Universitat Autònoma de Barcelona

Facultat d'Economia i Empresa

Bachelor's Degree Final Project

Faculty of Economics and Business

What are the **determinant variables** of fiscal fraud perception in **Spain?**

Author: Mario Granados de la Torre

Tutor: Judith Panadés Martí

Degree in Economics

Universidad Autónoma de Barcelona

30/05/2024

AGRADECIMIENTOS

A mi familia, Angelina y la Miu

Resumen

Este estudio tiene como objetivo identificar los principales determinantes de la percepción del fraude fiscal por parte de los contribuyentes en España. Con la ayuda de los modelos de regresión desarrollados, somos capaces de afirmar que la percepción del fraude fiscal es una variable extremadamente compleja, que viene determinada por variables de todo tipo, desde socioeconómicas hasta experiencias personales pasando por, obviamente, la opinión sobre los impuestos.

Palabras clave: Percepción del fraude fiscal, variables socioeconómicas, opinión sobre los impuestos, experiencias personales.

Resum

Aquest estudi té com a objectiu identificar els principals determinants de la percepció del frau fiscal per part dels contribuents a Espanya. Amb l'ajuda dels models de regressió desenvolupats, som capaços d'afirmar que la percepció del frau fiscal és una variable extremadament complexa, que ve determinada per variables de tota mena, des de socioeconòmiques fins a experiències personals passant per, òbviament, l'opinió sobre els impostos

Paraules clau: Percepció del frau fiscal, variables socioeconòmiques, opinió sobre els impostos, experiències personals.

Abstract

This study aims to identify the main determinants of taxpayers' perception of tax fraud in Spain. With the help of the regression models developed, we can affirm that the perception of tax fraud is an extremely complex variable, which is determined by variables of all kinds, from socioeconomic to personal experiences, including, obviously, the opinion about taxes.

Keywords: Fiscal fraud perception, socioeconomic variables, taxes, opinion about taxes, personal experiences.

CONTENTS

1. INTRODUCTION 5

2. LITERATURE REVISION 5

3. DATA SET 10

3.1. SOCIO-ECONOMIC VARIABLES 12
3.2. FISCAL PERCEPTION VARIABLES 12
3.3. PERSONAL PERCEPTION VARIABLES 13

4. METHODOLOGY 15

4.1. THE MODELS 15
4.2. EVALUATION OF THE MODELS 19

5. RESULTS 19

5.1. THE FIRST MODEL: ONLY SOCIOECONOMIC VARIABLES 19
5.2. THE SECOND MODEL: ADDING FISCAL PERCEPTION VARIABLES 22
5.3. THE THIRD MODEL: ADDING PERSONAL PERCEPTION VARIABLES 27

6. CONCLUSION 32

A. APPENDIX 36

1. Introduction

Tax fraud is more than just a financial transgression and it casts a long shadow on societies. It erodes public trust, undermines essential public services, and widens economic inequalities. In Spain, the issue holds particular significance, with estimates suggesting a substantial shadow economy that lowers public revenue. This final project examines in detail this problem by examining public perceptions of fiscal fraud in Spain and which are the determinants behind these perceptions.

This study delves into the widespread belief that fraud exists, exploring who is most seen as engaging in it. Are these perceptions driven by cultural norms that tolerate certain forms of evasion, by economic disparities that breed resentment toward those perceived as unfairly benefiting, or by their political positioning? We will dissect the social influences that may interact with an individual’s perception, examining if friends, family, or media shape public opinion. Crucially, we are trying to investigate the impact of these social perceptions. I would like to answer what determines that someone believes tax evasion is common.

First, we will dive into the vast pool of existing research to understand the landscape, learning from previous studies and identifying key questions to address. Next, we meticulously craft our methodology, outlining how we will gather and analyze data and explaining the dataset used for the models.

We will then focus on interpreting the meaning of the data, drawing conclusions, and uncovering the determinant variables that shape fiscal fraud perception, we discover that fiscal perception variables are the ones that influence the most in the perception of taxpayers, variables like the level of studies, being religious or the happiness of the taxpayer are also very important predictors of the dependent variable. Finally, we culminate our exploration in the “Conclusion” section, synthesizing our findings and offering their broader implications.

2. Literature Revision

Traditional approaches to tax evasion primarily focus on strict enforcement, emphasizing punishment as the key deterrent. Allingham and Sandmo (1972) argue that tax evasion involves a calculated decision under uncertainty. Individuals choose to report either their full income or a lower amount, understanding that the latter option carries the risk of detection and penalties. If undetected, tax evasion provides a financial benefit. However, if caught, the individual faces significant consequences, including repaying the evaded taxes with penalties and potentially damaging their reputation. Importantly, Allingham and Sandmo (1972) highlight that the effectiveness of penalties depends on their structure. Individuals will always be incentivized to underreport if the penalty for evading a certain amount is lower than simply paying the tax. This suggests the need for strong, proportional penalties to deter evasion. Beyond penalties, Allingham and Sandmo (1972) explore other factors influencing tax evasion, such as reputational damage and the risk of detection. They note that authorities often view high-income earners as more likely to evade, but low-income reporting can also raise suspicion. Their conclusion aligns with the traditional view that increasing penalties leads to higher reported income and that individuals are more eager to evade if they are risk averse.

Further research by Friedland et al. (1978) supports this first notion, finding that fines have a positive deterrent effect, while tax rates have a negative one. Interestingly, their study also suggests gender differences, with women evading less than men. Additionally, they emphasize the role of perceived fairness in tax systems, highlighting how beliefs about the justice of the tax burden can influence compliance. These findings shift the focus from solely punitive measures to understanding taxpayer behavior and the sociological environment. Social factors, like perceptions of fairness and stigma associated with evasion, emerge as important determinants alongside traditional enforcement strategies. This calls for a multifaceted approach that combines deterrence with addressing underlying behavioral factors to combat tax evasion effectively.

While traditional approaches to tax evasion rely heavily on penalties and deterrence, more nuanced insights emerge when considering taxpayer psychology and behavior. Building on the work of Kahneman and Tversky (1979), who explored decision-making under uncertainty, we can understand how individuals approach the decision to evade taxes. The prospect theory proposed by this study highlights the influence of loss aversion and framing effects. This suggests that individuals are more sensitive to potential losses than gains, and their choices are influenced by how information is presented. In the context of tax evasion, this translates to a greater aversion to the potential penalties and negative consequences of getting caught compared to the perceived benefits of evading taxes. However, the effectiveness of penalties depends on their structure. Individuals will always be incentivized to underreport if the penalty for evading a certain amount is lower than simply paying the tax. This highlights the need for strong, proportional penalties that make evasion a less attractive option. Beyond penalties, social factors such as perceived fairness and stigma associated with evasion play a significant role, confirming the statements by Friedland et al. (1978). If individuals view the tax system as unfair or unjust, they may be more likely to engage in evasion. Additionally, the social stigma associated with getting caught can act as a deterrent.

While Kahneman and Tversky (1979) research offers valuable insights, exploring the influence of cultural dimensions through the framework provided by Hofstede (1980) can further enrich our understanding of tax evasion. His work categorizes countries based on four key indicators:

1. Power Distance Index (PDI): This measures the acceptance of hierarchy and inequality. Societies with high PDI might view tax evasion as a normal exercise of power by the powerful, while those with low PDI might find it more offensive and socially unacceptable.

2. Masculinity (MASC): This reflects the emphasis on material success and competitiveness. In highly masculine societies, individuals might be more attracted by accumulating wealth and success, potentially increasing tax evasion to achieve that. Conversely, societies that value emotional well-being and cooperation will behave the opposite way.

3. Individualism (IND): This measures the degree of independence and self-reliance. In individualistic societies, tax compliance might be viewed as a personal responsibility, while collectivistic societies might prioritize group loyalty and obedience to authority.

4. Uncertainty Avoidance Index (UAI): This reflects society's tolerance for ambiguity and risk. Societies with high UAI tend to prefer structured rules and regulations. Conversely, cultures with low UAI might be more accepting of flexibility and bending the rules.

By analyzing these cultural dimensions, we gain a more nuanced understanding of the complex factors influencing tax evasion behavior. This complicated approach can inform the development of targeted interventions that address not just the act of evasion itself, but also the underlying cultural norms and values that may contribute to it.

Building upon the previous insights, Andreoni et al. (1998) offer a broader framework for understanding tax behavior. Their work focuses more on the psychological and social factors that shape individual decisions to comply with tax regulations. This shift in focus goes beyond solely examining the effectiveness of enforcement strategies and acknowledges the complex relation of motivations and social influences that guide taxpayer behavior.

Andreoni et al. (1998) highlight the importance of individual decision-making in the context of tax compliance. They present various economic models that depict tax evasion as a calculated decision involving trade-offs between potential benefits (avoiding taxes) and risks (getting caught and facing penalties). The study also explores the role of psychological factors such as altruism and fairness perceptions. They argue that individuals may be more likely to comply if they believe the tax system is fair and the collected revenue is used effectively for the public good.

Furthermore, the research emphasizes the significance of social norms and enforcement mechanisms. The study suggests that strong social disapproval of tax evasion and efficient enforcement strategies can significantly deter individuals from engaging in such behavior. By synthesizing these various elements, Andreoni et al. (1998) contribute to a deeper understanding of tax compliance. Their work highlights the need to consider not just deterrence through penalties, but also incentives, social norms, and fairness perceptions when designing effective strategies to combat tax evasion and promote long-term compliance within a more equitable tax system.

Tsakumis et al. (2007) further explored these indicators, investigating the influence of cultural dimensions on this issue. Their research examines how national cultural characteristics can indirectly affect tax compliance behaviors. By considering these cultural dimensions alongside traditional economic factors, Tsakumis et al. (2007) offer a more nuanced understanding of the factors influencing tax evasion. Their findings suggest that cultural values and norms can significantly influence perceptions of fairness, risk tolerance, and individual responsibility, which ultimately impact tax compliance behavior. This highlights the need for a multifaceted approach that considers not just economic factors, but also the influence of culture when designing effective strategies to combat tax evasion and promote a more equitable tax system.

Slemrod (2007) explores the complex dynamics of tax evasion and its implications for economic policy and tax enforcement strategies. His comprehensive analysis delves into how personal incentives, along with legal consequences, influence individuals' and businesses' decisions to evade taxes. The research articulates the multifactorial nature of tax evasion, emphasizing that it is not merely an act of breaking the law but also a response to the incentives created by the tax system itself.

By examining both historical and contemporary data, the author identifies the various methods and motivations behind tax evasion, noting that while some are driven by economic benefit, others might be influenced by perceptions of fairness or the effectiveness of government spending. His findings suggest that while legal penalties and auditing are essential, they are insufficient on their own to stop tax evasion significantly. Instead, he advocates for a holistic approach that includes improving public trust in tax administration, enhancing transparency, and potentially reforming the tax policy to align better with socioeconomic objectives.

This comprehensive understanding points to the necessity of considering both psychological and economic factors in designing more effective tax enforcement strategies. The study highlights the role of government policy in shaping tax compliance behavior and underscores the importance of a balanced approach that addresses the underlying reasons for evasion, beyond mere deterrence.

For a more updated view of the present situation, Poço et al. (2015) dives deep into the complex relationship between sociological factors and tax compliance behaviors in Portugal. Their study investigates how societal norms and personal ethics contribute to individual decisions regarding tax evasion and fraud. By integrating sociological dimensions with traditional economic considerations, the authors present a more detailed exploration of the factors driving fiscal noncompliance. Their findings reveal that societal perceptions of the tax system's fairness, the burden of taxation, and the integrity of governmental expenditure significantly sway public attitudes toward tax obligations. These insights underscore the necessity of a comprehensive approach in policy design, emphasizing the importance of cultural and ethical considerations alongside economic strategies to enhance tax compliance and ensure a fairer tax system.

While the research explored above studies several factors influencing tax evasion, the picture remains incomplete without considering the impact of social pressure and the broader societal context. This last section shifts the focus toward perceptions of fiscal fraud and how external influences can shape individual compliance behavior and its perception. In today's interconnected world, information about tax evasion, both real and perceived, can spread rapidly through social media and news outlets. This constant exposure can create a desensitization effect, making tax evasion seem more prevalent and potentially even acceptable. Individuals may observe others engaging in, or seemingly benefiting from, fiscal fraud, leading to a normalization of non-compliance within their social circles. This perceived social acceptance can weaken internal morals and potentially drive individuals towards similar behavior, even if they wouldn't have considered it otherwise.

Furthermore, social media platforms can become breeding grounds for misinformation and distorted narratives about the tax system. This can lead to a distrust of tax authorities and a belief that the system is unfair or inefficient. Such negative perceptions can further erode the sense of moral obligation to comply and contribute to a climate where fiscal fraud appears less shocking. Understanding the complex connection between social pressure, media portrayals, and individual perceptions is crucial in addressing tax evasion effectively. Our study aims to contribute to the extensive body of research on tax evasion by focusing on the under-explored area of social pressure and its influence on individual compliance behavior. By analyzing these factors, we hope to bring answers to how the broader societal context shapes individual perceptions about fiscal fraud.

3. Data set

This part of the study will explain what set of variables I will use to study the determinants of the perception of fiscal fraud. The variables used in this study will be cross-sectional and not expressed as change over time, as we use a survey provided by the CIS (Centro de Investigaciones Sociológicas) as a database. We have just one period from the 2023 wave and a sample of 3011 individuals. I have decided to select this survey as the database for the study because it is a very respected and reliable source with many potentially good variables.

From all these variables provided by the database to choose from I chose P18 as our dependent variable. This variable measures from 1 to 4 the degree of perception one individual has about fiscal fraud in Spain, more precisely it asked: “In your opinion, do you think that in Spain exists, very little, little, quite a lot or a lot of fiscal fraud?” to which the possible answers were: “1: There is a lot of fiscal fraud, 2: There is quite a lot of fiscal fraud, 3: There is little fiscal fraud, 4: There is very little fiscal fraud, 8: Does not know, 9: Does not answer”[1]. I decided after that to select variables that could have some relation to the perception of fiscal fraud. For that, I determine diverse groups, to make the explanation of the picked variables simpler.

All these variables will be described after. First, we will explain the process of cleaning all the available data. As I mentioned before I selected the ones that I thought would be the best for describing our dependent variable, but with this kind of survey there is a problem, they have the option of “NS/NC” which translates to “Does not know/Does not answer”, thus we had to clean all the observations having that in any of the variables, but to clean all the observations we had to make sure that the representativeness of the sample was untouched, or little touched. I did that process to ensure that the study would be as rigorous as possible. Panel (a) will show how the average and the standard deviation of the socio-economic variables as well as the percentage of the gender of the sample varied during the process of cleaning these Null observations. For now, a summarized view we provide is the net difference between the before and the after of the cleaning, having disqualified a total of 974 observations, but as it can be seen the objective of maintaining the representativeness was accomplished.

[1] For methodological reasons, we have reversed all scales from "a lot to a little" to "a little to a lot," including the variable in question.

Table 1: Difference between the average and variance of several socio-economic variables as well as the percentage of gender of the sample.[2]

Variable	Normal	RELIGION
Age Average	49,679	47,58
Age Variance	15,826	15,348
% Men	52,81%	56,26%
% Women	47,19%	43,74%
Studies Average	4,964	5,044
Studies Variance	1,273	1,186
Rent Average	2716,341	2882,89
Rent Variance	1521,837	1434,423

Final Difference
2,099
0,478
-3,45%
3%
-0,08
0,087
-166,549
87,414

3.1. Socio-economic variables

We consider socioeconomic variables the ones that are used to describe an individual's social and economic conditions. These are the fundamental variables in all social science studies. In this specific survey we will take as socioeconomic variables the following ones:

- SEXO: This variable is a dummy describing whether an individual is male "1" or female "0".
- EDAD: The age of the individual, starting from 18 years old.
- ESTUDIOS: Level of studies of the individual, going from without studies "1" to superior studies "6".
- SITLAB: We extract a dummy variable from this question meaning that the individual, works "1", or does not work "0".
- INGREHOG: Amount of income that arrives to the household, going from 550€ to 5500€.

3.2. Fiscal perception variables

I have considered as fiscal perception variables all the variables that keep a relation to fiscal matters. Such as opinions on the different taxes or questions about personal

[2] "Normal" marks the start of the data set, before being cleaned, and "RELIGION" is the last variable I cleaned, marking the end of the process, thus representing the sample that will be used during the study.

experiences with taxes. They refer to how individuals respond to the different fiscal policies, taxes, and governmental resource use. Here is a complete list of the ones I use:

- P7: This first variable translates the opinion of taxpayers and we transform it into a dummy, being "1" a positive opinion and "0" a negative one.
- P12: Opinion of taxpayers about the amount of tax that the Spanish population pays, going from little "1" to a lot "3".
- P15: Justice in the paying of taxes, that means, the richest pay the most, being yes "1" or no "0".
- P16: Opinion of the consciousness of the Spanish population when paying taxes, going from little "1" to a lot "3".
- P19 IRPF: Question about if the individual thinks that their acquaintances declare all of their income. From none "1" to everyone or almost everyone "4".
- P20: Question about if the individual thinks that their acquaintances that are obligated by law to declare the aggregated value tax (professionals, self-employed) declare all of their income. From none "1" to everyone or almost everyone "4".
- P24: Opinions of the degree of effort that public administration is putting in to fight against fiscal fraud. From very little "1" to a lot "4".
- P24A: Opinions of the degree of effort that public administration is putting in to explain the destination of these taxes. From very little "1" to a lot "4".
- P27_1: Asks if the mentioned behaviors (defrauding the treasury) could be tolerated by their neighbors. Being yes "1" or no "0".
- P27_2: Asks if the mentioned behaviors (defrauding the treasury) could be tolerated by their friends. Being yes "1" or no "0".
- P27_3: Asks if the mentioned behaviors (defrauding the treasury) could be tolerated by their families. Being yes "1" or no "0".
- INTERVENESTADO: Opinion on the degree of governmental intervention in the economy. Goes from 0 "Should not intervene in the economy" to 4 "Should intervene in every aspect of the economy".

3.3. Personal perception variables

To finish and to complete our third model I decide to add variables that refer to how the individuals see and value aspects of their life and environment. These perceptions are fully subjective and can influence the population's behavior, decision-making, and opinions. I will now enlist the variables I added to this model.

- ESCAFELI: Scale of personal happiness, from “0” to “10”.
- ESCACONFIANZA: Scale of trust, from “0” to “10”.
- DESIGUALDAD: Degree of perception of social inequality, from little inequality “1” to big inequalities “3”.
- ESCIDEOL: Scale of ideological self-location, from left “1” to right “10”.
- ECIVIL: Dummy variable defining if the individual is married “1” or not married “0”.
- SITCONVIVEN: Dummy variable explaining if the individual lives alone “1” or with others “0”.
- RELIGION: Dummy variable for the faith status of the individual, being a believer of any religion “1” and a non-believer “0”.

Here is the list of all the variables classified by type.

Table 2: List of independent variables classified by type

Socioeconomic Variables	SEXO
	EDAD
	ESTUDIOS
	SITLAB
	INGREHOG
Fiscal Perception Variables	P7
	P12
	P15
	P16
	P19 IRPF
	P20 IVA
	P24
	P24A
	P27_1
	P27_2
	P27_3
	INTERVENESTADO
Personal Variables	ESCAFELI
	ESCACONFIANZA
	DESIGUALDAD
	ESCIDEOL
	ECIVIL
	SITCONVIVEN
	RELIGION

4. Methodology

As mentioned, this study will analyze the variables that were explained earlier to identify the determinants of the fiscal fraud perception of taxpayers in Spain. To achieve this objective, we will use a progressive three-stage modeling methodological approach[3]. With progressive I mean that we will add variables in each model, starting with socio-economic variables in the first three models, then we will add fiscal perception variables to those for the next three models, and finally, I will add personal perception variables to further enrich the three models. In the first stage, we will use the Ordinary Least Squares (OLS) regression model to identify potential influencing factors of the perception of fiscal fraud in Spain. This will be the main regression model we will use to investigate the database. We will after that re-do the OLS by robusting its residuals, that way we lower the heteroscedasticity. Finally, we will double-check that regression model in the second stage, in which we will utilize a Probit model to assess the determinants of the likelihood of holding such a perception.

4.1. The Models

The first stage will analyze the data set utilizing an OLS regression model. This methodology will allow us to assess the linear relationship between one dependent variable (in the case of this study, the grade of perception of fiscal fraud in Spain), and one or more independent variables hypothesized to influence the dependent one. The chosen independent variables will encompass factors that we believe can contribute to the perception of fiscal fraud an individual may have and as mentioned earlier it will include socioeconomic characteristics, studies, religion, trust in institutions, and exposure to fiscal fraud, as we mentioned earlier.

This first approach will provide an initial understanding of the direction and also the strength of the associations between the dependent variable and the independent ones. It

---

[3] . In the first place, I planned to do a two-stage approach, but when doing the regressions we detected heteroscedasticity in the data, which is why we then went from a two to three-stage methodological approach.

will enable us to estimate the change in perception of fiscal fraud with a unit change in each independent variable, holding all other variables constant. This will allow us to read some noticeably clear results of our study.

The OLS model will be formulated as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \varepsilon \quad (1)$$

Where:

- Perception of fiscal fraud is the dependent variable (y).
- x_1, x_2, ..., x_n are the independent variables that we believe influence the perception of fiscal fraud. We will try to explain the perception of fiscal fraud through these selected independent variables.
- β_0 is the constant term or intercept.
- β_1, β_2, ..., β_n are the regression coefficients to be estimated, which will indicate the direction and strength of the relationship between each independent variable and the perception of fiscal fraud.
- ε is the error term. It's a random variable that will represent non-observable factors different from the independent variables but also affect y.

To employ this model, we will need to make some suppositions:

1. Linearity in Parameters: The relationship between the dependent variable (y) and the independent variables (x_1, x_2, ..., x_k) is assumed to be linear. This means that the change in y is proportional to the change in each x, holding all other x's constant.

2. Random Sampling: The observations (y_i, x_{1i}, ..., x_{ki}) are assumed to be drawn from a random sample of the population. This means that each observation has an equal chance of being selected and that the observations are independent of each other.

3. Zero Conditional Mean: The expected value of the error term is zero:

$$E(u|x_1, \ldots, x_k) = 0 \quad (2)$$

This means that, on average, the errors are zero for each level of the independent $_k$ variables.

4. No Perfect Multicollinearity: There is no perfect multicollinearity among the independent variables. This means that no independent variable can be expressed as a perfect linear combination of the other independent variables.

5. Constant Variance (Homoscedasticity): The variance of the error term (u_i) is constant across all levels of the independent variables:

$$var\ (u_i) = \sigma^2 \quad (3)$$

This means that the spread of the errors is the same for all values of the independent variables.

6. Normality of Errors: The error terms (u_i) are normally distributed. This means that the errors follow a bell-shaped curve, with most errors close to the mean and fewer errors farther away from the mean.

As we discovered there is heteroscedasticity in the data, which isn't necessarily bad in terms of the estimations the model does, but can transform the standard errors into inefficient ones and can then lead to misleading conclusions about the study, that is the main reason of why I decided to do as well the Robust OLS. When doing that, the process is very similar to the normal OLS, the only thing we do differently is the calculation of the variance thanks to the covariance matrix of Huber-White, described as follows:

$$Var(\widehat{\beta}) = (X'X)^{-1}(\sum_{t=1}^{T} e_t^2\, X_t X_t')(X'X)^{-1} \quad (4)$$

Where we know that:

$$Var(u|X) = \sigma^2\, \Omega \quad (5)$$

Being Ω a diagonal matrix with e_t^2 in the diagonal.

This way we reduce the variance problems that we experienced in the basic OLS models. Compare equation "3" to "5".

Following the different OLS estimations, we will employ a Probit model to analyze the determinants of the likelihood of perceiving fiscal fraud. The Probit model is suited for situations where the dependent variable is binary or has very low variability (in this case, the degree of perception of fiscal fraud an individual perceives). The Probit model will be specified as follows:

$$y = \Phi\ (\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n \quad (6)$$

Where:

- y represents the probability of an individual perceiving fiscal fraud.
- Φ denotes the cumulative distribution function of the standard normal distribution.
- β0, β1, β2, ..., βn are the coefficients to be estimated, similar to the OLS model.

The probit model, like OLS, relies on a set of assumptions to ensure its validity and the accuracy of its results. Here's a breakdown of these assumptions:

1. Binary Outcome: The dependent variable (y) in a probit model can only take two values, typically coded as 0 and 1. Also like in our case can take values that vary very little. This signifies the presence or absence of a certain outcome, thus being able to check our previous results analyzed by the OLS model.

2. Linearity in the Index Function: While the outcome itself is binary, the underlying relationship between the independent variables (x_1, x_2, ..., x_k) and the probability of the outcome is assumed to be linear. This relationship is captured by an index function that combines the independent variables with their respective coefficients.

3. Random Sampling: Similar to linear regression, the observations (y_i, x_{1i}, ..., x_{ki}) are assumed to be drawn from a random sample of the population. This ensures that each observation has an equal chance of being selected and that the observations are independent of each other.

4. Independence of Irrelevant Alternatives (IIA): This assumption states that the relative odds of choosing one outcome over another are independent of the availability of other irrelevant choices. In simpler terms, the presence or absence of additional options shouldn't affect the choice between the two existing options in the model.

5. Normality of Errors: The error terms (u_i) in a probit model are assumed to be normally distributed with a mean of zero. These errors represent the unexplained influence on the outcome variable that is not captured by the independent variables.

4.2. Evaluation of the Models

I will evaluate the fitness of the OLS model using standard diagnostics such as R-squared and adjusted R-squared[4]. For the Probit model, we will assess the model's performance by comparing its regressors. The ultimate test will be to put all the regressors in one table, that way we will be able to analyze the progressions each variable has in the 3 models. Additionally, we will employ appropriate tests for normality (Residual plots and Shapiro-Wilk test), homoscedasticity (Histogram of residuals and Breusch-Pagan Test), and finally multicollinearity where we will do a map of the correlation matrix, supported by a Variance Inflation Factor (VIF) table so the reader can see the results very clearly to ensure the validity of our outcomes in both models.

5. Results

In this section, I analyze the previously explained models and how they explain the dependent variable. As I mentioned, I will present the results of the first model, one that only has socioeconomic variables. After that, I proceed to present the results of the second model, where I add fiscal perceptions variables. Finally, I show the third model, adding personal perception variables.

5.1. The first model: Only socioeconomic variables

This first model does not have the intention of explaining the dependent variable, it serves more as a basis to then compare with the other two models.

Table 3: Model 1 (OLS)

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	3.497e+00	7.347e-02	47.595	< 2e-16
SEXO	-8.626e-02	2.458e-02	-3.509	0.000456
EDAD	1.375e-03	8.516e-04	1.614	0.106559
ESTUDIOS	-4.507e-02	1.085e-02	-4.155	3.35e-05
SITLAB	-1.811e-02	2.902e-02	-0.624	0.532552
INGREHOG	-3.928e-06	9.179e-06	-0.428	0.668741

[4] The same evaluation will be done for the robust OLS.

From this first approach, we can extract some initials readings, for example, the significant socioeconomic variables are the gender (SEXO), with a coefficient of -0,086 and being highly significant for ($p<0,01$) suggests that a unit change in gender makes the perception of fiscal fraud decrease in -0,086. This translates into men perceiving less fiscal fraud than women. The other significant independent variable is the level of studies (ESTUDIOS), with a coefficient of -0,045 and being highly significant for ($p<0,01$) tells us that a unit change in the level of studies means a decrease of perception of fiscal fraud in -0,045 points. This tells us that higher educated people perceive less fiscal fraud. The other socioeconomic variables show no effect on the perception of fiscal fraud. After doing the model I do the tests I talked about, Panel (b) will show all the graphical support for the tests.

The first test we do is the Shapiro-Wilk normality test (b.1), this test will analyze the distribution of our model, the null hypothesis being that the population is normally distributed. We do have a statistic “W”, a higher “W” will indicate more normality and a p-value lower than 0,05 will indicate that there is no normality in the data. To further analyze the normality I do a plot of residuals of the model (b.2), ending with the conclusion that the data in this model is not following a normal distribution. This could be due to many reasons the main one being that the dependent variable is taking very few values, this is supported by the figure (b.3) where we can see that the distribution of residuals is multimodal.

After looking at normality I changed the focus to heteroscedasticity, where thanks to figure (b.3) and then the Breusch-Pagan test (b.4) where your null hypothesis is that there is homoscedasticity in the model. As we can see in the figures there is no such homoscedasticity in the model.

The last test we do is a multicollinearity test, first the VIF (b.5) where I check the variables are independent between them. To further enrich the analysis, I do a correlation matrix and then a correlation map (b.6). Telling me that there exists a bit of multicollinearity in the model, between the wealth of the household (INGREHOG) and the level of studies (ESTUDIOS), something that we could expect due to the low number of variables this model has.

As a general conclusion to this first OLS model, we can say it is not a good one to explain the dependent variable and we can check that just by looking at the R^2, saying that we are only explaining a 1,7% of the perception of fiscal fraud with our model.

After checking the OLS, we can proceed with the robust model to then analyze the results of it.

Table 4: Model 1 (Robust OLS)

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	3.496777e+00	7.184956e-02	48.6680301	0.000000e+00
SEXO	-8.625823e-02	2.434767e-02	-3.5427713	4.023690e-04
EDAD	1.374775e-03	8.572076e-04	1.6037829	1.088739e-01
ESTUDIOS	-4.507212e-02	1.028960e-02	-4.3803581	1.228054e-05
SITLAB	-1.811107e-02	2.892177e-02	-0.6262087	5.312287e-01
INGREHOG	-3.927848e-06	9.440862e-06	-0.4160475	6.774069e-01

If I compare the original OLS model to the robust one, each variable holds very similar coefficients and significance levels. However, if looked at with more detail one can see how the standard errors decreased from the original one, being this is the main objective of doing a robust OLS. Returning to the coefficients and significance levels gender (SEXO) and the level of studies (ESTUDIOS) are still the only variables that are significant predictors of our dependent variable, fiscal fraud perception (P18).

Table 5: Model 1 (PROBIT)

```
Call:
polr(formula = as.factor(P18) ~ SEXO + EDAD + ESTUDIOS + SITLAB +
    INGREHOG, data = datosm1, method = "probit")

Coefficients:
              Value Std. Error t value
SEXO     -1.458e-01  4.220e-02 -3.4540
EDAD      2.366e-03  1.107e-03  2.1369
ESTUDIOS -8.070e-02  1.564e-02 -5.1601
SITLAB   -2.967e-02  4.767e-02 -0.6225
INGREHOG -7.351e-06  1.639e-05 -0.4485

Intercepts:
    Value     Std. Error t value
1|2   -2.7508    0.0061   -452.9362
2|3   -1.7477    0.0166   -105.4383
3|4   -0.0761    0.0389     -1.9572

Residual Deviance: 5346.791
AIC: 5362.791
```

However, when taking a look at the PROBIT model one can observe one very interesting thing, one that the linear models could not reveal, and that is, that now, besides gender (SEXO) and level studies (ESTUDIOS) there is another independent variable that becomes a significant predictor, that is the age (EDAD). While the working situation and the household income are still being not significant for any of the models. Worth mentioning that the residual deviance and the Akaike Information Criterion (AIC) tell us this model is a reasonably good fit for the data. I will provide a table comparing all the coefficients amongst the three different models (b.7). Once said that, and with the 3 different models I can take the next conclusions on this first model. First, the household income, or the fact that you're working or not, does not influence the perception one individual has about fiscal fraud. Switching to significant coefficients, being a female makes you perceive more fiscal fraud, having a higher level of studies will lower your perception of fiscal fraud, and finally thanks to the PROBIT model we can also acknowledge that if the individual is older will perceive more fiscal fraud.

5.2. The second model: Adding fiscal perception variables

When adding fiscal perception variables, I aim to increase the R^2 , giving more significance to the model but as well trying to unveil more determinant variables that could give some insight into individual perception of fiscal fraud.

Table 6: Model 2 (OLS)

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	4.476e+00	1.485e-01	30.144	< 2e-16
SEXO	-4.003e-02	2.702e-02	-1.482	0.13862
EDAD	3.321e-04	9.708e-04	0.342	0.73235
P7	-7.181e-02	3.838e-02	-1.871	0.06147
P12	2.096e-03	2.324e-02	0.090	0.92814
P15	-1.809e-01	3.325e-02	-5.439	5.99e-08
P16	-1.313e-01	2.063e-02	-6.364	2.42e-10
\`P19 IRPF\`	-4.876e-02	2.024e-02	-2.409	0.01607
\`P20 IVA\`	-8.660e-02	1.780e-02	-4.865	1.23e-06
P24	-1.335e-01	1.551e-02	-8.603	< 2e-16
P24A	-2.323e-02	2.096e-02	-1.108	0.26788
P27_1	3.586e-03	3.687e-02	0.097	0.92252
P27_2	3.116e-02	4.286e-02	0.727	0.46732
P27_3	-6.994e-02	3.870e-02	-1.807	0.07090
INTERVENESTADO	5.564e-02	1.887e-02	2.948	0.00323
ESTUDIOS	-3.537e-02	1.228e-02	-2.879	0.00402
SITLAB	-2.493e-02	3.124e-02	-0.798	0.42499
INGREHOG	2.139e-06	1.001e-05	0.214	0.83080

When looking at this model one can instantly realize that is much better than the first model and can take much more clear insights into the determinant's variables of the level of perception of fiscal fraud. First, I compared it to the first model, and I realized that gender (SEXO) is not significant when adding fiscal perception variables, nor age (EDAD). Interestingly, the level of studies (ESTUDIOS) keeps being an important predictor of perceiving or not fiscal fraud, and now with a unit change in the level of studies, the perception of fiscal fraud of an individual will lower -0,035. Now let us change the focus to the fiscal perception variables. Starting with the opinion of taxpayers (P7), seeing that a positive opinion of taxes will lower the perception of fiscal fraud by -0,072, with a low significance level ($p<0,1$). If I go in order the next significant predictor is believing that there is justice in the payment of taxes (P15), with a coefficient of -0,181 and a high significance level of ($p<0,01$) it means that if the taxpayer believes there is justice in the payment of taxes it will lower its perception of fiscal fraud by -0,181. After that, the next in the list would be the opinion an individual has about the consciousness of the Spanish population when paying taxes (P16), similarly to the last one it offers a high coefficient of -0,131 with a high significance level of ($p<0,01$) saying that a positive opinion on the consciousness of the Spanish population when paying taxes will lead to a decrease of -0,131 in the perception of fiscal fraud of the individual. Now if I look at the declaration questions (P19 IRPF) and (P20 IVA) I see that both are significant, more significant is the belief that acquaintances who are obliged by law to declare IVA do not declare all the IVA, with a coefficient of -0,087 and a high level of significance, while the belief of acquaintances not declaring all of their income in their statement has a lower significance level ($p<0,05$) and a lower coefficient as well (-0,049), this information means that the higher number of persons in your environment you belief that declare all of their income (rather it be IRPF or IVA), the lower your perception of fiscal fraud will be. Following that, the opinion about the government fighting fiscal fraud (P24) with a coefficient of -0,133 and a high significance level ($p<0,01$) tells that the higher your opinion about the government fighting fiscal fraud the lower your perception of fiscal fraud will be. If I keep the order in the list, then we jump into tolerance to fiscal fraud by the family (P27_3) with a coefficient of -0,070 and a low significance level ($p<0.1$) mentioning that if the family of the individual could tolerate defrauding the treasury the perception of fiscal fraud will lower. Finally, the last significant predictor is your opinion about state intervention in the economy (INTERVENESTADO) with a coefficient of 0,056 and a high significance level (p<0,01) stating that an augment of 1 unit in your opinion on how much the state intervenes in the economy will augment your fiscal fraud perception in 0,056.

If I now switch back to the tests, I will do the same tests as for model 1, that way we can compare how all these statistical matters, and like before all the graphical support will be provided in Panel (c). First, as I did in model 1we take a look at Shapiro-Wilk's test (c.1), and it keeps indicating that there is no normality in the data provided, but it's worth mentioning that the normality of the data has improved because it has a higher W. To support this notion I do again a QQ Plot of the residuals (c.2) to check the test done, and as happened in model 1 the results are the same, there is no normality, but when looking at the histogram of residuals (c.3) interestingly we see that there is a change from a multi-modal distribution to a bi-modal distribution.

Regarding homoscedasticity tests, thanks to (c.3) and then the support of the Breusch-Pagan test (c.4) I see that the heteroscedasticity of the model has augmented, this means that the variability of the errors is less constant from model 1 to model 2. This could lead to some major changes when comparing later with the robust OLS.

Finally, I look at multicollinearity with both methods, first the VIF (c.5), where I see that there is no dangerous collinearity, because for that the VIF factor of a variable should be higher than 5, and as we see in (c.5) the highest value is 2.62. To sum multicollinearity up I provide a map (c.6) made with the correlation matrix where we see that the higher collinearity that exists is between the P19 and P20, which makes a ton of sense cause those variables explain the belief of someone of your environment not declaring all their income, rather it be IRPF or IVA. With the highest collinearity, there is the tolerance by "x" (P27_x) variables, which is kind of obvious due to the nature of the question, because it is asking the same but for different environment elements, and normally this environment will behave the same way cause the people it's going to share the same values and ethics, for example it is reasonable to think that if your friends and neighbors will not tolerate fiscal fraud, your family will not as well.

As a starting conclusion for this model, we can say it's much better compared to the first model, for its R^2 has increased to 15,2% which means that now our independent variables are explaining a 15,2% of the perception of fiscal fraud, therefore while the model has a good explanatory power for this dataset, there may be factors not included in the model that also influence.

Now as this second model experiences heteroscedasticity as well I will proceed with the analysis of the robust model.

Table 7: Model 2 (Robust OLS)

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	4.475890e+00	1.521904e-01	29.40980463	3.450042e-159
SEXO	-4.003123e-02	2.684181e-02	-1.49137622	1.360149e-01
EDAD	3.320655e-04	9.690830e-04	0.34265952	7.318894e-01
P7	-7.181381e-02	3.961142e-02	-1.81295733	6.998298e-02
P12	2.095882e-03	2.224443e-02	0.09422050	9.249431e-01
P15	-1.808648e-01	3.502006e-02	-5.16460547	2.639994e-07
P16	-1.312773e-01	2.223017e-02	-5.90536779	4.101490e-09
\`P19 IRPF\`	-4.876225e-02	2.016600e-02	-2.41804254	1.568996e-02
\`P20 IVA\`	-8.660208e-02	1.820103e-02	-4.75808703	2.089180e-06
P24	-1.334795e-01	1.658605e-02	-8.04769193	1.406179e-15
P24A	-2.323149e-02	2.143742e-02	-1.08368868	2.786289e-01
P27_1	3.586171e-03	3.625376e-02	0.09891859	9.212125e-01
P27_2	3.115949e-02	4.365323e-02	0.71379577	4.754338e-01
P27_3	-6.994071e-02	3.958376e-02	-1.76690395	7.739144e-02
INTERVENESTADO	5.563703e-02	1.951727e-02	2.85065665	4.406055e-03
ESTUDIOS	-3.536989e-02	1.200145e-02	-2.94713428	3.243149e-03
SITLAB	-2.492786e-02	3.163213e-02	-0.78805515	4.307546e-01
INGREHOG	2.138874e-06	1.019255e-05	0.20984680	8.338079e-01

As experienced before the effect on the coefficient or the significance levels of the independent variables is not moved, both are generally consistent with the original OLS model, but as explained, the fact of doing a robust model does provide a more reliable inference in the presence of heteroscedasticity, which is our case.

The fact that the significance of the predictors stays almost untouched from OLS to robust OLS gives the notion that they are good for explaining the dependent variable, although the final test will be to check the probit model.

Table 8: Model 2 (PROBIT)

```
Call:
polr(formula = as.factor(P18) ~ SEXO + EDAD + ESTUDIOS + SITLAB +
    INGREHOG + P7 + P12 + P15 + P16 + `P19 IRPF` + `P20 IVA` +
    P24 + P24A + P27_1 + P27_2 + P27_3 + INTERVENESTADO, data = datosm2,
    method = "probit")

Coefficients:
                    Value Std. Error t value
SEXO           -6.764e-02  5.141e-02 -1.3158
EDAD            7.074e-04  1.708e-03  0.4142
ESTUDIOS       -6.657e-02  2.236e-02 -2.9767
SITLAB         -4.747e-02  5.957e-02 -0.7969
INGREHOG        5.113e-06  1.949e-05  0.2624
P7             -1.413e-01  1.683e-02 -8.3912
P12             8.850e-03  3.667e-02  0.2414
P15            -3.397e-01  6.135e-02 -5.5365
P16            -2.511e-01  3.983e-02 -6.3043
`P19 IRPF`     -9.755e-02  3.884e-02 -2.5116
`P20 IVA`      -1.680e-01  3.431e-02 -4.8954
P24            -2.585e-01  3.012e-02 -8.5837
P24A           -5.605e-02  3.838e-02 -1.4603
P27_1          -5.007e-03  2.137e-02 -0.2343
P27_2           6.915e-02  2.158e-02  3.2049
P27_3          -1.368e-01  1.874e-02 -7.2997
INTERVENESTADO  1.088e-01  3.109e-02  3.5005

Intercepts:
    Value      Std. Error t value
1|2    -5.0084     0.0035 -1446.9250
2|3    -3.8108     0.0114  -334.7282
3|4    -1.9548     0.0473   -41.3637

Residual Deviance: 3648.289
AIC: 3688.289
```

The probit model suggests a different perspective when modeling fiscal fraud perception (P18), therefore a perfect final touch when doing the models. When taking a deep look at (Table 8) I can see that the majority of the variables maintain the level of significance that they had before, but for variable tolerance of fiscal fraud by friends (P27_2) in the previous versions of the second model I encountered no significance, but now with the PROBIT I indeed can see that it is a significant variable for explaining fiscal fraud perception (P18), which makes sense due to its relationship with other tolerance variables like the tolerance of fiscal fraud by the family (P27_3) that is significant in all three versions of the model. This whole model 2 can show how fiscal perception variables can affect the perception an individual has about fiscal fraud, all the already mentioned significant predictors show strong effects on this perception, and in a lower measure, the tolerance of fiscal fraud by friends (P27_2) as showed in the PROBIT to be significant in a certain way. Suggesting that the rest variables are indeed not significant for how the population perceives fiscal fraud, but anyhow, there is still a lot to know about the perception of fiscal fraud and there may be other factors not included in this model that influence the perception as well. Also, it is worth mentioning that the residual deviance and the AIC of PROBIT model 2 are lower, suggesting that model 2 is a better fit to unveil fiscal fraud perception. To see a detailed view of the evolution of coefficients and significance look at (c.7).

We do realize that the opinions and experiences of the taxpayers are important. For example, the higher the number of people around the taxpayer is not declaring all their income (P19 IRPF and P20 IVA), (or at least the taxpayer thinks they are not) the lower the perception of the individual. Then we have the opinion of the taxpayer about the taxes (P7) and the consciousness of the Spanish population when tax-paying (P16), both negatively affecting fiscal fraud perception. For a finishing touch regarding fiscal matters, the harder an individual thinks that the government is fighting fiscal fraud (P24), the lower their perception will be, and the more agree your opinion about the state intervening in the economy is (INTERVENESTADO), the higher your fiscal fraud perception will be, this could be due to ideological preferences, but as we saw, the ideology of a person (ESCIDEOL) was not significant in any of the models, something that surprised us.

5.3. The third model: Adding personal perception variables

Personal perception and personal environment variables are fundamental to describing the perception of any dependent variable, which is why I am adding these kinds of variables as well, expecting to explain more about the fiscal fraud perception.

Table 9: Model 3 (OLS)

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	4.061e+00	1.797e-01	22.599	< 2e-16
SEXO	-3.128e-02	2.714e-02	-1.152	0.24935
EDAD	1.518e-04	1.116e-03	0.136	0.89181
ESCAFELI	1.691e-02	9.470e-03	1.786	0.07431
ESCACONFIANZA	-2.939e-02	7.309e-03	-4.020	6.03e-05
P7	-5.324e-02	3.952e-02	-1.347	0.17806
P12	2.132e-02	2.454e-02	0.869	0.38501
P15	-1.523e-01	3.346e-02	-4.550	5.69e-06
P16	-1.131e-01	2.077e-02	-5.444	5.84e-08
\`P19 IRPF\`	-5.341e-02	2.027e-02	-2.635	0.00848
\`P20 IVA\`	-7.715e-02	1.784e-02	-4.324	1.61e-05
P24	-1.280e-01	1.556e-02	-8.223	3.51e-16
P24A	-1.270e-02	2.116e-02	-0.600	0.54838
P27_1	-3.328e-03	3.681e-02	-0.090	0.92796
P27_2	6.231e-02	4.264e-02	1.461	0.14412
P27_3	-7.528e-02	3.835e-02	-1.963	0.04982
DESIGUALDAD	1.438e-01	2.359e-02	6.094	1.32e-09
INTERVENESTADO	3.560e-02	1.936e-02	1.839	0.06608
ESCIDEOL	-7.951e-03	6.824e-03	-1.165	0.24408
ECIVIL	6.559e-02	3.313e-02	1.980	0.04789
SITCONVIVEN	-3.246e-03	4.322e-02	-0.075	0.94014
ESTUDIOS	-2.497e-02	1.258e-02	-1.985	0.04723
RELIGION	-8.747e-02	2.925e-02	-2.990	0.00282
SITLAB	-1.984e-02	3.132e-02	-0.633	0.52648
INGREHOG	2.784e-06	1.062e-05	0.262	0.79329

This final model aims to give some extra insights about personal matters that may not be able to be read in the last two models. For instance, we can see that most variables that were significant in the past model are significant in model 3 also. Except for the opinion of taxpayers about taxes (P7) which was found to have a positive effect on perception, but with a low level of significance, which may explain why it is not significant anymore. The rest, including the level of studies (ESTUDIOS), keep showing a significant level of significance in this model. Regarding personal perception variables we see that a few of the newly added ones show some meaningful relationship with fiscal fraud perception (P18), let's dive deeper into that. The first independent variables to show significance are the personal scale of happiness (ESCAFELI) and the personal scale of trust (ESCACONFIANZA). Regarding the first one we see that on a low significance level ($p<0,1$) when this variable goes up by 1 unit it will add 0,017 to the fiscal fraud perception of the individual, differently the second, with a high significance level ($p<0,01$) shows a negative relationship with fiscal fraud perception (P18), indicating that when the user increases the level of trust by 1 unit, the fiscal fraud perception will lower by -0,029. Following these different scales, we have the believing or not in a religion (RELIGION) variable, which also shows a high significance level ($p<0,01$) relation with fiscal fraud perception (P18), the model tells us that believing in any religion will lower the individual's fiscal fraud perception by -0,087. Following that and with a high significance level as well, inequality perception (DEISGUALDAD) will tell that a higher inequality perception will lead to an augment of the fiscal fraud perception of 0,144. Finally, and with a lower significance level ($p<0,05$), the civil status (ECIVIL) can show that if the individual is married will add 0,066 on the fiscal fraud perception scale.

I will continue now by doing the prompt tests, graphical support for those will be in Panel (D). Normality goes first as earlier, first Shapiro-Wilk's test (d.1), showing that while the W improved, this means that our model adjusts better to normality, does still not follow a normal distribution, ($p<0,05$), aiming to support that I provide a QQ Plot of the residuals (d.2) and the histogram of residuals (d.3), concluding that our study is not based on a normally distributed database, as I stated earlier this is most probably since our dependent variable can only take 4 values. Secondly, I take a look at the homoscedasticity of the model with the same histogram of residuals (d.3) and the Breusch-Pagan test (d.4) to conclude that our database does not have homoscedasticity it has heteroscedasticity, thus the robust OLS models. Finally, we arrive at the last kind of test I am realizing, the VIF multicollinearity test (d.5) supported graphically by a map of the matrix of correlations (d.6) stating the same correlations as in model 2.

To conclude this first contact with model 3 I would like to add some comments on how well it adjusts to the dependent variable (fiscal fraud perception, P18), and the truth is that actually while a lot of the reasons for fiscal fraud perception (P18) remain unknown because our model is only capable of explaining 18,2%, we discover that there are a lot of personal perception variables that are of some significance to explain the fiscal fraud perception of the Spanish population.

Table 10: Model 3 (Robust OLS)

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	4.060880e+00	1.814652e-01	22.37829053	3.107710e-99
SEXO	-3.127706e-02	2.702920e-02	-1.15715825	2.473451e-01
EDAD	1.517903e-04	1.103166e-03	0.13759516	8.905741e-01
ESCAFELI	1.690943e-02	8.944916e-03	1.89039572	5.884864e-02
ESCACONFIANZA	-2.938527e-02	7.846133e-03	-3.74519211	1.853240e-04
P7	-5.323501e-02	4.126810e-02	-1.28997961	1.972060e-01
P12	2.132099e-02	2.359342e-02	0.90368349	3.662714e-01
P15	-1.522562e-01	3.506811e-02	-4.34172614	1.483864e-05
P16	-1.130931e-01	2.233346e-02	-5.06384342	4.483485e-07
`P19 IRPF`	-5.341276e-02	2.028632e-02	-2.63294456	8.529598e-03
`P20 IVA`	-7.715052e-02	1.843644e-02	-4.18467640	2.978614e-05
P24	-1.279527e-01	1.667463e-02	-7.67349437	2.590760e-14
P24A	-1.270333e-02	2.165652e-02	-0.58658208	5.575502e-01
P27_1	-3.328180e-03	3.663220e-02	-0.09085396	9.276177e-01
P27_2	6.231246e-02	4.379032e-02	1.42297354	1.548989e-01
P27_3	-7.527514e-02	3.919247e-02	-1.92065308	5.491665e-02
DESIGUALDAD	1.437842e-01	2.451288e-02	5.86566088	5.217276e-09
INTERVENESTADO	3.559925e-02	2.016927e-02	1.76502405	7.771141e-02
ESCIDEOL	-7.951306e-03	6.877160e-03	-1.15619038	2.477406e-01
ECIVIL	6.558564e-02	3.302818e-02	1.98574784	4.719686e-02
SITCONVIVEN	-3.246224e-03	4.066578e-02	-0.07982693	9.363828e-01
ESTUDIOS	-2.497264e-02	1.253534e-02	-1.99217897	4.648636e-02
RELIGION	-8.747130e-02	2.931693e-02	-2.98364423	2.882656e-03
SITLAB	-1.984113e-02	3.181362e-02	-0.62366793	5.329164e-01
INGREHOG	2.783525e-06	1.106929e-05	0.25146365	8.014813e-01

The robust version of model 3 serves to diminish the standard errors ensuring that the inference I can make in the normal OLS is accurate despite the potential issues with non-constant variables. The significant predictors and the non-significant predictors are the same in both models, defining their strong and consistent effects on fiscal fraud perception. Finally, the last part of the study is the PROBIT version of model 3 to ensure that the significant variables are indeed significant.

Table 11: Model 3 (PROBIT)

```
Call:
polr(formula = as.factor(P18) ~ ESCAFELI + ESCACONFIANZA + DESIGUALDAD +
    ESCIDEOL + ECIVIL + SITCONVIVEN + RELIGION + SEXO + EDAD +
    ESTUDIOS + SITLAB + INGREHOG + P7 + P12 + P15 + P16 + `P19 IRPF` +
    `P20 IVA` + P24 + P24A + P27_1 + P27_2 + P27_3 + INTERVENESTADO,
    data = datosm3, method = "probit")

Coefficients:
                    Value Std. Error  t value
ESCAFELI        3.430e-02  1.781e-02   1.9259
ESCACONFIANZA  -6.297e-02  1.470e-02  -4.2839
DESIGUALDAD     2.830e-01  4.340e-02   6.5194
ESCIDEOL       -1.703e-02  1.343e-02  -1.2674
ECIVIL          1.324e-01  4.893e-02   2.7069
SITCONVIVEN    -9.771e-03  2.699e-02  -0.3620
RELIGION       -1.720e-01  5.471e-02  -3.1435
SEXO           -5.342e-02  5.084e-02  -1.0507
EDAD            4.078e-04  1.876e-03   0.2174
ESTUDIOS       -4.670e-02  2.348e-02  -1.9890
SITLAB         -3.767e-02  5.859e-02  -0.6430
INGREHOG        5.943e-06  2.077e-05   0.2861
P7             -1.093e-01  1.303e-02  -8.3897
P12             4.619e-02  4.397e-02   1.0504
P15            -2.914e-01  2.409e-02 -12.0957
P16            -2.195e-01  4.086e-02  -5.3730
`P19 IRPF`     -1.101e-01  4.008e-02  -2.7473
`P20 IVA`      -1.529e-01  3.545e-02  -4.3118
P24            -2.547e-01  3.084e-02  -8.2565
P24A           -3.414e-02  3.990e-02  -0.8554
P27_1          -1.778e-02  2.192e-02  -0.8111
P27_2           1.347e-01  2.238e-02   6.0202
P27_3          -1.523e-01  1.935e-02  -7.8718
INTERVENESTADO  7.111e-02  3.504e-02   2.0292
Intercepts:
    Value     Std. Error t value
1|2    -4.3418    0.0029 -1493.8801
2|3    -3.1081    0.0102  -305.5730
3|4    -1.2061    0.0496   -24.3344

Residual Deviance: 3474.842
AIC: 3528.842
```

When reviewing the PROBIT version of model 3 one can see that there are no new variables to have in mind, but curiously, the previous versions of model 3 did not detect the significance of friends' tolerance to fiscal fraud (P27_2) and the PROBIT versions do, just as happened in model 2. Worth mentioning as well that taxpayers' opinions about taxes (P7) is significant in the last version but not in the other ones. As a conclusion for personal perception variables, we can conclude that almost all the added ones except for the ideology and the fact of living alone or not are significant to explain the fiscal fraud perception of the individuals. Finally, when comparing the residual deviance and the AIC of this model we can see that model 3 has a lower one of each, but in a very discreet way, this means that while adding personal perception variables makes the model a better fit for fiscal fraud perception (P18) it is not that big of a change.

To sum up personal matters, we can see that being happier (ESCAFELI), thinking that there are a lot of inequalities (DESIGUALDAD), and being married (ECIVIL) will lead to a higher level of fiscal fraud perception. On the contrary, being a trustful person (ESCACONFIANZA) or believing in a religion (RELIGION) will decrease your fiscal fraud perception.

6. Conclusion

This study based itself on its predecessors to choose independent variables and how to make the best possible approach, studies like Poço et al. (2015) remarked that the fiscal fraud perception depended on how individuals perceive other related matters, like tax system fairness, the burden of taxation and how the government spends those taxes, which is a bit different of what we found based on our results, because as we see variables like the justice in the payment of taxes (P15) are very significant since the first moment they appear. In exchange, variables that based on other studies like the burden of taxation (P12), although this could be because it is an opinion on the whole of the population not on the individual itself.

Regarding our results, we can conclude that our methodology approach was correct. We see that with each model we did approach increasingly to the explanation of the fiscal fraud perception (Table E). We see that variables of diverse types are significant, from socioeconomic to personal ones, counting the fiscal perception predictors. One of the strongest predictors and more constant predictors we found is the level of studies of the population, suggesting that a highly educated individual will perceive less fiscal fraud. Switching to fiscal perception variables, we can observe that the individual environment is mostly affected by the opinion of their families, showing that if the family of the individual could tolerate fiscal fraud, the perception of fiscal fraud will go higher, this could perfectly be because the family itself is already defrauding the treasury. The friends are not read because in some models are significant and in others not, but we can say that the tolerance of the neighbors does not significantly affect the fiscal fraud perception. Really what we observe is that fiscal opinions or fiscal perceptions are the ones that shape taxpayers' fiscal fraud perception the most, followed in a much more reduced way, by personal perceptions or personal experiences.

To conclude this study, we can firmly say that fiscal fraud perception is an exceedingly difficult variable to analyze. It is a very complex and very discreet variable that does not allow for a complete study on the determinants of why this variable can go up or down, nevertheless, we are proud to say that our approach reached a good level of explanation of the variable, that while may not explain all of it, can give us some very interesting insights about the way taxpayers act and think. To proceed with a more detailed study and reach out for more explanation of the fiscal fraud perception, we think that a much more detailed, complex, and personal database with multiple years would be necessary, this data could provide for a better analysis and thus a better understanding of what are the determinants of fiscal fraud perception.

References

Bibliographic sources

Allingham, M. G., & Sandmo, A. (1972). Uncertainty and the incidence of taxation. Journal of Public Economics, 1(3), 195-210. (This study laid the foundation for the theoretical framework of tax evasion as a decision under uncertainty.). https://doi.org/10.1016/0047-2727(72)90010-2

Nehemiah Friedland, Shlomo Maital & Aryeh Rutenberg. (1978). A simulation study of income tax evasion. Journal of Public Economics, Volume 10, Issue 1, Pages 107-116,

ISSN 0047-2727. https://doi.org/10.1016/0047-2727(78)90008-7.

Andreoni, J., Erard, B., & Feinstein, J. (1998). Tax Compliance. Journal of Economic Literature, 36(2), 818–860. http://www.jstor.org/stable/2565123. RePEc:aea:jeclit:v:36:y:1998:i:2:p:818-860

Slemrod, J. (2007). Cheating Ourselves: The Economics of Tax Evasion. The Journal of Economic Perspectives, 21(1), 25–48. http://www.jstor.org/stable/30033700. 10.1257/jep.21.1.25

TSAKUMIS, George T., CURATOLA, Anthony P. e PORCANO, Thomas M. (2007), The relation between national cultural dimensions and tax evasion. Journal of International Accounting, Auditing and Tax. 10.1016/j.intaccaudtax.2007.06.004

ALM, James e TORGLER, Benno (2006), Culture differences and tax morale in the United States and in Europe, Journal of Economic Psychology 27 (2006) 224–246. 10.1016/j.joep.2005.09.002

Kahneman, D., & Tversky, A. (1979). PROSPECT THEORY: AN ANALYSIS OF DECISION UNDER RISK. Econometrics (Pre-1986), 47(2), 263. 10.1016/0012-9682(79)47021-4

Hofstade (1980) Culture's Consequences: International Differences in Work-Related Values

Maria Poço & Cidália Lopes & Alexandre Silva, (2015) "Perception of tax evasion and tax fraud in Portugal: a sociological study," OBEGEF Working Papers 039, OBEGEF - Observatório de Economia e Gestão de Fraude;OBEGEF Working Papers on Fraud and Corruption.

- DOI: RePEc:por:obegef:039

Database and R packages

CIS. (26-07-2023). Estudio 3418 sobre Opinión pública y política fiscal (XL) https://www.cis.es/visor?migrado=false&fichero=es3418marhtml

Wickham H, Bryan J (2023). readxl: Read Excel Files. https://readxl.tidyverse.org, https://github.com/tidyverse/readxl.

Fox J, Weisberg S (2019). An R Companion to Applied Regression, Third edition. Sage, Thousand Oaks CA. https://socialsciences.mcmaster.ca/jfox/Books/Companion/.

Wei T, Simko V (2021). R package 'corrplot': Visualization of a Correlation Matrix. (Version 0.92), https://github.com/taiyun/corrplot.

Wickham H (2016). ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag New York. ISBN 978-3-319-24277-4, https://ggplot2.tidyverse.org.

Zeileis A, Hothorn T (2002). “Diagnostic Checking in Regression Relationships.” R News, 2(3), 7–10. https://CRAN.R-project.org/doc/Rnews/.

Zeileis A, Köll S, Graham N (2020). “Various Versatile Variances: An Object-Oriented Implementation of Clustered Covariances in R.” Journal of Statistical Software, 95(1), 1–36. doi:10.18637/jss.v095.i01.

Zeileis A (2004). “Econometric Computing with HC and HAC Covariance Matrix Estimators.” Journal of Statistical Software, 11(10), 1–17. doi:10.18637/jss.v011.i10.

Venables WN, Ripley BD (2002). Modern Applied Statistics with S, Fourth edition. Springer, New York. ISBN 0-387-95457-0, https://www.stats.ox.ac.uk/pub/MASS4/.

A. Appendix

Table A.1: Verifying that the representativeness of the sample is not harmed in the first model.

	FIRST MODEL				
Variable	Normal	P18	Studies	SITLAB	INGREHOG
Age Average	49,679	49,544	49,485	49,469	49,377
Age Variance	15,826	15,799	15,778	15,772	15,67
% Men	52,81%	52,99%	53,03%	53,04%	53,40%
% Women	47,19%	47,01%	46,97%	46,96%	46,60%
Studies Average	4,964	4,967	4,967	4,966	4,978
Studies Variance	1,273	1,27	1,261	1,261	1,25
Rent Average	2716,341	2720,455	2721,518	2723,369	2825,194
Rent Variance	1521,837	1519,913	1520,361	1519,226	1451,812

Table A.2: Verifying that the representativeness of the sample is not harmed in the second model.

SECOND MODEL											
P7	P12	P15	P16	P19 IRPF	P20 IVA	P24	P24A	P27_1	P27_2	P27_3	INTERVENESTADO
49,29	49,143	49,147	49,063	48,873	48,547	48,514	48,401	47,938	47,74	47,648	47,604
15,662	15,633	15,59	15,589	15,57	15,49	15,475	15,439	15,395	15,383	15,37	15,346
53,68%	53,94%	54,16%	54,13%	54,18%	54,56%	54,99%	55,32%	55,74%	55,98%	56,00%	56,24%
46,32%	46,06%	45,84%	45,87%	45,82%	45,44%	45,01%	44,68%	44,26%	44,02%	44,00%	43,76%
4,986	4,994	4,998	5	5,012	5,02	5,019	5,027	5,031	5,032	5,03	5,03
1,249	1,233	1,23	1,229	1,218	1,21	1,21	1,203	1,196	1,194	1,193	1,194
2831,846	2840,587	2843,582	2844,848	2850,347	2848,694	2846,068	2852,307	2858,406	2856,809	2858,968	2866,289
1459,654	1449,317	1449,239	1450,9	1446,729	1446,925	1445,21	1444,052	1434,867	1434,903	1432,754	1432,515

Table A.3: Verifying that the representativeness of the sample is not harmed in the third model.

THIRD MODEL				
ESCACONFIANZA	DESIGUALDAD	ESCIDEOL	ECIVIL	RELIGION
47,597	47,589	47,575	47,582	47,58
15,347	15,346	15,35	15,35	15,348
56,27%	56,32%	56,27%	56,29%	56,26%
43,73%	43,68%	43,73%	43,71%	43,74%
5,03	5,03	5,042	5,041	5,044
1,194	1,194	1,188	1,188	1,186
2867,397	2867,318	2878,573	2879,27	2882,89
1431,961	1431,891	1433,637	1433,64	1434,423

Test B.1: Shapiro-Wilk's test (Model 1)

```
        Shapiro-Wilk normality test

data:  a$residuos1
W = 0.85979, p-value < 2.2e-16
```

Figure B.2: QQ Plot of residuals (Model 1)

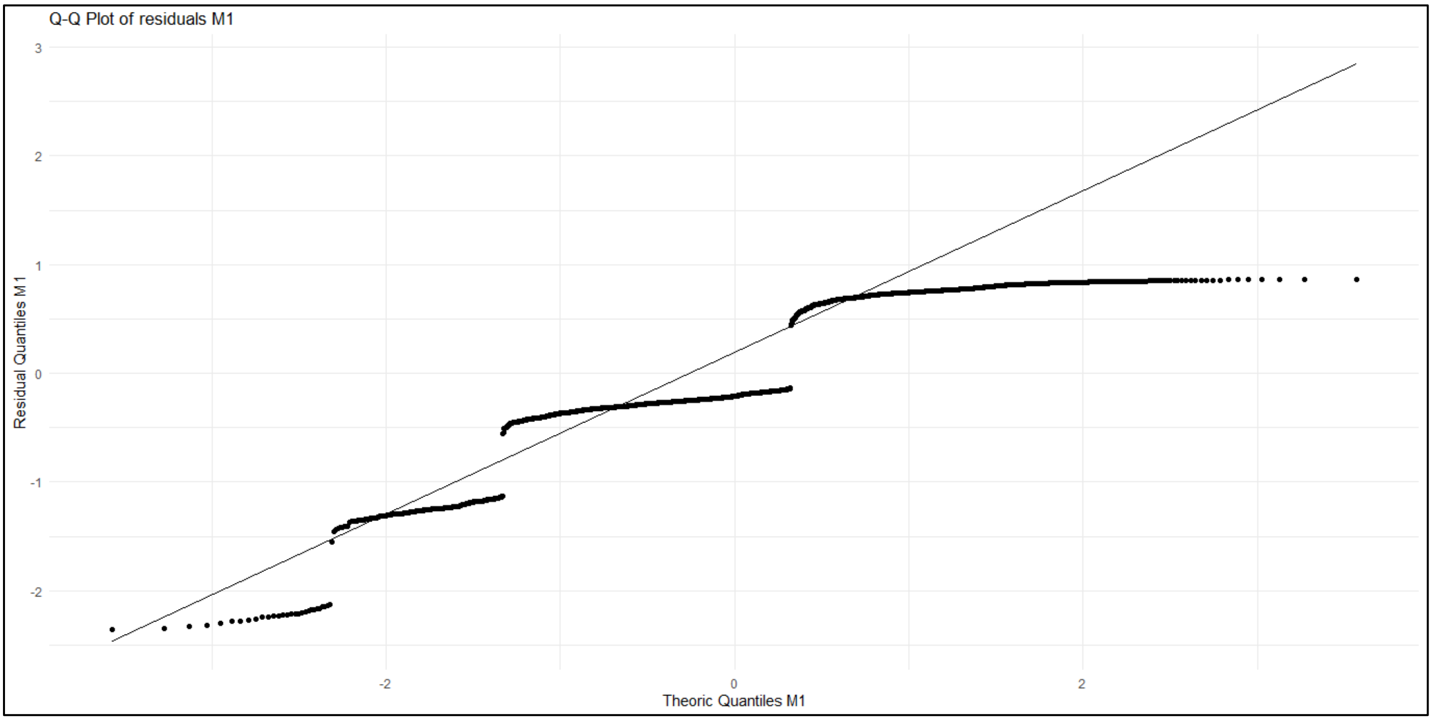
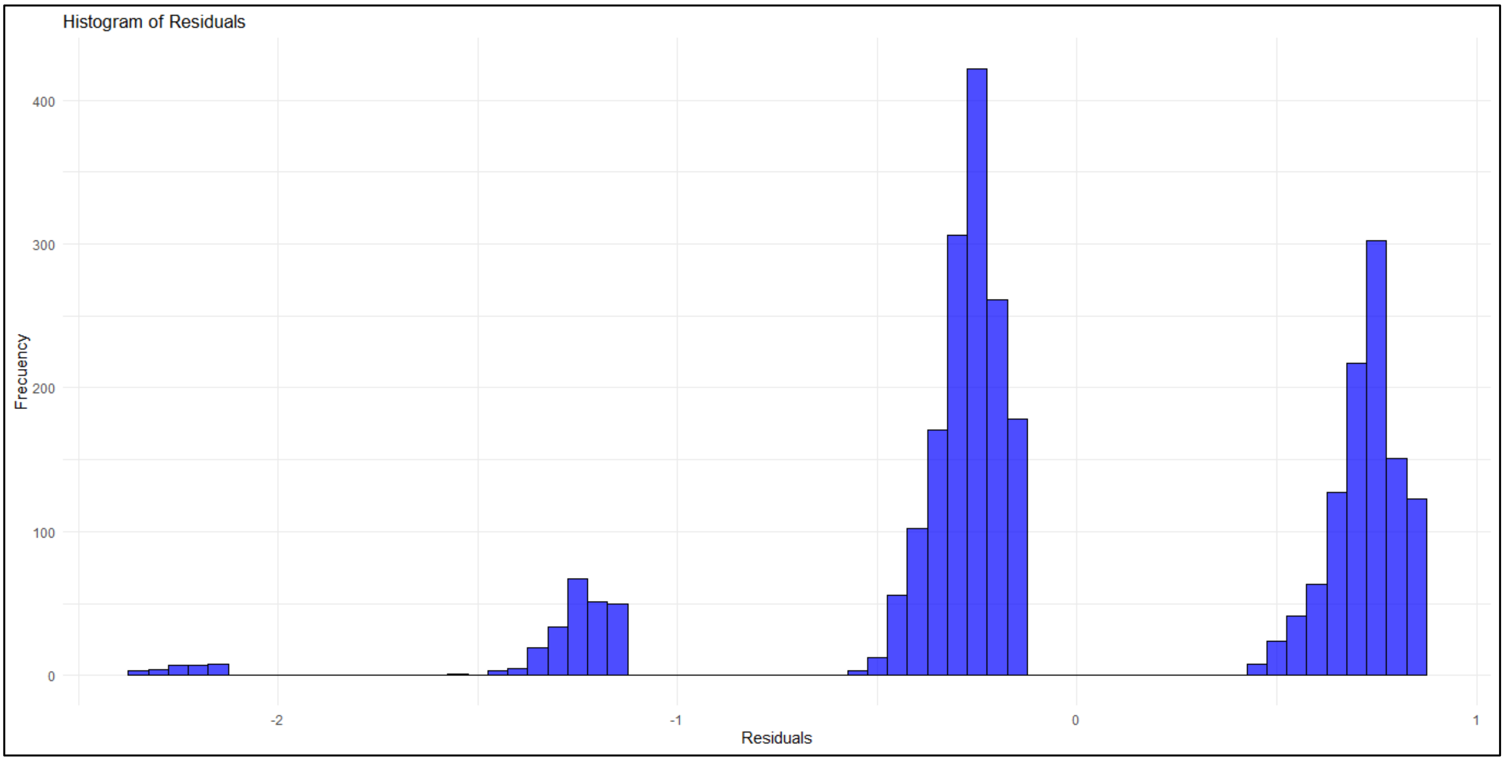


Figure B.3: Histogram of residuals (Model 1)



Test B.4: Breusch-Pagan's test (Model 1)

```
        studentized Breusch-Pagan test

data:  modelo1
BP = 35.75, df = 5, p-value = 1.066e-06
```

Figure B.5: VIF (Model 1)

SEXO	EDAD	ESTUDIOS	SITLAB	INGREHOG
1.020218	1.208056	1.249380	1.337647	1.204700

Figure B.6: Multicollinearity map (Model 1)

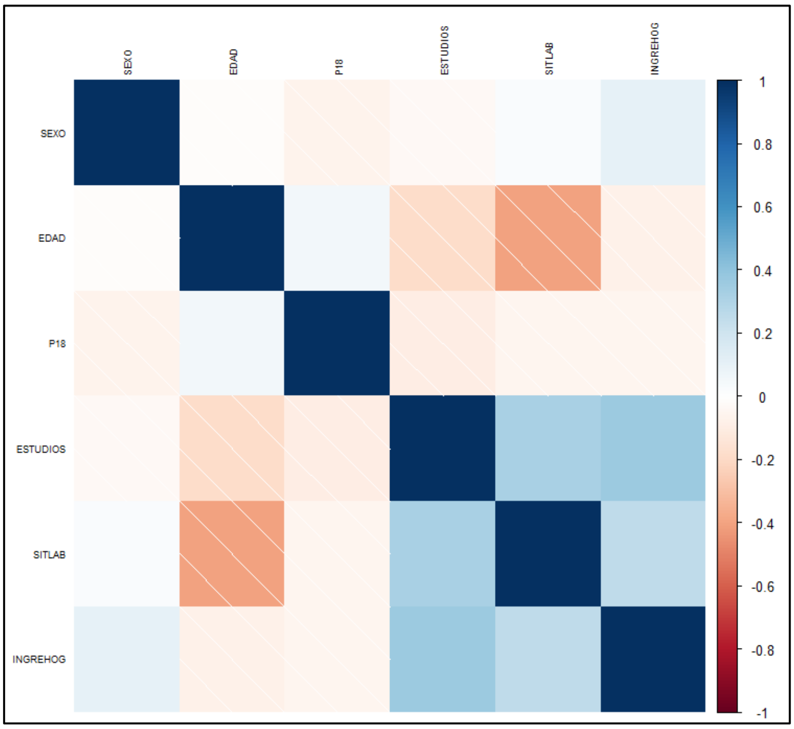


Table B.7: Regressor's table (Model 1)

		Model 1		
		OLS	Robust OLS	PROBIT
MODEL 1 / MODEL 2 / MODEL 3	INTERCEPT	3,497 (0,073)	3,496 (0,071)	1|2 -2,750 (0,006) 2|3 -1,747 (0,016) 3|4 -0,076 (0,038)
	SEXO	-0,086*** (0,025)	-0,086*** (0,024)	-0,145*** (0,042)
	EDAD	0,001 (0,001	0,001 (0,000)	0,002*** (0,001)
	ESTUDIOS	-0,045*** (0,011)	-0,045*** (0,010)	-0,080*** (0,015)
	SITLAB	-0,018 (0,029)	-0,018 (0,028)	-0,029 (0,047)
	INGREHOG	-0,000 (0,000)	-0,000 (0,000)	-0,000 (0,000)

(Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05)

Table C.1: Shapiro-Wilk's test (Model 2)

```
        Shapiro-Wilk normality test

data:  a2$residuos2
W = 0.97484, p-value < 2.2e-16
```

Table C.2: QQ Plot of residuals (Model 2)

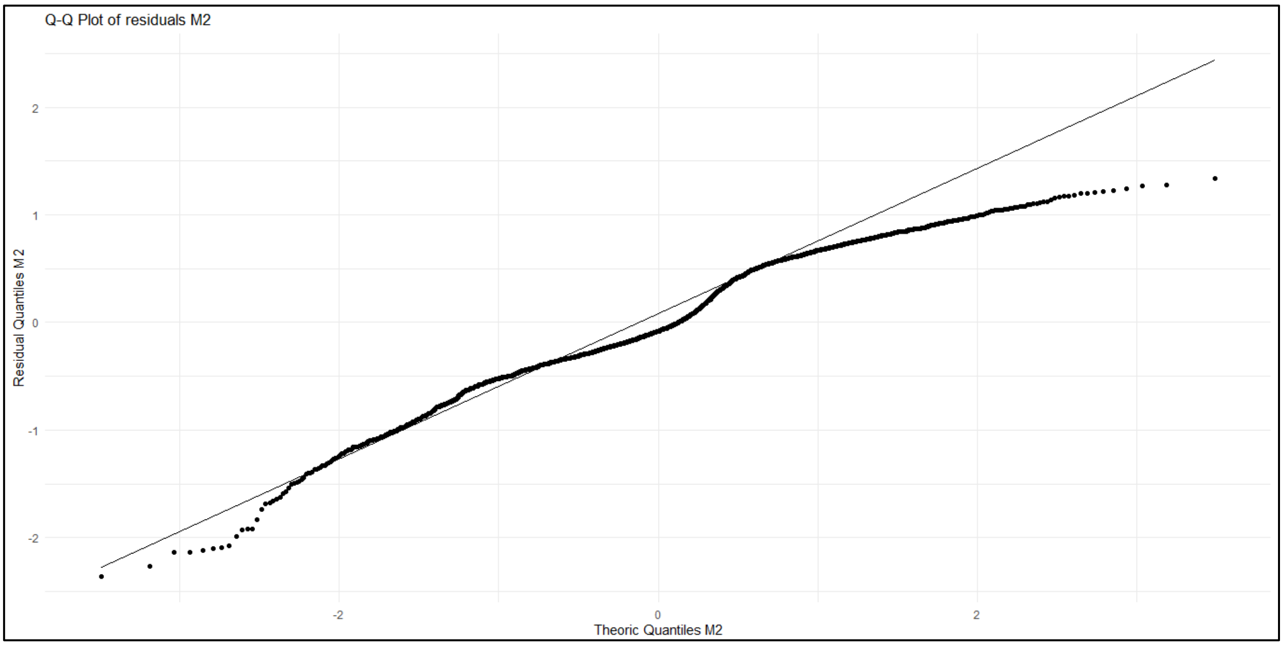


Table C.3: Histogram of residuals (Model 2)

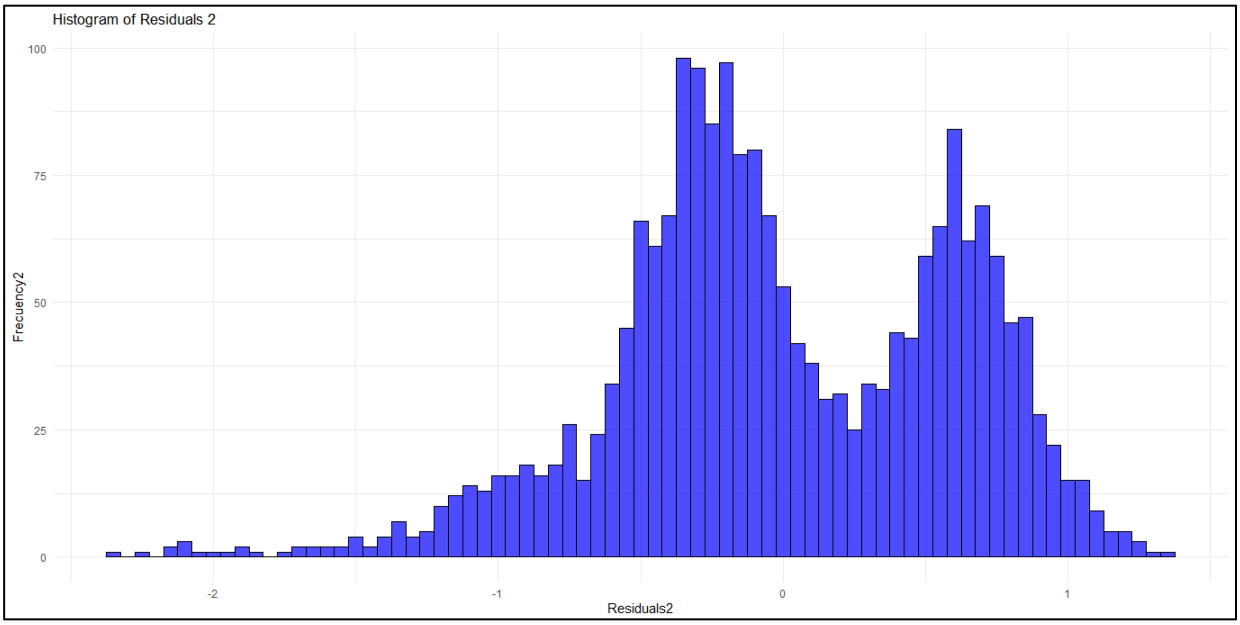


Table C.4: Breusch-Pagan's test (Model 2)

```
        studentized Breusch-Pagan test

data:  modelo2
BP = 74.553, df = 17, p-value = 3.498e-09
```

Table C.5: VIF (Model 2)

```
      SEXO           EDAD             P7            P12            P15            P16     `P19 IRPF`
  1.048186       1.294365       1.311596       1.334499       1.085935       1.151981       1.460877
`P20 IVA`            P24           P24A          P27_1          P27_2          P27_3 INTERVENESTADO
  1.459822       1.097977       1.161959       1.980996       2.626018       1.927851       1.192356
  ESTUDIOS         SITLAB       INGREHOG
  1.255314       1.287909       1.198673
```

Table C.6: Multicollinearity map (Model 2)

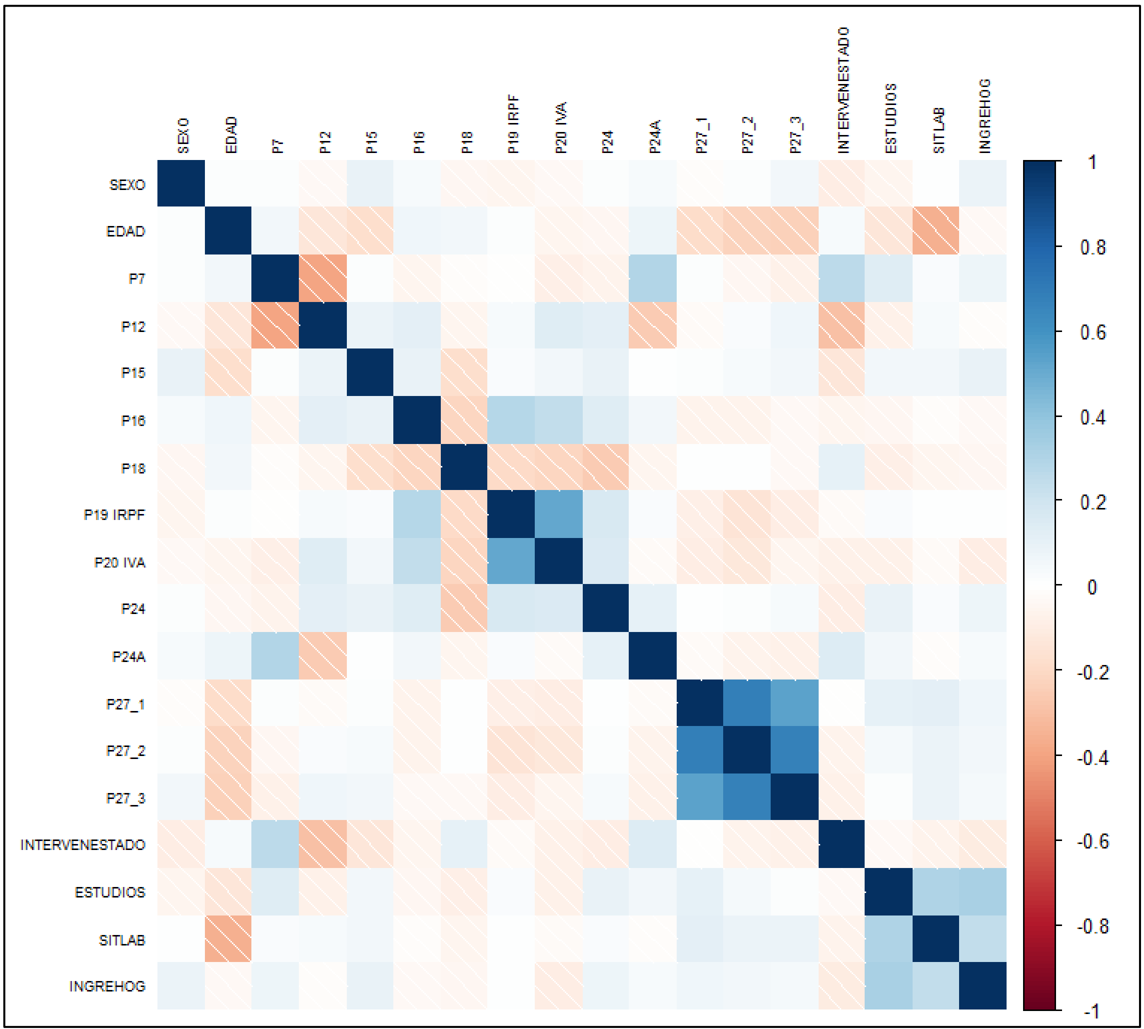


Table C.7: Regressor's table (Model 2)

				Model 2		
				OLS	Robust OLS	PROBIT
			INTERCEPT	4,476 (0,148)	4,475 (0,152)	1|2 -5,008 (0,003) 2|3 -3,810 (0,011) 3|4 -1,954 (0,047)
			SEXO	-0,040 (0,027)	-0,040 (0,026)	-0,067 (0,051)
			EDAD	0,000 (0,001)	0,000 (0,000)	0,000 (0,001)
MODEL 1			ESTUDIOS	-0,035*** (0,012)	-0,035*** (0,012)	-0,066*** (0,022)
			SITLAB	-0,025 (0,031)	-0,024 (0,031)	-0,047 (0,059)
			INGREHOG	0,000 (0,000)	0,000 (0,000)	0,000 (0,000)
			P7	-0,072* (0,038)	-0,071* (0,039)	-0,141*** (0,016)
			P12	0,002 (0,023)	0,002 (0,022)	0,008 (0,036)
	MODEL 2	MODEL 3	P15	-0,181*** (0,033)	-0,180*** (0,035)	-0,339*** (0,061)
			P16	-0,131*** (0,021)	-0,131*** (0,022)	-0,251*** (0,039)
			P19 IRPF	-0,049** (0,020)	-0,048** (0,020)	-0,097*** (0,038)
			P20 IVA	-0,087*** (0,018)	-0,086*** (0,018)	-0,167*** (0,034)
			P24	-0,133*** (0,016)	-0,133*** (0,016)	-0,258*** (0,030)
			P24A	-0,023 (0,021)	-0,023 (0,021)	-0,056 (0,038)
			P27_1	0,004 (0,037)	0,003 (0,036)	-0,005 (0,021)
			P27_2	0,031 (0,043)	0,031 (0,043)	0,069*** (0,021)
			P27_3	-0,070* (0,039)	-0,069* (0,039)	-0,136*** (0,018)
			INTERVENESTADO	0,056*** (0,019)	0,055*** (0,019)	0,108*** (0,031)

(Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05)

Table D.1: Shapiro-Wilk's test (Model 3)

```
        Shapiro-Wilk normality test

data:  a3$residuos3
W = 0.98132, p-value = 1.116e-15
```

Table D.2: QQ Plot of residuals (Model 3)

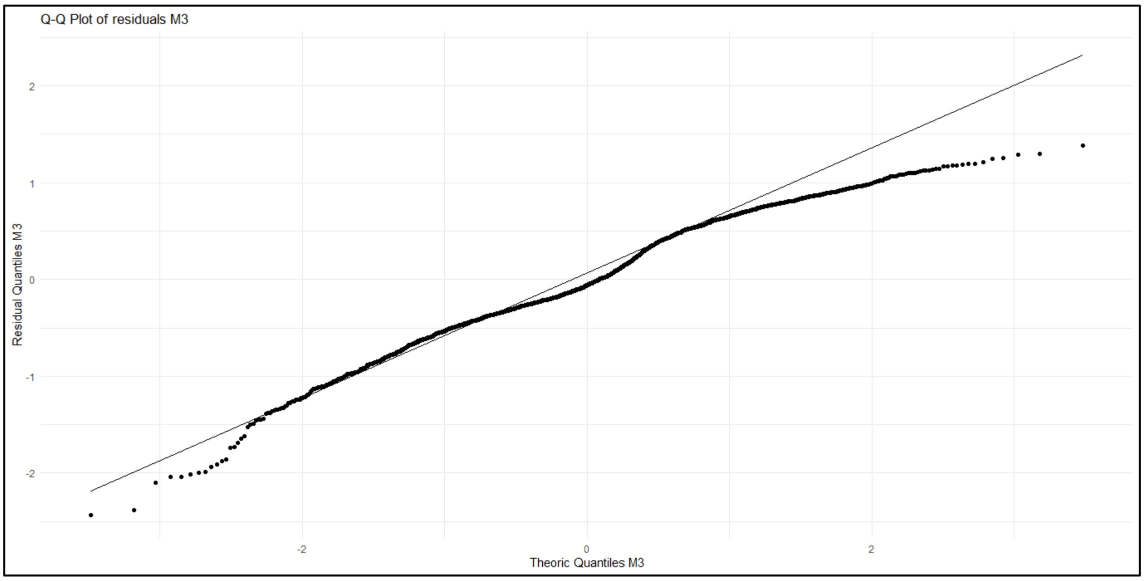


Table D.3: Histogram of residuals (Model 3)

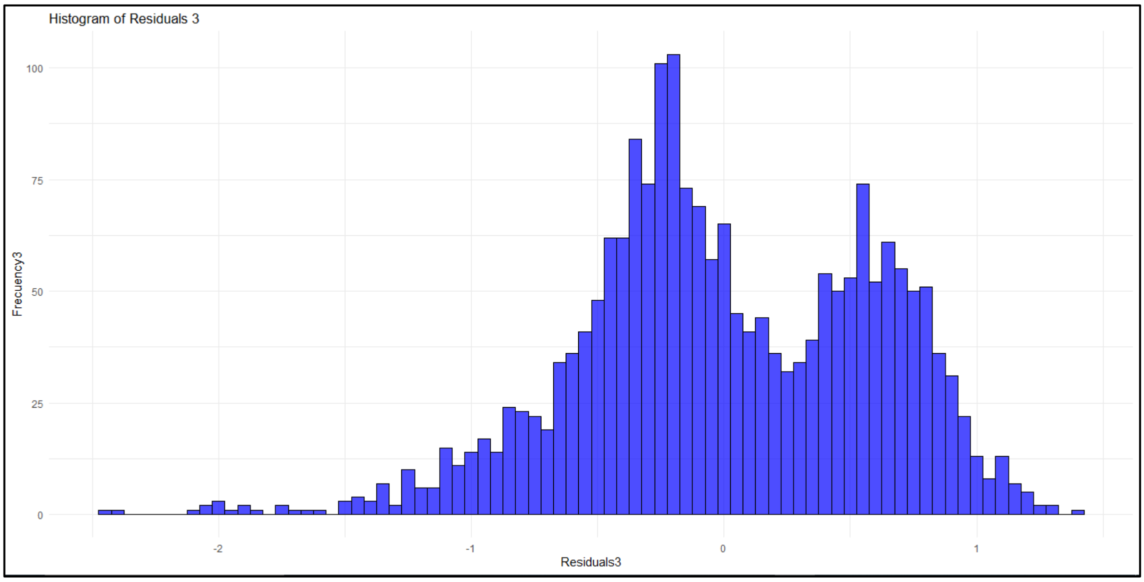


Table D.4: Breusch-Pagan's test (Model 3)

```
	studentized Breusch-Pagan test

data:  modelo3
BP = 81.323, df = 24, p-value = 3.739e-08
```

Table D.5: VIF (Model 3)

```
     SEXO        EDAD    ESCAFELI  ESCACONFIANZA          P7         P12         P15
 1.066829    1.725109    1.117568     1.202445      1.385656    1.496349    1.112202
      P16  `P19 IRPF`   `P20 IVA`          P24        P24A       P27_1       P27_2
 1.170686    1.474875    1.470363     1.108425      1.185271    1.991869    2.625605
    P27_3 DESIGUALDAD INTERVENESTADO  ESCIDEOL       ECIVIL  SITCONVIVEN    ESTUDIOS
 1.913350    1.124951    1.256108     1.568102      1.614440    1.330434    1.309676
 RELIGION      SITLAB    INGREHOG
 1.256575    1.305355    1.364972
```

Table D.6: Multicollinearity map (Model 3)

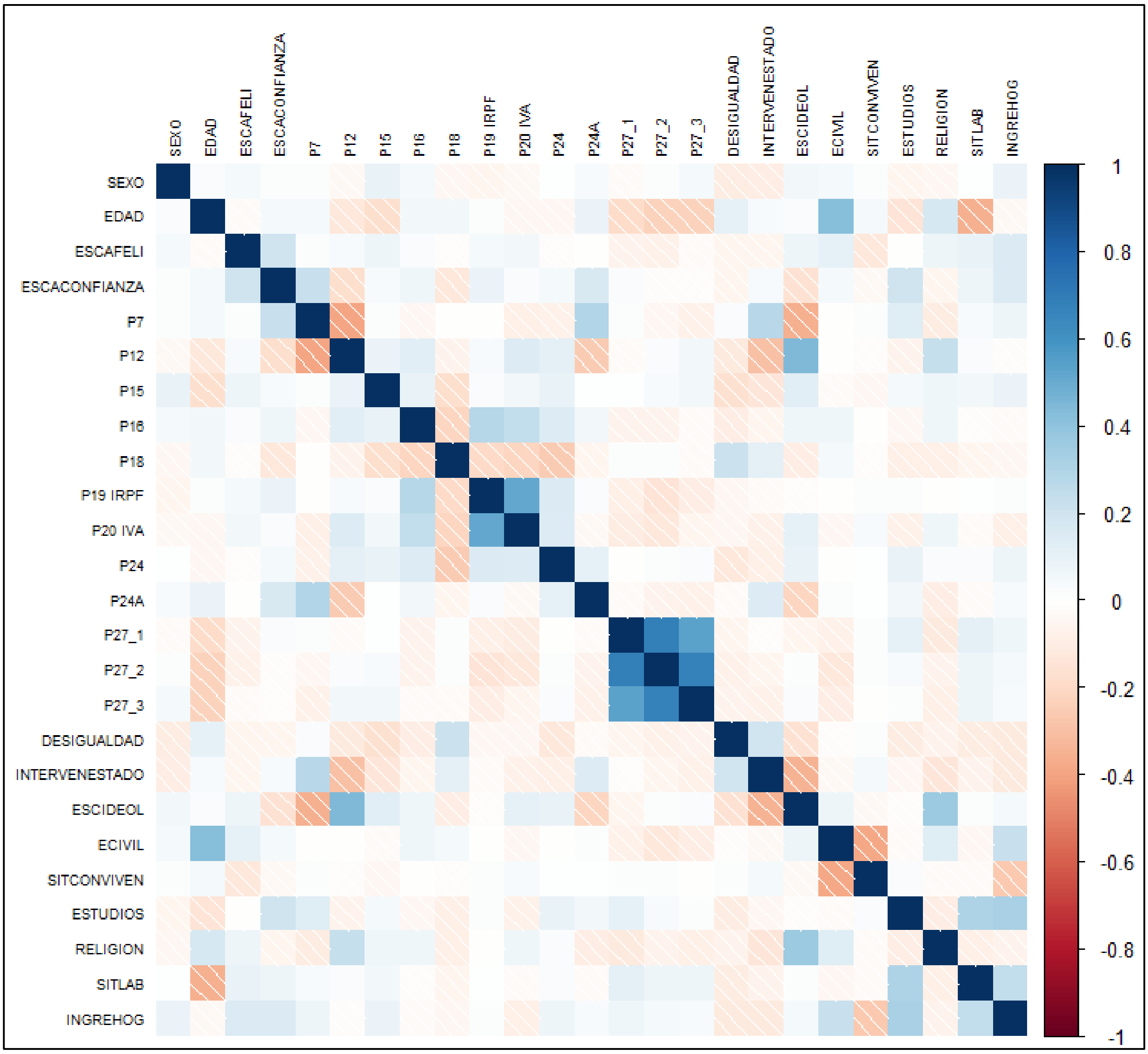


Table D.7: Regressor's table (Model 3)

				Model 3		
				OLS	Robust OLS	PROBIT
			INTERCEPT	4,061 (0,180)	4,060 (0,181)	1|2 -4,341 (0,003) 2|3 -3,108 (0,010) 3|4 -1,206 (0,049)
			SEXO	-0,031 (0,027)	-0,031 (0,027)	-0,053 (0,051)
MODEL 1			EDAD	0,000 (0,001)	0,000 (0,001)	0,000 (0,002)
			ESTUDIOS	-0,025** (0,013)	-0,025** (0,013)	-0,047*** (0,023)
			SITLAB	-0,020 (0,031)	-0,020 (0,032)	-0,038 (0,059)
			INGREHOG	0,000 (0,000)	0,000 (0,000)	0,000 (0,000)
			P7	-0,053 (0,040)	-0,053 (0,041)	-0,109*** (0,013)
			P12	0,021 (0,025)	0,021 (0,023)	0,046 (0,044)
	MODEL 2		P15	-0,152*** (0,033)	-0,152*** (0,035)	-0,291*** (0,024)
			P16	-0,113*** (0,021)	-0,113*** (0,022)	-0,220*** (0,041)
			P19 IRPF	-0,053*** (0,020)	-0,053*** (0,020)	-0,110*** (0,040)
			P20 IVA	-0,077*** (0,018)	-0,077*** (0,018)	-0,153*** (0,035)
		MODEL 3	P24	-0,128*** (0,016)	-0,128*** (0,017)	-0,255*** (0,031)
			P24A	-0,013 (0,021)	-0,013 (0,022)	-0,034 (0,040)
			P27_1	-0,003 (0,037)	-0,003 (0,037)	-0,018 (0,022)
			P27_2	0,062 (0,043)	0,062 (0,044)	0,135*** (0,022)
			P27_3	-0,075** (0,038)	-0,075** (0,039)	-0,152*** (0,020)
			INTERVENESTADO	0,036* (0,019)	0,036* (0,020)	0,071*** (0,036)
			ESCAFELI	0,017* (0,009)	0,017* (0,009)	0,034* (0,018)
			ESCACONFIANZA	-0,029*** (0,007)	-0,029*** (0,008)	-0,063*** (0,015)
			DESIGUALDAD	0,144*** (0,024)	0,144*** (0,025)	0,028*** (0,043)
			ESCIDEOL	-0,008 (0,007)	-0,008 (0,007)	-0,170 (0,013)
			ECIVIL	0,066** (0,033)	0,066** (0,033)	0,132*** (0,049)
			SITCONVIVEN	-0,003 (0,043)	-0,003 (0,041)	-0,010 (0,027)
			RELIGION	-0,087*** (0,029)	-0,087*** (0,029)	-0,172*** (0,055)

(Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05)

Table E: Regressor's table for all the models

		Model 1			Model 2			Model 3		
		OLS	Robust OLS	PROBIT	OLS	Robust OLS	PROBIT	OLS	Robust OLS	PROBIT
	INTERCEPT	3,497 (0,073)	3,496 (0,071)	1|2 -2,750 (0,006) 2|3 -1,747 (0,016) 3|4 -0,076 (0,038)	4,476 (0,148)	4,475 (0,152)	1|2 -5,008 (0,003) 2|3 -3,810 (0,011) 3|4 -1,954 (0,047)	4,061 (0,180)	4,060 (0,181)	1|2 -4,341 (0,003) 2|3 -3,108 (0,010) 3|4 -1,206 (0,049)
	SEXO	-0,086*** (0,025)	-0,086*** (0,024)	-0,145*** (0,042)	-0,040 (0,027)	-0,040 (0,026)	-0,067 (0,051)	-0,031 (0,027)	-0,031 (0,027)	-0,053 (0,051)
MODEL 1	EDAD	0,001 (0,001	0,001 (0,000)	0,002*** (0,001)	0,000 (0,001)	0,000 (0,000)	0,000 (0,001)	0,000 (0,001)	0,000 (0,001)	0,000 (0,002)
	ESTUDIOS	-0,045*** (0,011)	-0,045*** (0,010)	-0,080*** (0,015)	-0,035*** (0,012)	-0,035*** (0,012)	-0,066*** (0,022)	-0,025** (0,013)	-0,025** (0,013)	-0,047*** (0,023)
	SITLAB	-0,018 (0,029)	-0,018 (0,028)	-0,029 (0,047)	-0,025 (0,031)	-0,024 (0,031)	-0,047 (0,059)	-0,020 (0,031)	-0,020 (0,032)	-0,038 (0,059)
	INGREHOG	-0,000 (0,000)	-0,000 (0,000)	-0,000 (0,000)	0,000 (0,000)	0,000 (0,000)	0,000 (0,000)	0,000 (0,000)	0,000 (0,000)	0,000 (0,000)
	P7				-0,072* (0,038)	-0,071* (0,039)	-0,141*** (0,016)	-0,053 (0,040)	-0,053 (0,041)	-0,109*** (0,013)
	P12				0,002 (0,023)	0,002 (0,022)	0,008 (0,036)	0,021 (0,025)	0,021 (0,023)	0,046 (0,044)
MODEL 2	P15				-0,181*** (0,033)	-0,180*** (0,035)	-0,339*** (0,061)	-0,152*** (0,033)	-0,152*** (0,035)	-0,291*** (0,024)
	P16				-0,131*** (0,021)	-0,131*** (0,022)	-0,251*** (0,039)	-0,113*** (0,021)	-0,113*** (0,022)	-0,220*** (0,041)
	P19 IRPF				-0,049** (0,020)	-0,048** (0,020)	-0,097*** (0,038)	-0,053*** (0,020)	-0,053*** (0,020)	-0,110*** (0,040)
MODEL 3	P20 IVA				-0,087*** (0,018)	-0,086*** (0,018)	-0,167*** (0,034)	-0,077*** (0,018)	-0,077*** (0,018)	-0,153*** (0,035)
	P24				-0,133*** (0,016)	-0,133*** (0,016)	-0,258*** (0,030)	-0,128*** (0,016)	-0,128*** (0,017)	-0,255*** (0,031)
	P24A				-0,023 (0,021)	-0,023 (0,021)	-0,056 (0,038)	-0,013 (0,021)	-0,013 (0,022)	-0,034 (0,040)
	P27_1				0,004 (0,037)	0,003 (0,036)	-0,005 (0,021)	-0,003 (0,037)	-0,003 (0,037)	-0,018 (0,022)
	P27_2				0,031 (0,043)	0,031 (0,043)	0,069*** (0,021)	0,062 (0,043)	0,062 (0,044)	0,135*** (0,022)
	P27_3				-0,070* (0,039)	-0,069* (0,039)	-0,136*** (0,018)	-0,075** (0,038)	-0,075** (0,039)	-0,152*** (0,020)
	INTERVENESTADO				0,056*** (0,019)	0,055*** (0,019)	0,108*** (0,031)	0,036* (0,019)	0,036* (0,020)	0,071*** (0,036)
	ESCAFELI							0,017* (0,009)	0,017* (0,009)	0,034* (0,018)
	ESCACONFIANZA							-0,029*** (0,007)	-0,029*** (0,008)	-0,063*** (0,015)
	DESIGUALDAD							0,144*** (0,024)	0,144*** (0,025)	0,028*** (0,043)
	ESCIDEOL							-0,008 (0,007)	-0,008 (0,007)	-0,170 (0,013)
	ECIVIL							0,066** (0,033)	0,066** (0,033)	0,132*** (0,049)
	SITCONVIVEN							-0,003 (0,043)	-0,003 (0,041)	-0,010 (0,027)
	RELIGION							-0,087*** (0,029)	-0,087*** (0,029)	-0,172*** (0,055)

(Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05)