasion (Liang et al., 2020). Lastly, these individuals are likely well-positioned socially and financially, often equating to a greater ability to bear tax pressure without causing significant financial strain. Their social standing may also involve a belief in civic duty, including paying their fair share of taxes. As such, they may interpret tax payments less as a financial burden and more as a reflection of their societal contributions.

The welfare recipients' group (23.00%) is the most morally demanding in our study, possibly due to their high reliance on the system's effectiveness and fairness in distributing resources. Since they could be among the primary beneficiaries of public services, they may require taxable contributions from others to maintain their livelihood (Parry & Bento, 2001). This can make them tolerate tax evasion, especially if they believe the system is unfairly burdensome towards certain groups. The tendency towards distrust and unhappiness (the lowest values) might be due to various factors. They probably feel a little marginalized or neglected by society or discontent with their socio-economic position. Despite their dissatisfaction, they might still express satisfaction with public services, as they rely on them most. Given their tax contributions, they might view these public services as their rightful benefit. Finally, being at the lower end of the social elevator, they feel a great sense of tax pressure (the second position in our analysis). The financial burden of taxes can be significant when struggling with limited income, particularly if they perceive a lack of upward mobility to improve their income level.

Our study's NetPower beneficiaries (12.47%) have the lowest moral demand and may emphasize personal network gain and pragmatism over strict moral or ethical guidelines (highest value in ESCAPOSICION). This tendency might be driven by their focus on leveraging networks to achieve professional or personal success. Their slight distrustfulness can result from operating within power networks, where competition can breed wariness. Also, skepticism might arise from interactions with various parties having different agendas. Despite their high networking confidence, this is one of the group's most unhappiness in our study, possibly due to their environment's competitive and high-pressure nature. Persistent competition and the need to always be networking can potentially lead to unhappiness.

6. Conclusions

This study aims to identify different citizen profiles within the social capital framework, specifically concerning public opinion and fiscal policy. By identifying statistically significant characteristics, we can analyze the economic behavior of these groups and determine their societal significance. This analysis will help formulate hypotheses about the potential consequences of economic dynamics.

It focuses on classifying individuals based on social capital fiscal features: “Intolerance towards tax evasion (F1)”, “Dissatisfaction with Public Services (F2)”, and “Perceived tax pressure (F4).” As well as variables different from the fiscal environment: “Trust in people (P3)”, “Happiness (F3)”, “Assessment of factors contributing to a particular economic position (ESCAPOSICION), “Social Elevator (F5)” and “Moral Demand (F6).”

Methodologically, we have achieved the goal of identifying quantitatively consistent profiles that correspond to actors in social capital theory. Discriminant analysis and neural networks are a powerful combination for understanding the boundaries that separate profiles and measuring their consistency. The discriminant analysis allows us to identify how predictor variables affect the separation of groups and neural networks; if we have a sufficient sample size for model training, we offer a higher level of accuracy in classification by including nonlinear relationships.

The principle of interpretability is mainly associated with factor analysis. However, our study demonstrates that interpretability can also be employed in developing profiles. By utilizing the information extracted from centroids or mean value vectors, we can hypothesize about the behavior of these actors.

Based on the research, the findings related to social capital in the area of taxation can be summarized as follows:

Concerning the citizen profiles, the Welfare recipients have the lowest position in the social elevator, are the most tolerant of tax evasion, and are the most satisfied with public services. Trustees occupy the highest position on the social elevator yet are the most tolerant of tax evasion and show the most significant dissatisfaction with public services. In the NetPower groups, they are in an intermediate situation. As social status increases, tolerance for tax evasion and dissatisfaction with public services increases, except for Resilient citizens.

Regarding social capital, we can observe that although Welfare recipients tend to have high moral standards, they are among the groups that evade taxes the most. Additionally, they exhibit low levels of happiness but have high trust in networking. It suggests they are dissatisfied with the State's public services, leading to tax non-compliance and a lack of expected resources from the State.

The Resilient citizens' group has a high level of intolerance of tax evasion and generally enjoys a higher stock of social capital: they rank second highest in happiness and trust in others. Since they consider personal effort to outweigh networking for a good social position, they are ranked highest. Their satisfaction level with public services is average, and they are the most affected by the tax burden. We infer that an increase in the social capital variables jointly increases fiscal loyalty, one of the most relevant values being trust in personal effort and trust in others.

Social capital can impact hierarchical dynamics and maintain influential networks, giving individuals access to resources and the power to drive tax-related behaviors (Fredrickson & Joiner, 2002; Portes, 1998). Power networks consist of connections between individuals or groups that allow them to influence resource allocation and decision-making processes. These connections provide opportunities for gaining power and exerting influence in social and political spheres. Interestingly, participation in these networks may be associated with reduced moral standards and increased distrust (Dubois et al., 2015; Portes, 1998).

While these networks provide resources and opportunities, they might also foster diminished moral standards due to competitive and inequitable tactics, breeding distrust among its members. The ever-present competition and focus on personal advancement can also affect emotional wellbeing. The capacity for empathy, or understanding and sharing others' feelings, can significantly alter the responses of influential individuals or those emotionally distanced from unethical actions. Notably, highly empathetic individuals may exhibit less tolerance for unscrupulous behavior, attributed to their ability to empathize with the detrimental effects of such actions on others (Drumwright & Cunningham, 2022).

Individuals with high moral standards often express dissatisfaction with public services while perceiving their tax burden to be reduced. This seemingly contradictory combination of characteristics can be understood differently (S. James et al., 2019). One possible explanation is that individuals with strong moral values may feel that the quality of public services does not align with the taxes they pay (Sasaki et al., 2018). Moreover, their perception of a reduced tax burden could stem from their improved socio-economic status, which allows them to take advantage of economic opportunities and effectively manage their tax obligations.

Although individuals in this group express discontent with the public services they receive, their socio-economic status enables them to maintain a sense of happiness and effectively navigate the complexities of economic and social aspects of life. This implies that these individuals possess the necessary resources and abilities to manage their circumstances despite encountering certain difficulties.

By examining the connection between tax evasion, social capital, personal satisfaction, and public services, researchers have gained a deeper insight into how these factors impact individual characteristics and attitudes toward tax evasion and moral obligation. This analysis allows for a more comprehensive understanding of how social elements like social networks, shared norms, and trust can assist or hinder compliance with taxation regulations.

Examining these aspects provides insights into how specific types of individuals can impact tax compliance, both positively and negatively. One notable group is the "Trustees," characterized by their strong moral principles and trust in others, which may result in a greater inclination to fulfill tax responsibilities. Conversely, the "Resilient citizens" who primarily rely on themselves and prioritize self-sufficiency might also display a higher tendency to meet their tax obligations and actively engage with the community.

Additionally, individuals classified as "NetPower beneficiaries" and "Welfare Recipients" exhibit distinct relationships with social capital and its impact on tax evasion. "NetPower beneficiaries," leveraging their extensive networks and trust in them for personal gain, may access information and resources that enable them to minimize their tax obligations without engaging in illegal activities. Conversely, "Welfare recipients," heavily reliant on government assistance, tend to place a higher value on public services. However, they may face limited social mobility and lower wellbeing due to dependence on state support and lack of confidence in improving their circumstances, factors that can influence overall happiness levels. These profiles offer valuable insights for developing effective public policies by considering diverse patterns of societal engagement.

References

Aggarwal, C. C. (2018). *Neural Networks and Deep Learning: A Textbook*. Springer.

Akçomak, S., & Weel, B. (2007). *How do social capital and government support affect innovation and growth? Evidence from the EU regional support programmes*.

Alm, J., Clark, J., & Leibel, K. (2011). *Socio-economic Diversity, Social Capital, and Tax Filing Compliance in the United States*. http://hdl.handle.net/10092/6404

Alm, J., & Gomez, J. L. (2008). Social capital and tax morale in Spain. *Economic Analysis and Policy*, *38*(1), 73–87. https://doi.org/10.1016/S0313-5926(08)50007-5

Alm, J., & Torgler, B. (2006). Culture differences and tax morale in the United States and in Europe. *Journal of Economic Psychology*, *27*(2), 224–246. https://doi.org/10.1016/j.joep.2005.09.002

Almunia, M., & Lopez Rodriguez, D. (2014). *Heterogeneous Responses to Effective Tax Enforcement: Evidence from Spanish Firms* (SSRN Scholarly Paper 2471467). https://doi.org/10.2139/ssrn.2471467

Almunia, M., & Lopez-Rodriguez, D. (2012). The efficiency cost of tax enforcement: Evidence from a panel of spanish firms. *MPRA Paper*, Article 44153. https://ideas.repec.org//p/pra/mprapa/44153.html

Alvarez-Garcia, M., Ibar-Alonso, R., & Arenas-Parra, M. (2024). A comprehensive framework for explainable cluster analysis. *Information Sciences*, *663*, 120282. https://doi.org/10.1016/j.ins.2024.120282

Andrews, R. (2012). Social capital and public service performance: A review of the evidence. *Public Policy and Administration*, *27*(1), 49–67. https://doi.org/10.1177/0952076710394399

Andrews, R., & Wankhade, P. (2015). Regional variations in emergency service performance: Does social capital matter? *Regional Studies*, *49*(12), 2037–2052. https://doi.org/10.1080/00343404.2014.891009

Arabie, P. (1991). *Multivariate analysis of data in sensory science*. Elsevier Science Pub. Co.

Atwood, T. J., Drake, M. S., Myers, J. N., & Myers, L. A. (2012). Home country tax system characteristics and corporate tax avoidance: International evidence. *The Accounting Review*, *87*(6), 1831–1860. https://doi.org/10.2308/accr-50222

Bagautdinov, T., Alahi, A., Fleuret, F., Fua, P., & Savarese, S. (2017). Social scene understanding: End-to-end multi-person action localization and collective activity recognition. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 4315–4324. https://openaccess.thecvf.com/content_cvpr_2017/html/Bagautdinov_Social_Scene_Understanding_CVPR_2017_paper.html

Bartlett, M. S. (1950). The test of significance in factor analysis. *Psychometrika*, *15*(3), 77–83.

Batinti, A., Andriani, L., & Filippetti, A. (2019). Local government fiscal policy, social capital and electoral payoff: Evidence across Italian municipalities. *Kyklos*, *72*(4), 503–526. https://doi.org/10.1111/kykl.12209

Beck, N., King, G., & Zeng, L. (2000). Improving quantitative studies of international conflict: A conjecture. *The American Political Science Review*, *94*(1), 21. https://doi.org/10.2307/2586378

Bentler, P. M. (1990). Comparative Fit Indexes in Structural Models. *Psychological Bulletin*, *107*(2), 238–246.

Bilgin, C. (2014). Determinants of tax morale in Spain and Turkey: An empirical analysis. *European Journal of Government and Economics*, *3*, 60–74. https://doi.org/10.17979/ejge.2014.3.1.4297

Birdi, B., Wilson, K., & Mansoor, S. (2012). 'What we should strive for is Britishness': An attitudinal investigation of ethnic diversity and the public library. *Journal of Librarianship and Information Science*, *44*(2), 118–128. https://doi.org/10.1177/0961000611426299

Bishop, C. M. (2006). *Pattern Recognition and Machine Learning*. Springer.

Bobek, D. D., Hageman, A. M., & Kelliher, C. F. (2013). Analyzing the role of social norms in tax compliance behavior. *Journal of Business Ethics*, *115*(3), 451–468. https://doi.org/10.1007/s10551-012-1390-7

Bobek, D. D., Roberts, R. S., & Sweeney, J. A. (2007). The social norms of tax compliance: Evidence from Australia, Singapore, and the United States. *Journal of Business Ethics*, *74*(1). https://doi.org/10.1007/s10551-006-9219-x

Bonatti, L., & Lorenzetti, L. (2018). The co-evolution of tax evasion, social capital and policy responses: A theoretical approach. *International Review of Economics*, *65*(3), 381–401. https://doi.org/10.1007/s12232-018-0301-3

Brink, W. D., & Porcano, T. M. (2016). The impact of culture and economic structure on tax morale and tax evasion: A country-level analysis using SEM. In *Advances in Taxation* (Vol. 23, pp. 87–123). Emerald Group Publishing Limited. https://doi.org/10.1108/S1058-749720160000023004

Cantero-Galiano, J. (2022). Trust in institutions and tax compliance. A multilevel analysis of the regions of Spain. *Finanse i Prawo Finansowe*, 81–97. https://doi.org/10.18778/2391-6478.S.2022.06

Cascavilla, A., Ripollés, J., & Morone, A. (2024). Tax morale and social capital: An empirical investigation among European citizens. *Annals of Public and Cooperative Economics*, *95*(2), 441–476. https://doi.org/10.1111/apce.12443

Cattell, R. B. (1966). The scree test for the number of factors. *Multivariate Behavioral Research*, *1*(2), 245–276.

Chang, J., & Lai, C. (2004). Collaborative tax evasion and social norms: Why deterrence does not work. *Oxford Economic Papers*, *56*(2), 344–368.

Chircop, J., Fabrizi, M., Ipino, E., & Parbonetti, A. (2018). Does social capital constrain firms' tax avoidance? *Social Responsibility Journal*, *14*(3), 542–565. https://doi.org/10.1108/SRJ-08-2017-0157

Christoforou, A. (2011). Social capital: A manifestation of neoclassical prominence or a path to a more pluralistic economics? *Journal of Economic Issues*, *45*(3), 685–702. https://doi.org/10.2753/JEI0021-3624450309

CIS. (2022). *Encuesta de Opinión Pública y Política Fiscal (CIS, estudio 3332)*. https://www.cis.es/cis/opencms/ES/NoticiasNovedades/InfoCIS/2021/Documentacion_3332.html

Ciziceno, M. (2024). What shapes tax morality in younger generations? A comparative analysis between Gen Y and Gen Z. *Sociology Compass*, *18*(2), e13179. https://doi.org/10.1111/soc4.13179

Cooper, J. C. B. (1999). Artificial neural networks versus multivariate statistics: An application from economics. *Journal of Applied Statistics*, *26*(8), 909–921. https://doi.org/10.1080/02664769921927

Costello, A. B., & Osborne, J. W. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical Assessment, Research & Evaluation*, *10*(7), 1–9.

Cummings, R. G., Martinez-Vazquez, J., McKee, M., & Torgler, B. (2009). Tax morale affects tax compliance: Evidence from surveys and an artefactual field experiment. *Journal of Economic Behavior & Organization*, *70*(3), 447–457. https://doi.org/10.1016/j.jebo.2008.02.010

Daude, C., Gutierrez, H., & Melguizo, Á. (2013). What drives tax morale? A focus on emerging economies. *Revista Hacienda Pública Española*, *207*, 9–40. https://doi.org/10.7866/HPE-RPE.13.4.1

Davidson, T. (2019). Black-box models and sociological explanations: Predicting high school grade point average using neural networks. *Socius*, *5*, 1–11. https://doi.org/10.1177/2378023118817702

de Castro, F. (2006). The macroeconomic effects of fiscal policy in Spain. *Applied Economics*, *38*(8), 913–924. https://doi.org/10.1080/00036840500369225

de Marchi, S., Gelpi, C., & Grynaviski, J. D. (2004). Untangling neural nets. *American Political Science Review*, *98*(2), 371–378. https://doi.org/10.1017/S0003055404001200

Delgado-Rodríguez, M. J., & De Lucas-Santos, S. (2021). Tax compliance, public spending and happiness in Europe. *Corporate Governance: The International Journal of Business in Society*, *22*(3), 577–591. https://doi.org/10.1108/CG-05-2021-0202

Díez-Vial, I., & Montoro-Sanchez, A. (2014). Social capital as a driver of local knowledge exchange: A social network analysis. *Knowledge Management Research & Practice*, *12*. https://doi.org/10.1057/kmrp.2014.7

Drumwright, M. E., & Cunningham, P. H. (2022). Unethical Newsroom Behavior: Paradoxes and a Perfect Storm. *Journalism Practice*, *16*(5), 963–983. https://doi.org/10.1080/17512786.2020.1825114

Dubois, D., Rucker, D. D., & Galinsky, A. D. (2015). Social class, power, and selfishness: When and why upper and lower class individuals behave unethically. *Journal of Personality and Social Psychology*, *108*(3), 436–449. https://doi.org/10.1037/pspi0000008

Elgar, F. J., Davis, C. G., Wohl, M. J., Trites, S. J., Zelenski, J. M., & Martin, M. S. (2011). Social capital, health and life satisfaction in 50 countries. *Health & Place*, *17*(5), 1044–1053. https://doi.org/10.1016/j.healthplace.2011.06.010

Enciso de Yzaguirre, V. (2006). Fiscalidad y desarrollo rural en España: Los beneficios fiscales en el mundo rural español. *CIRIEC - España. Revista de economía pública, social y cooperativa*, *55*, 91–124.

Everitt, B. S., Landau, S., & Leese, M. (2001). *Cluster Analysis* (4th ed.). Oxford University Press, Inc.

Fabrigar, L. R., Wegener, D. T., MacCallum, R. C., & Strahan, E. J. (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological Methods*, *4*(3), 272.

Falat, L., & Pancikova, L. (2015). Quantitative modelling in economics with advanced artificial neural networks. *Procedia Economics and Finance*, *34*, 194–201. https://doi.org/10.1016/S2212-5671(15)01619-6

Fisher, R. A. (1936). The Use of Multiple Measurements in Taxonomic Problems. *Annals of Eugenics*, *7*(2), 179–188.

Fol, S., & Gallez, C. (2014, June 18). *Social inequalities in urban access: From mobility to accessibility policies*. City Futures III - Cities as strategic places and players in a globalized world. https://shs.hal.science/halshs-01070312

Fowler, J. H., & Christakis, N. A. (2008). Dynamic spread of happiness in a large social network: Longitudinal analysis over 20 years in the Framingham Heart Study. *BMJ*, *337*, a2338. https://doi.org/10.1136/bmj.a2338

Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. *Review of Educational Research*, *74*(1), Article 1.

Fredrickson, B. L., & Joiner, T. E. (2002). Positive emotions trigger upward spirals toward emotional well-being. *Psychological Science*, *13*(2). https://doi.org/10.1111/1467-9280.00431

Fujiwara, T., & Kawachi, I. (2008). A prospective study of individual-level social capital and major depression in the United States. *Journal of Epidemiology &Amp; Community Health*, *62*(7). https://doi.org/10.1136/jech.2007.064261

Fukuyama, F. (2001). Social capital, civil society and development. *Third World Quarterly*, *22*(1), 7–20. https://doi.org/10.1080/713701144

Gambäck, B., & Sikdar, UK. (2017). Using convolutional neural networks to classify hate-speech. *Proceedings of the First Workshop on Abusive Language Online*, 85–90. https://doi.org/10.18653/v1/W17-3013

Gao, Z., Lu, L. Y., & Yu, Y. (2019). Local social environment, firm tax policy, and firm characteristics. *Journal of Business Ethics*, *158*(2), 487–506. https://doi.org/10.1007/s10551-017-3765-2

Golub, G. H., & Van Loan, C. F. (2012). *Matrix computations* (Vol. 3). JHU press.

González, S., Delorme, F., Pilon, G., & Lamy, R. (2000). *Neural Networks for Macroeconomic Forecasting: A Complementary Approach to Linear Regression Models*. https://www.semanticscholar.org/paper/Neural-Networks-for-Macroeconomic-Forecasting-%3A-A-Gonz%C3%A1lez-Delorme/17cfe6431e77bb56fba518a4e249ad73658972cb

González-Martel, C., Hernández, J. M., & Manrique-de-Lara-Peñate, C. (2021). Identifying business misreporting in VAT using network analysis. *Decision Support Systems*, *141*, 113464. https://doi.org/10.1016/j.dss.2020.113464

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT press.

Granovetter, M. (1977). Reply to morgan and rytina. *American Journal of Sociology*, *83*(3), 727–729. https://doi.org/10.1086/226604

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate Data Analysis* (8th ed.). Pearson.

Hatala, J.-P. (2009). Assessing individual social capital capacity: The development and validation of a network accessibility scale. *Performance Improvement Quarterly*, *22*(1), 53–68. https://doi.org/10.1002/piq.20045

Haykin, S. (1998). *Neural networks: A comprehensive foundation*. Prentice Hall PTR.

Herbrich, R., Keilbach, M., Graepel, T., Bollmann-Sdorra, P., & Obermayer, K. (1999). Neural Networks in Economics. In T. Brenner (Ed.), *Computational Techniques for Modelling Learning in Economics* (pp. 169–196). Springer US. https://doi.org/10.1007/978-1-4615-5029-7_7

Hinton, G. E., & Salakhutdinov, R. R. (2006). Reducing the dimensionality of data with neural networks. *Science*, *313*(5786), 504–507.

Hoogerbrugge, M. M., & Burger, M. J. (2018). Neighborhood-based social capital and life satisfaction: The case of Rotterdam, The Netherlands. *Urban Geography*, *39*(10), 1484–1509. https://doi.org/10.1080/02723638.2018.1474609

Horn, J. L. (1965). A rationale and test for the number of factors in factor analysis. *Psychometrika*, *30*(2), 179–185.

Hotelling, H. (1933). Analysis of a complex of statistical variables into principal components. *Journal of Educational Psychology*, *24*(6), 417–441.

Hyvärinen, A., Karhunen, J., & Oja, E. (2001). *Independent component analysis*. John Wiley & Sons.

IBM Corp. (2021). *IBM SPSS Statistics for Windows* (29.0) [Computer software]. IBM Corp.

James, G., & al, et. (2022). *An Introduction to Statistical Learning: With Applications in R*. Springer.

James, S., McGee, R. W., Benk, S., & Budak, T. (2019). How seriously do taxpayers regard tax evasion? A survey of opinion in England. *Journal of Money Laundering Control*, *22*(3), 563–575. https://doi.org/10.1108/JMLC-09-2018-0056

Jean, N., Burke, M., Xie, M., Davis, W. M., Lobell, D. B., & Ermon, S. (2016). Combining satellite imagery and machine learning to predict poverty. *Science*, *353*(6301), 790–794. https://doi.org/10.1126/science.aaf7894

Jimenez, P., & Iyer, G. S. (2016). Tax compliance in a social setting: The influence of social norms, trust in government, and perceived fairness on taxpayer compliance. *Advances in Accounting*, *34*, 17–26. https://doi.org/10.1016/j.adiac.2016.07.001

Jolliffe, I. (2016). Principal component analysis. *International Encyclopedia of Statistical Science*, 1094–1096.

Jolliffe, I. T. (2002). *Principal component analysis*. Wiley Online Library.

Jottier, D., & Heyndels, B. (2012). Does social capital increase political accountability? An empirical test for Flemish municipalities. *Public Choice*, *150*(3), 731–744. https://doi.org/10.1007/s11127-010-9727-1

Kaiser, H. F. (1958). The varimax criterion for analytic rotation in factor analysis. *Psychometrika*, *23*(3), 187–200. https://doi.org/10.1007/BF02289233

Kaiser, H. F. (1970). A Second Generation Little Jiffy. *Psychometrika*, *35*(4), 401–415. https://doi.org/10.1007/BF02291817

Kaiser, H. F. (1974). An index of factorial simplicity. *Psychometrika*, *39*(1), 31–36.

Kemme, D. M., Parikh, B., & Steigner, T. (2017). Tax havens, tax evasion and tax information exchange agreements in the OECD. *European Financial Management*, *23*(3), 519–542. https://doi.org/10.1111/eufm.12118

Knack, S. (1999). *Social capital and the quality of government: Evidence from the United States*. The World Bank. https://doi.org/10.1596/1813-9450-2504

Kondelaji, M. H., Sameti, M., Amiri, H., & Moayedfar, R. (2016). Analyzing determinants of tax morale based on social psychology theory: Case study of Iran. *Iranian Economic Review*, *20*, 581–598.

Li, Y., & Ma, W. (2010). Applications of artificial neural networks in financial economics: A survey. *2010 International Symposium on Computational Intelligence and Design*, *1*, 211–214. https://doi.org/10.1109/ISCID.2010.70

Liang, J., Shi, Y., Osman, M., Shrestha, B., & Wang, P. (2020). The association between social integration and utilization of essential public health services among internal migrants in china: A multilevel logistic analysis. *International Journal of Environmental Research and Public Health*, *17*(18), Article 18. https://doi.org/10.3390/ijerph17186524

Liao, WH., Huang, YT., Yang, TH., & Wu, YC. (2019). Analyzing social network data using deep neural networks: A case study using Twitter posts. *2019 IEEE International Symposium on Multimedia (ISM)*, 237–2371. https://doi.org/10.1109/ISM46123.2019.00053

Lin, K. Z., Cheng, S., & Zhang, F. (2017). Corporate social responsibility, institutional environments, and tax avoidance: Evidence from a subnational comparison in China. *The International Journal of Accounting*, *52*(4), 303–318. https://doi.org/10.1016/j.intacc.2017.11.002

Llacer, T. (2014). Resentimiento fiscal. Una propuesta de mecanismo explicativo de la relación entre la edad y la moral fiscal. *Revista Internacional de Sociología*, *72*(1), Article 1. https://doi.org/10.3989/ris.2011.12.22

López-Ruiz, V.-R., Huete-Alcocer, N., Alfaro-Navarro, J.-L., & Nevado-Peña, D. (2021). The relationship between happiness and quality of life: A model for Spanish society. *PLOS ONE*, *16*(11), e0259528. https://doi.org/10.1371/journal.pone.0259528

Maffini, G. (2009). Tax haven activities and the tax liabilities of multinational groups. *Working Papers*, Article 0925. https://ideas.repec.org//p/btx/wpaper/0925.html

Majeed, M. T., & Samreen, I. (2020). Social capital as a source of happiness: Evidence from a cross-country analysis. *International Journal of Social Economics*, *48*(1), 159–179. https://doi.org/10.1108/IJSE-10-2019-0602

María-Dolores, R., Alarcón, G., & Garre, M. E. (2010). Tax morale in Spain: A study into some of its principal determinants. *Journal of Economic Issues*, *44*(4), 855–876. https://doi.org/10.2753/JEI0021-3624440401

Martinez-Vazquez, J., & Torgler, B. (2009). The evolution of tax morale in modern Spain. *Journal of Economic Issues*, *43*(1), 1–28. https://doi.org/10.2753/JEI0021-3624430101

Maset-Llaudes, A., & Fuertes Fuertes, I. (2015). *The role of bonding bridging and linking social capital in life satisfaction A case of migrants in Spain*. 55–58. https://doi.org/10.15224/978-1-63248-081-1-44

McLachlan, G. J. (2004). *Discriminant Analysis and Statistical Pattern Recognition*. Wiley Interscience.

Minsky, M. (1974). *A Framework for Representing Knowledge* (Memo 306). MIT-AI Laboratory.

Minsky, M., & Papert, S. (1969). *Perceptrons: An Introduction to Computational Geometry*. MIT Press.

Mochón Morcillo, F., & de Juan Díaz, R. (2016). Happiness and social capital: Evidence from Latin American countries. In M. Rojas (Ed.), *Handbook of Happiness Research in Latin America* (pp. 143–161). Springer Netherlands. https://doi.org/10.1007/978-94-017-7203-7_9

Morales, L., & Ramiro, L. (2011). Gaining political capital through social capital: Policy-making inclusion and network embeddedness of migrants' associations in Spain. *Mobilization: An International Quarterly*, *16*(2), 147–164. https://doi.org/10.17813/maiq.16.2.a3547l7803327738

Muñoz-Goy, C. (2013). Social capital in Spain: Are there gender inequalities? *European Journal of Government and Economics*, *2*, 79–94. https://doi.org/10.17979/ejge.2013.2.1.4288

Musson, A., & Rousselière, D. (2020). *Social capital and Life Satisfaction: A new approach* [Post-Print]. HAL. https://econpapers.repec.org/paper/haljournl/hal-02479982.htm

Nahapiet, J., & Ghoshal, S. (1998). Social capital, intellectual capital, and the organizational advantage. *The Academy of Management Review*, *23*(2), 242–266. https://doi.org/10.2307/259373

Nannicini, T., Stella, A., Tabellini, G., & Troiano, U. antonio. (2010). *Social Capital and Political Accountability* (SSRN Scholarly Paper 1622136). https://doi.org/10.2139/ssrn.1622136

Nielsen, F. (2016). *Introduction to HPC with MPI for Data Science*. Springer.

Núnez-Barriopedro, E., Penelas-Leguía, A., López-Sanz, J. M., & Loranca-Valle, M. C. (2023). A public service management model as an antecedent for citizen satisfaction and fiscal policy. *Management Decision*, *62*(2), 725–739. https://doi.org/10.1108/MD-11-2022-1547

Oney, E., & Oksuzoglu-Guven, G. (2015). Confidence: A critical review of the literature and an alternative perspective for general and specific self-confidence. *Psychological Reports*, *116*(1), 149–163. https://doi.org/10.2466/07.PR0.116k14w0

Oussi, R., & Chtourou, W. (2020). Social capital dimensions and employee creativity: Does cognitive style matter? *Competitiveness Review: An International Business Journal*, *30*(1), 4–21. https://doi.org/10.1108/CR-11-2019-0124

P, V., H, S., & B.*, J. (2017). An assessment of tax morale among Mauritian taxpayers. *Journal of Accounting and Taxation*, *9*(1), 1–10. https://doi.org/10.5897/JAT2016.0224

Parry, I. W. H., & Bento, A. (2001). Revenue recycling and the welfare effects of road pricing. *The Scandinavian Journal of Economics*, *103*(4), 645–671. https://doi.org/10.1111/1467-9442.00264

Piñeira Mantiñán, M. J., Lois González, R. C., & González Pérez, J. M. (2019). New models of urban governance in Spain during the post-crisis period: The fight against vulnerability on a local scale. *Territory, Politics, Governance*, *7*(3), 336–364. https://doi.org/10.1080/21622671.2018.1485595

Piñeira-Mantiñán, M. J., Durán-Villa, F. R., & Taboada-Failde, J. (2018). Urban Vulnerability in Spanish Medium-Sized Cities during the Post-Crisis Period (2009–2016). The Cases of A Coruña and Vigo (Spain). *Urban Science*, *2*(2), Article 2. https://doi.org/10.3390/urbansci2020037

Ponzetto, G., & Troiano, U. (2018). *Social capital , government expenditures, and growth*. https://www.semanticscholar.org/paper/Barcelona-GSE-Working-Paper-Series-Working-Paper-n-Ponzetto-Troiano/5a52b4665a87d641118ed0a23a156e2a88ae25a4

Portela Maseda, M., & Neira Gómez, I. (2012). *Capital social y bienestar subjetivo. Un análisis para España considerando sus regiones*. https://ebuah.uah.es/dspace/handle/10017/27179

Portes, A. (1998). Social capital: Its origins and applications in modern sociology. *Annual Review of Sociology*, *24*(1), 1–24. https://doi.org/10.1146/annurev.soc.24.1.1

Prieto-Pastor, I., Martín-Pérez, V., & Martín-Cruz, N. (2018). Social capital, knowledge integration and learning in project-based organizations: A CEO-based study. *Journal of Knowledge Management*, *22*(8), 1803–1825. https://doi.org/10.1108/JKM-05-2017-0210

Pukelis, L., & Stančiauskas, V. (2019). The Opportunities and Limitations of Using Artificial Neural Networks in Social Science Research. *Politologija*, *94*(2), 56–80. https://doi.org/10.15388/Polit.2019.94.2

Rabadán Pérez, F. (2009). *Economía simbiótica* [THES]. CEU San Pablo University.

Rabadán Pérez, F. (2015). *Neofisiocracia. Método AIRO. La economía del orden natural y la empresa Española* [THES]. CEU San Pablo University.

Rosenblatt, F. (1958). The perceptron: A probabilistic model for information storage and organization in the brain. *Psychological Review*, *65*(6), 386–408. https://doi.org/10.1037/h0042519

Rothengatter, M. R. (2005). Social networks and tax (non-)compliance in a multicultural nation: Emerging themes from a focus-group study among ethnic minorities in Australia. *International Journal of Entrepreneurial Behavior & Research*, *11*(4), 280–314. https://doi.org/10.1108/13552550510603306

Rumelhart, D. E., Hinton, G. E., & Williams, R. J. (1986). Learning representations by back-propagating errors. *Nature*, *323*(6088), 533–536. https://doi.org/10.1038/323533a0

Sá, C., Gomes, C., & Martins, A. (2017). Tax morale dimensions analysis in Portugal and Spain. *International Journal of Economics and Management Engineering*, *10*(12), 3969–3975.

Salganik, M. J., Lundberg, I., Kindel, A. T., Ahearn, C. E., Al-Ghoneim, K., Almaatouq, A., & others. (2020). Measuring the predictability of life outcomes with a scientific mass collaboration. *Proceedings of the National Academy of Sciences*, *117*(15), 8398–8403. https://doi.org/10.1073/pnas.1915006117

Sanzo, M. J., Santos, M. L., García, N., & Trespalacios, J. A. (2012). Trust as a moderator of the relationship between organizational learning and marketing capabilities: Evidence from Spanish SMEs.

International Small Business Journal, *30*(6), 700–726. https://doi.org/10.1177/0266242611418907

Sasaki, I., Kondo, K., Kondo, N., Aida, J., Ichikawa, H., Kusumi, T., Sueishi, N., & Imanaka, Y. (2018). Are pension types associated with happiness in Japanese older people?: JAGES cross-sectional study. *PloS One*, *13*(5), e0197423. https://doi.org/10.1371/journal.pone.0197423

Somarriba Arechavala, N., Zarzosa Espina, P., & López Pastor, A. T. (2022). The importance of the neighbourhood environment and social capital for happiness in a vulnerable district: The case of the Pajarillos district in Spain. *Journal of Happiness Studies*, *23*(5), 1941–1965. https://doi.org/10.1007/s10902-021-00479-x

Stevens, J. (1996). *Applied multivariate statistics for the social sciences*. Lawrence Erlbaum Associates.

Tabachnick, B. G., & Fidell, L. S. (2013). *Using multivariate statistics*. Pearson.

Tavits, M. (2006). Making democracy work more? Exploring the linkage between social capital and government performance. *Political Research Quarterly*, *59*(2), 211–225. https://doi.org/10.1177/106591290605900204

Torgler, B. (2003). To evade taxes or not to evade: That is the question. *The Journal of Socio-Economics*, *32*(3), 283–302. https://doi.org/10.1016/S1053-5357(03)00040-4

Torgler, B., & Schneider, F. (2004). *Does Culture Influence Tax Morale? Evidence from Different European Countries*.

Torgler, B., & Schneider, F. (2009). The impact of tax morale and institutional quality on the shadow economy. *Journal of Economic Psychology*, *30*(2), 228–245. https://doi.org/10.1016/j.joep.2008.08.004

Valdaliso, J., & Etxabe, I. (2016). Measuring structural social capital in a cluster policy network: Insights from the Basque Country. *European Planning Studies*, *24*. https://doi.org/10.1080/09654313.2015.1117582

Van Der Maaten, L., & Hinton, G. (2008). Visualizing data using t-SNE. *Journal of Machine Learning Research*, *9*(Nov), 2579–2605.

Wahl, I., Kastlunger, B., & Kirchler, E. (2010). Trust in authorities and power to enforce tax compliance: An empirical analysis of the “slippery slope framework.” *Law & Policy*, *32*(4), 383–406. https://doi.org/10.1111/j.1467-9930.2010.00327.x

Waldfogel, J., Craigie, T. A., & Brooks -Gunn, J. (2010). Fragile families and child wellbeing. *The Future of Children*, *20*(2), 87–112. https://doi.org/10.1353/foc.2010.0002

Watkins, M. W. (2018). Exploratory Factor Analysis: A Guide to Best Practice. *Journal of Black Psychology*, *44*(3), 219–246. https://doi.org/10.1177/0095798418771807

Williams, C. C., & Krasniqi, B. (2017). Evaluating the individual- and country-level variations in tax morale: Evidence from 35 Eurasian countries. *Journal of Economic Studies*, *44*(5), 816–832. https://doi.org/10.1108/JES-09-2016-0182

Woolcock, M., & Narayan, D. (2000). Social capital: Implications for development theory, research, and policy. *World Bank Research Observer*, *15*, 225–249. https://doi.org/10.1093/wbro/15.2.225

Yeomans, K. A., & Golder, P. A. (1982). The Guttman-Kaiser Criterion as a Predictor of the Number of Common Factors. *Journal of the Royal Statistical Society. Series D (The Statistician)*, *31*(3), 221–229.

Zhao, X., Liu, Q., Zhang, S., Li, T., & Hu, B. (2022). The impact of psychological capital and social capital on residents' mental health and happiness during covid-19: Evidence from China. *Frontiers in Psychology*, *13*. https://www.frontiersin.org/articles/10.3389/fpsyg.2022.962373

Zucman, G. (2014). Taxing across borders: Tracking personal wealth and corporate profits. *Journal of Economic Perspectives*, *28*(4), 121–148. https://doi.org/10.1257/jep.28.4.121

Annexes. Methodology

We proceed with constructing tables to interpret the factors derived from the Rotated Factor Matrix while considering the orientation of the survey. The factors are listed in descending order of their loading values, highlighting their importance for each corresponding factor. The PCA produced 6 factors:

F1—Tolerance towards tax evasion (IRPF and VAT). Based on survey data from section P26 (Table 8), measure the degree of intolerance towards various types of tax fraud.

Table 8. Tolerance towards tax evasion. Source: Own elaboration

Variables	Loading	Scale
P26_5.- Ser autónomo/a y no cobrar el IVA	0.717	+
P26_8.- Que una pequeña empresa eluda o evite pagar el impuesto de sociedades	0.679	+
P26_6.- Ser autónomo/a y deducirse gastos personales (ropa, compra del supermercado, etc.) como gastos de empresa que no le corresponden	0.643	+
P26_7.- Que una gran empresa eluda o evite pagar el impuesto de sociedades	0.637	+
P26_4.- Recibir una prestación social a la que no se tiene derecho (fingir una enfermedad para conseguir una baja en el trabajo o cobrar una prestación por desempleo cuando se realiza un trabajo remunerado)	0.584	+
P26_3.- Aplicarse una deducción que no le corresponde al realizar el pago de impuestos (declaración de IVA o IRPF)	0.558	+
P26_2.- Pagar sin factura una reparación doméstica para evitar abonar el IVA	0.548	+
P26_9.- Montar una empresa que opere solo en Internet para pagar menos impuestos	0.434	+

F2—Satisfaction with public services. This factor incorporates a range of elements representative of public services that impact all citizens (P6). However, the item related to support for dependent individuals (P6_9) is not included in the assessment as the factor increases.

Table 9. Satisfaction with public services. Source: Own elaboration

Variables	Loading	Scale
P6_6.- Los servicios sociales	0.574	+
P6_1.- La enseñanza	0.545	+
P6_5.- La seguridad ciudadana	0.518	+
P6_4.- La Administración de Justicia	0.498	+
P6_3.- La gestión de las pensiones	0.491	+
P6_2.- La asistencia sanitaria	0.484	+
P6_8.- Las obras públicas (carreteras, depuradoras, etc.)	0.47	+
P10.- Contraprestaciones insuficientes que recibe la sociedad por el pago al Estado/administraciones públicas de los impuestos y cotizaciones	0.451	+

F3—Happiness (of the interviewee). This factor includes questions aimed at measuring respondent satisfaction with various aspects of their life.

Table 10. Happiness. Source: Own elaboration

Variables	**Loading**	**Scale**
P2ESCAFELI.- Escala de felicidad personal (0-10)	0.748	+
P1_3.- Su vida social	0.685	+
P1_1.- Su vida familiar	0.631	+
P1_2.- Su salud	0.538	+

F4—Perceived tax pressure. The question formed in this manner reflects the individual's perception of fiscal pressure on a reverse scale.

Table 11. Perceived tax pressure. Source: Own elaboration

Variables	**Loading**	**Scale**
P12.- Percepción personal de la presión fiscal	0,79	-
P13.- Comparación de la presión fiscal de España con Europa	0,66	-
P9ESCAIMPUESTOS.- Escala de valoración (0-10) del aumento de los impuestos para tener mejores servicios públicos y prestaciones sociales (inversa)	-0,479	-

F5—Social elevator (on revers scale). This factor represents the social and economic mobility within a society. A functioning social elevator means that merit, effort, and talent are more important than birth or privilege in determining wealth and social status. As this factor increases, individuals may see changes in their position on the social ladder.

Table 12. Social elevator. Source: Own elaboration

Variables	**Loading**	**Scale**
ESTUDIOS.- Estudios de la persona entrevistada	0.709	+
INGREHOG.- Nivel de ingresos del hogar	0.544	-
CLASESUB.- Identificación subjetiva de clase	0.535	-
SITECONOM.- Valoración de la situación económica personal actual	-0.519	-

F6—Moral demand. This factor highlights the significance of specific attitudes in being a good citizen. It pertains to moral or ethical obligations and duties that influence behavior according to notions of morality.

Table 13. Moral demand. Source: Own elaboration

Variables	**Loading**	**Scale**
P4_6.- Ser una persona responsable y honesta	0.638	+
P4_4.- Cumplir siempre las leyes y las normas	0.554	+
P4_5.- Respetar las opiniones de los/as demás aunque sean diferentes de las propias	0.549	+
P4_1.- Ser solidario/a con la gente que está peor que Ud.	0.38	+

Table 14. KMO and Bartlett's Test. Source: Own elaboration

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.819
Bartlett's Test of Sphericity	Approx. Chi-Square	10554.021
	df	465
	Sig.	<.001

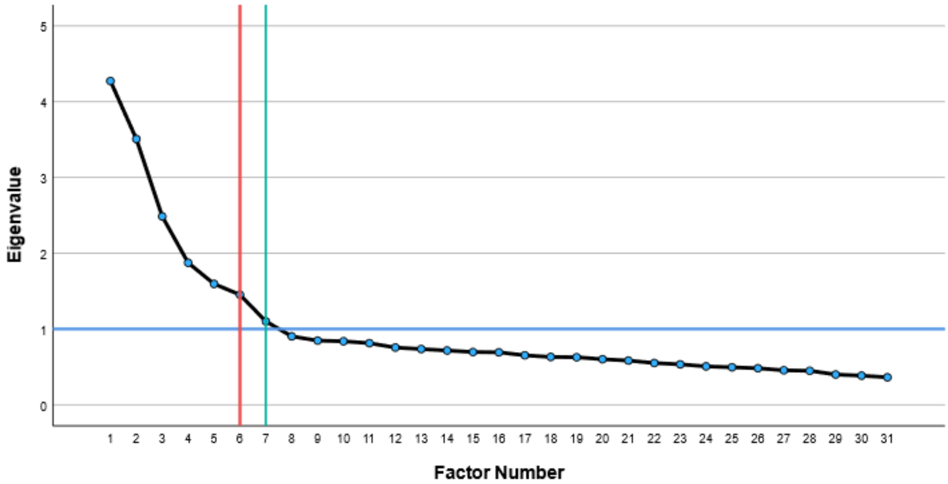

Figure 5. Scree plot. Source: Own elaboration

Above the Kaiser criterion, we could extract 7 factors (blue line), but the seventh factor lacks interpretability (which is confirmed for 6 factors, red line). In Figure 5, we selected 6 factors explaining 48.99% of the total variance before rotation. We extract using maximum likelihood and perform a varimax rotation.

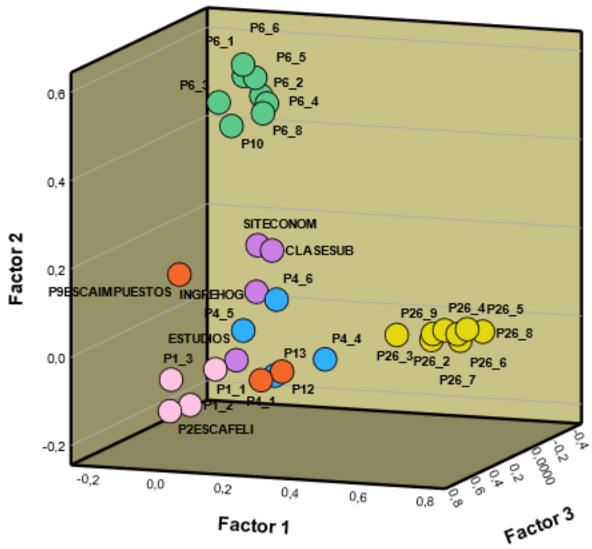

Figure 6. Component plot in rotated space. Source: Own elaboration with SPSS 29.

Table 15. The area under the curve. Source: Own elaboration

Area Under the Curve		
		Area
Cluster Number of Case	1	.999
	2	1.000
	3	.999
	4	.999