Universidad de San Andrés

Departamento de Economía

Maestría en Economía

Citizen engagement and political trust in LAC

Natalia PECORARI

33.345.395

Mentor: Walter SOSA ESCUDERO

Buenos Aires

21 de julio, 2022

Tesis de Maestría en Economía de

Natalia PECORARI

“Participación ciudadana y confianza en el gobierno en América Latina y el Caribe”

Resumen

Examinando las respuestas a la encuesta Latinobarómetro 2020, este trabajo avanza en la comprensión del vínculo entre la confianza en el gobierno y la participación ciudadana en América Latina y el Caribe (ALC). Dos teorías en conflicto abordan este vínculo: los defensores de la llamada “Stealth democracy” argumentan que existe una relación inversa entre la confianza en el gobierno y la participación ciudadana, mientras que los teóricos de la democracia deliberativa afirman lo contrario. A la luz de estas miradas opuestas, buscamos determinar qué teoría describe mejor dicha relación en ALC. Nos basamos tanto en la econometría tradicional como en técnicas de aprendizaje automático más sofisticadas para identificar los factores clave que impulsan el vínculo entre la confianza en el gobierno y la participación ciudadana en ALC. Encontramos que el estatus socioeconómico impulsa la participación y que el éxito de dichas teorías en explicar el grado de involucramiento ciudadano depende del tipo de foro de participación. Es importante señalar, además, que complejas relaciones no lineales afectan la participación ciudadana.

Palabras clave: Participación ciudadana; confianza en el gobierno; *Stealth democracy*; América Latina y el Caribe; *Machine learning*; *Lasso; Random Forest*

“Citizen engagement and political trust in LAC”

Abstract

By examining responses to the Latinobarometro 2020 survey, this paper advances the understanding of the linkage between trust in government and citizen participation in Latin-America and the Caribbean (LAC). Conflicting theories address this linkage: stealth democracy proponents argue that an inverse relationship exist between political trust and citizen engagement, whilst deliberative democracy theorists claim that the opposite is true. In light of this opposing views, we seek to determine which theory most accurately describes this relationship in LAC. We rely on both traditional econometrics and more sophisticated machine learning techniques to identify the key factors driving the linkage between trust in government and citizen involvement in LAC. We find that socioeconomic status drives participation and that whether deliberative or stealth democracy is more effective in explaining engagement depends on the type of participation forum. Importantly, intricate non-linear patterns affect citizen participation.

Keywords: Citizen participation; political trust; Stealth democracy; Latin-America and Caribbean; Machine learning; Lasso; Random Forest

Códigos JEL: C45; D72; D91

Universidad de San Andrés

Citizen engagement and political trust in LAC

Natalia Pecorari*

*Corresponding author: pecorarinatalia@gmail.com

Abstract

By examining responses to the Latinobarometro 2020 survey, this paper advances the understanding of the linkage between trust in government and citizen participation in Latin-America and the Caribbean (LAC). Conflicting theories address this linkage: stealth democracy proponents argue that an inverse relationship exist between political trust and citizen engagement, whilst deliberative democracy theorists claim that the opposite is true. In light of this opposing views, we seek to determine which theory most accurately describes this relationship in LAC. We rely on both traditional econometrics and more sophisticated machine learning techniques to identify the key factors driving the linkage between trust in government and citizen involvement in LAC. We find that socioeconomic status drives participation and that whether deliberative or stealth democracy is more effective in explaining engagement depends on the type of participation forum. Importantly, intricate non-linear patterns affect citizen participation.

Keywords: Citizen participation; political trust; Stealth democracy; Latin-America and Caribbean; Machine learning; Lasso; Random Forest

1 Introduction

The purpose of this paper is to investigate the relationship between trust in government and citizen participation in Latin-American and the Caribbean (LAC). We seek to disentangle how trust in governmental institutions affects people's willingness to participate in government processes as well as to shed some light on the key factors driving citizen participation. Given that Latin American countries have the lowest levels of trust in government of any region in the world, the study of political trust in Latin America and how it affects key outcomes of democracy such as citizen engagement becomes critical (Caceres, 2019).

According to Verba and Nie (1987), citizen engagement can be defined as "an instrumental activity through which citizens attempt to influence the government to act in ways the citizens prefer". These activities are crucial to democracy because they empower citizens to send messages to public leaders while also influencing the public agenda. In practice, citizen engagement allows government officials to incorporate local expertise into decision-making (Lee and Schachter, 2019).

Citizen engagement, often known also as "voice, participation, and accountability," can help to establish a more inclusive society. According to the World Bank Group (2014), an inclusive society requires institutions, structures, and processes that enable all groups to participate and hold governments accountable.

The study of government trust in developed and emerging countries continues to be of great interest. The fact that trust offers legitimacy to the political system, strengthens democracy, and contributes to increased economic growth has piqued this interest (Zak and Knack, 2001). Following related literature (see for instance, Rizzo, 2021), throughout this work, the term trust will be used to refer to political trust in order to distinguish it from related notions such as social trust (which refers to trust between citizens), reciprocity, and interpersonal trust (trust involved in personal relationships or commercial transactions). We define political trust as the degree to which citizens have faith in governmental institutions to do the right thing. In the context of this study, political trust will refer to people's confidence in institutions and actors (e.g., the executive, legislative, judiciary, the police, the electoral body).

Trust in the government— or political trust — is a crucial requirement for representative democracy (Van der Meer and Zmerli, 2017). The loss of faith in government is regarded to signal a democratic crisis, with direct

QUAERERE VERUM
Universidad de San Andrés

and serious ramifications for representative democracy's quality and effectiveness, as well as its institutions and players (Kumagai and Iorio, 2020; Crozier, Huntington, and Watanuki, 1978).

Two theories address the issue of the link between political trust and participation, but their perspectives on how trust in the government accounts for citizen engagement differ greatly. On the one hand, researchers who follow the stealth democracy school of thought believe that trust in government is inversely related to citizen participation. According to this view, citizens only participate when they believe it is important to prevent corrupt politicians from feathering their own nests at the expense of the public. They contend that individuals' lack of trust in the government may push them to speak out in order to obtain a more sympathetic administration. Similarly, people who have confidence in the government see no reason to engage since they trust their officials to do what is best for them. According to this view, trust in government discourages citizen involvement (Lee and Schachter, 2019; Theiss-Morse and Hibbing, 2005).

Deliberative theorists, on the other hand, believe that a trustworthy political system encourages citizens to participate in government processes. Apathy stems from a lack of trust; responsive government prompts citizen participation (Lee and Schachter, 2019; Neblo et al., 2010). We believe that figuring out which of the two theories prevails in Latin-America and the Caribbean is of great importance, in particular for policy-makers aiming at raising participation levels in societies where low levels of citizen involvement prevail like it is the case in most LAC countries.

While there is a growing body of research linking citizen engagement and accountability, there is very little rigorous and comparable empirical studies linking citizen participation and trust. As a result, little is known about the mechanisms that dictate the relationship between participation and trust (Rizzo, 2021). The main relationship investigated in the literature is between citizens' willingness to obey laws, rules, and tax demands and their trust in government. There is evidence, though, that poor citizen trust in government can erode the social contract and lead to citizens disengaging from the state in a number of ways (Arizti et al. 2010; Kumagai and Iorio, 2020).

To understand the link between trust and citizen participation we rely on data from the Latinobarometro 2020. We address the following questions: Is there a link between trust in government and citizen involvement in LAC? If so, in what direction does the link operate? In a recent paper, Lee and Schachter (2019) investigate the relationship between trust in government and citizen participation using data for the United States from the World Values Survey. They specifically model civic participation by signing petitions, participating in protests and demonstrations, and voting. Their findings confirm the deliberative democracy theory, which contends that citizens who have high levels of trust in government are more inclined to vote and sign a petition than those who have low levels of trust in government.

Furthermore, we are interested in investigating additional factors influencing citizen engagement, whether socioeconomic, demographic, or based on attitudes. A large body of literature has identified socioeconomic status as the primary factor determining citizen participation. In this view, the higher an individual's socioeconomic level, the greater their possibilities of participation (Lee and Schachter, 2019; Dalton, Burklin and Drummond, 2001; Gastil et al., 2008; Newman, Johnson, and Lown, 2014; Verba and Nie, 1987).

The Latinobarometro Survey offers a range of questions that allow us to address the aforementioned questions. In particular, we will make use of the following indicators contained in the survey: i) trust in governmental institutions (National government, Police, Electoral body and the Parliament); ii) citizen participation indicators (signing a petition; taking part in authorized demonstrations and work for a problem that affects you or your community).

We will rely on both traditional econometrics and more advanced machine learning methods to identify the key factors driving the link between trust in government and citizen involvement. Given the importance of citizen participation for democracy and the development of more inclusive societies, and in light of the fact that neither previous empirical research on the subject nor theoretical work provide a straightforward and/or unanimous view on the relationship between political trust and citizen engagement globally, and even less so regionally, we believe it is important to investigate this relationship using a flexible approach to let the data speak rather than forcing it to fit a given pre-established model. As a result, appealing to models that are as flexible as possible to study that relationship is necessary. This work will use flexible models embedded in machine learning techniques to explore such relationship in LAC.

Basic logit models will serve as the foundation for the analyses, which will then be supplemented by decision trees and regularization methods such as ridge, lasso, and elastic net. These methods are especially useful in predicting whether an individual in LAC will participate politically or not based on her socioeconomic characteristics and trust in government institutions; however, the purpose of this study will not be to predict such behavior but rather to investigate the factors that influence it and, in particular, the role of trust in government will be addressed. Because of the way logit models are built, they are unable to detect non-linear interactions between independent variables. In order to overcome this limitation we will advance the use of decision trees models, which are especially useful for disentangling non-linear patterns between explanatory variables that influence the outcome variable. Section 4 delves into these methods in detail.

There are, however, two major limitations to the survey approach of evaluating citizen participation and trust. First, when examining survey data, it's difficult to tell whether the coefficients measure what they're supposed to measure and whether trust is correlated to other -perhaps omitted- determinants of participation. Second, surveys are designed to measure intentions rather than actual behavior (Kumagai and Iorio, 2020).

We contribute to the current body of research that studies the relationship between trust in government -or political trust- and citizen participation in LAC by providing a quantitative analysis that relies on micro-level data. As Rizzo (2021) mentions, empirical work on participatory institutions in Latin America should shift from a largely case-study-based and macro-level perspective to micro-level studies from the standpoint of citizens. The absence of a citizen viewpoint in most regional research makes it difficult to gain a deeper understanding of outcomes such as political trust, which is normally conceived at the individual level. We aim to contribute by providing a quantitative analysis stemming from the citizen angle.

Most importantly, our work provides an innovative approach to analyzing the relationship between political trust and citizen participation by investigating the presence of non-linearities in the way explanatory variables interact with one another and have an impact on the dependent variable, that is, citizen engagement in the various forms considered in this study. Looking beyond linearity can provide fascinating insights into the complexity of such a relationship.

The paper is structured as follows: In the next section, we discuss the current state as well as some trends in trust in government and citizen participation in LAC. We then describe the data utilized in the analyses that follow and provide some descriptive analytics in section 3. In section 4 we briefly describe the methodologies used to examine the relationship between political trust and citizen engagement, and in section 5 we present the findings. Finally, in section 6, we come to a close.

2 Trust in government and citizen participation in LAC

Low levels of trust in the government persist in the region. Less than a third (27.3%) of the population in LAC has confidence in the government. In some countries, trust levels are very high like in El Salvador (72.4%), Dominican Republic (52.3%) or Uruguay (57.4%). However, for most LAC countries trust levels remain below 40% (Latinobarometro, 2020). When compared to the rest of the globe, LAC has some of the lowest levels of trust in the government (see figure 1). [1]

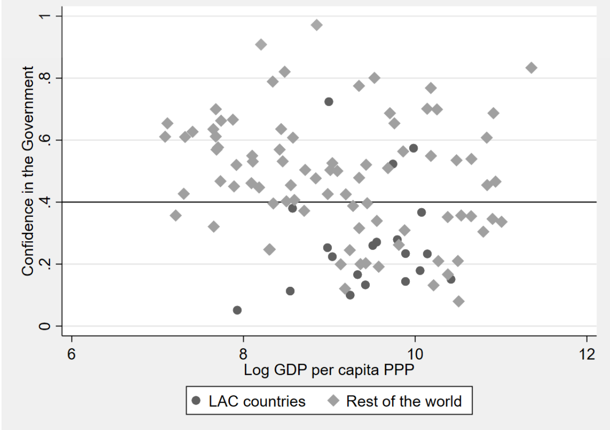


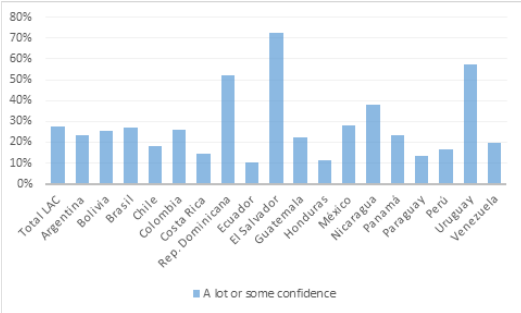
Figure 1: Confidence in the Government around the world

As illustrated in Figures 2-3, and in accordance with global trends, confidence in the government has been declining in recent years for most countries in the region. There are few notable exceptions, such as El Salvador,

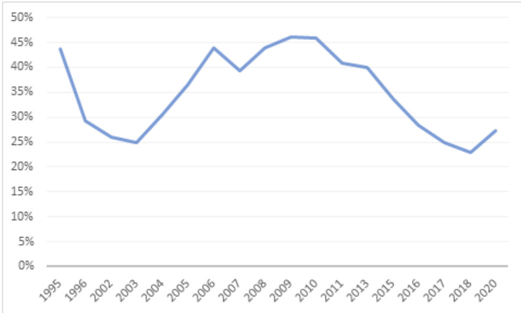
[1] All figures in this section are generated using data from the Latinobarometro 2020, except for figure 1 and 6 which also incoporate data from the 2022 World Bank Social Sustainability Global Database.

Universidad de San Andrés

where confidence climbed by over 60 percentage points (from 12.9% to 72.4%), and the Dominican Republic, where trust increased by nearly 25 percentage points (from 28.2% to 52.3%) between 2017 and 2020. While confidence levels fell in the majority of LAC countries, they rose somewhat in a few exceptions. On average, however, the trend for government trust has been negative in the region since 2009 (see figure 2(b)).



(a) Confidence in the Government in LAC countries, 2020



(b) Confidence in government over the years in LAC

Figure 2: Confidence in government in LAC

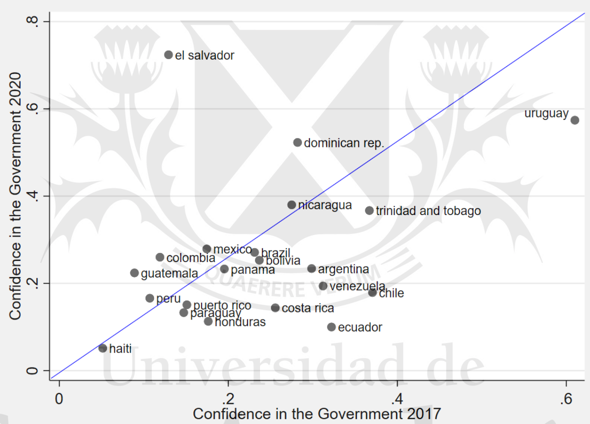
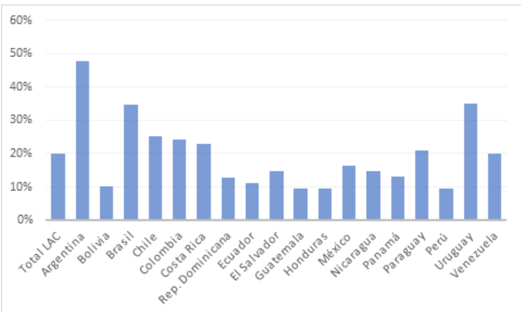


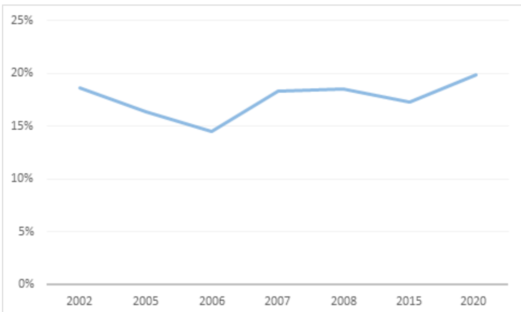
Figure 3: Confidence in the Government in LAC 2017 vs 2020, by country

Universidad de San Andrés

When looking at citizen participation variables, the picture becomes more mixed. Signing a petition, for example, does not appear to be extremely popular in the region, with the regional average standing at 20%. It is worth highlighting, however, the situation of Argentina, where nearly half of individuals say they have ever signed a petition. Brazil and Uruguay likewise have significant levels of engagement, with percentages approaching 35% in both cases. Over the last two decades, the proportion of people who have ever signed a petition has stayed below 20%, with a modest upward trend since 2006.



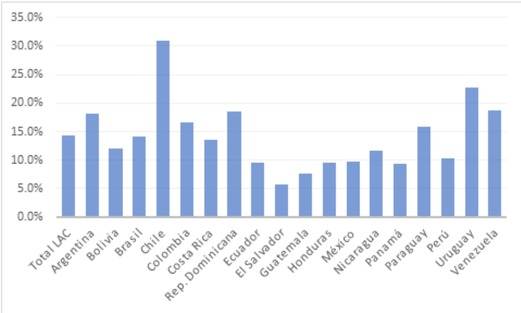
(a) Signing a petition in LAC, 2020



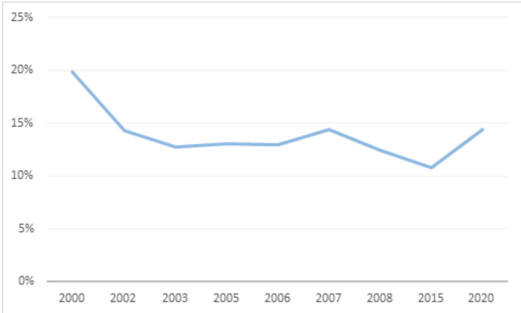
(b) Signing a petition over the years

Figure 4: Signing a petition in LAC

Participation in authorized demonstrations is also uncommon, with the regional average reaching only 15% of the population. Chile ranks out in this regard, with almost a third of the population reporting having taken part in legal demonstrations. As seen in figure 7, in the last two decades, participation in demonstrations in LAC has experienced a negative trend. When compared to the rest of the globe, participation in demonstrations in Latin America is in line with the global average of 12% (see figure 6) (World Bank's Social Sustainability and Inclusion Global Database, 2022).

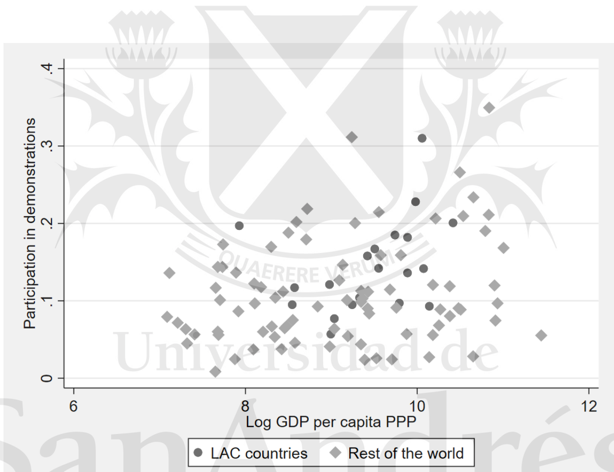


(a) Share of respondents who ever took part in authorized demonstrations, 2020



(b) Participation in demonstrations in LAC over the years

Figure 5: Participation in authorized demonstrations in LAC



Universidad de San Andrés

Figure 6: Participation in demonstrations around the world

Another way to participate in a society is to make oneself available or to work with others to solve problems at the community level on a consistent basis. In this sense, Latin-Americans appear to be less committed, since just a quarter of respondents indicate working on issues that impact them or their community on a regular or frequent basis. National averages are pretty much in line with the regional benchmark. Over the previous two decades, the proportion of persons working to tackle community problems has remained stable at roughly 20-25% of the population.

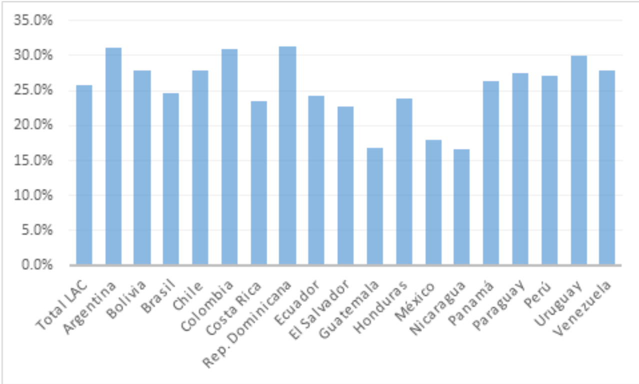


Figure 7: Share of respondents who ever worked for a problem affecting them or their communities, 2020

Given the low levels of citizen involvement in the region and the downward trend in confidence levels over the last decade, it is critical to investigate the key factors that influence citizen engagement and to shed some light on the nature of the relationship between citizen engagement and government trust. Only by understanding the mechanism that underpins such a relationship will it be possible to begin addressing the root causes of the problem and possibly reversing the trust-building trend of the last 10 years, with the ultimate goal of achieving higher levels of citizen participation in the region.

3 Data

The data employed in this work comes from the Latinobarometro Survey 2020. The Latinobarometro Corporation conducts the annual study to determine individual perceptions on socioeconomic and political issues in Latin American countries. The survey, which is the largest regional database on citizen attitudes towards democracy, covers 18 countries in Latin America and the Caribbean. It obtained representative national samples using a stratified random sampling process that was weighted to reflect each country's population. The survey data was released in October 2021 and comprises 20,204 observations.

The field work in which the survey was carried out was applied face to face between October 26, 2020 and December, 15 of that same year . In ten countries of South America and Mexico, samples of 1200 representative cases of each country were taken to citizens aged 18 and over (16 years in Brazil), and 1000 cases in the six countries of Central America and in the Dominican Republic. The survey comprises a single questionnaire containing around 81 questions on perceptions and 30 questions on socioeconomic status.

For the purpose of our study, we made use of the following indicators:

- Share of respondents who say they have a lot or some trust in governmental institutions
- Share of respondents who say they have ever signed a petition
- Share of respondents who say they have ever taken part in authorized demonstrations
- Share of respondents who frequently and very frequently work for a problem that affects them or their community

A whole set of explanatory variables covering socioeconomic and demographic as well as perceptions and attitudes toward political and personal freedoms were also employed. The complete set is presented in Annex A.

Trust in government is the independent variable of this study. The survey inquired about respondents' trust in government institutions like the legislative, executive, and judicial branches, as well as the civil service. All these variables are used simultaneously as explanatory variables. The dependent variable in this study is citizen participation, which can take the form of signing a petition, participate in demonstrations or working to resolve community problems. Because trust may interact differently with each type of involvement, we will investigate the relationship between trust and all three types of participation.

This study includes various control variables that previous research has shown assist predict whether a person will participate. These include: sex, age, education, working status, household income, political interest and ideology, and social class, among others (Lee and Schachter, 2019). Although we do not attempt to predict citizen participation, we do include a set of control variables in order to avoid imposing unnecessary constraints on the algorithm that seeks to investigate the relationship between political trust and participation, while keeping the approach as flexible as possible.

For the majority of variables, missing values account for less than 5% of the sample. One exception is trust in the armed forces, which has roughly 15% missing values; as a result, we avoid adding such a variable in our regressions. Given this circumstance, we presume that missing values are completely random and have no effect on or bias the results.

3.1 Descriptive analytics

In this subsection we will briefly describe some of the most salient features of the sample relating mostly to the respondents' demographic and socioeconomic status. This is a crucial task that will help us understand the context in which citizen involvement and trust in government institutions will be examined. As mentioned above, 18 Latin-American countries were surveyed, taking between 1000 and 1200 observations by country. The sample is balanced in terms of gender with 52% of female respondents and 48% of males. Figure 8 below presents the distribution of age groups across the sample.

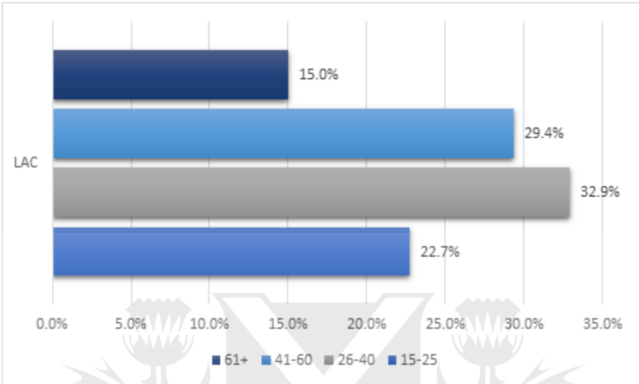


Figure 8: Age groups

In terms of education, around 26% of the respondents have complete secondary education, while only 13% have completed tertiary education. In addition, almost 8% of the respondents are illiterate. Figure 9 depicts respondents' perceptions of their own socioeconomic status. As can be seen, the majority of Latin-Americans identify as middle or lower middle class. Less than 2% of respondents declare to be upper class, while 6% claim to be upper middle class. Furthermore, a third (33.8%) declares to be middle class and another third (31.7%) claims to be low middle class.

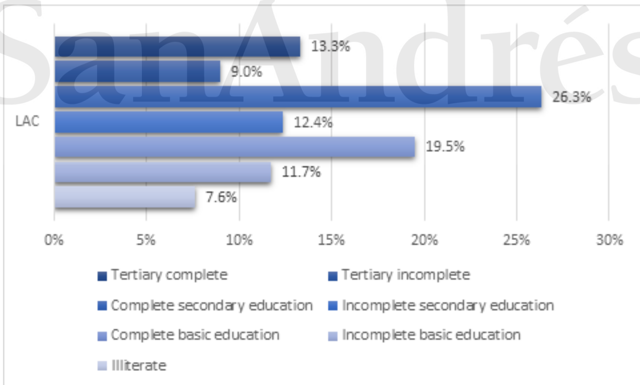


Figure 9: Education level

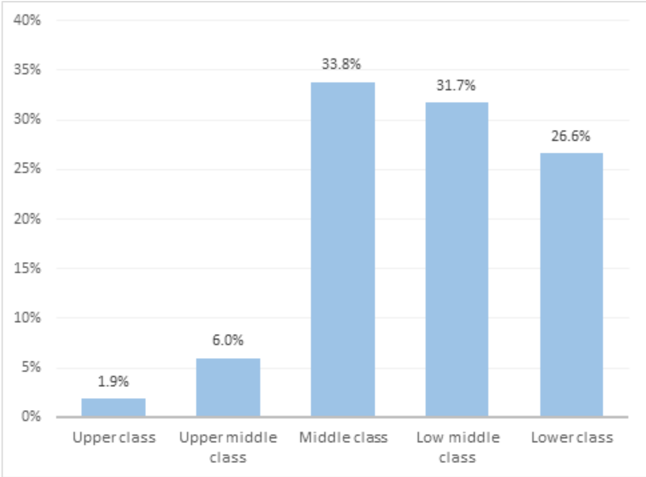
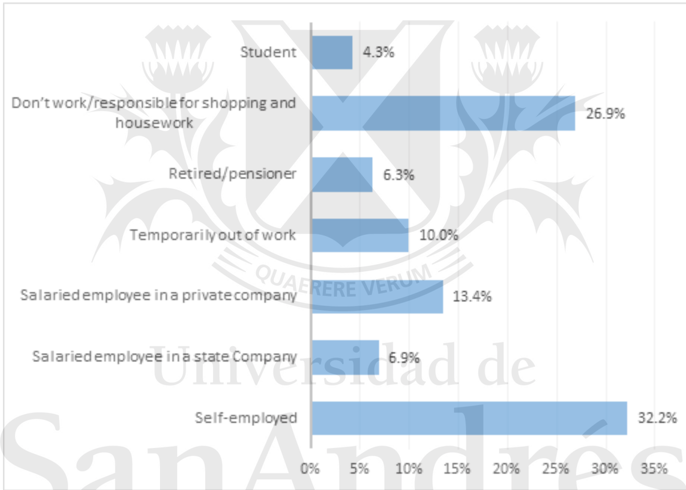


Figure 10: Subjective social class

When it comes to employment, roughly one-fifth of respondents are salaried employees, while about a quarter report not working or caring for family/household responsibilities. Notably, one-third of respondents report being self-employed, indicating that vulnerable employment is prevalent in the region.



QUAERERE VERUM
Universidad de
SanAndrés

Figure 11: Current employment situation

4 Methods

The approaches that will be utilized to investigate the relationship between trust in government and citizen participation are briefly described in this section. The justification for employing a variety of techniques ranging from classic econometrics methods such as logistic regression to more sophisticated machine learning techniques is to capitalize on the advantages that such methods provide over traditional methods. Firstly, the machine learning approaches utilized in this work are flexible enough in the sense that they minimize the constraints imposed on the data.This is particularly relevant considering that no prior models or empirical work provide consensus or an obvious framework for such a relationship. Secondly, the ability to capture non-linearities in how regressors interact to influence the outcome variable is another significant advantage of these approaches. This is accomplished by using decision tree models. Another key advantage of these methods is the ability to regularize the model, making it more parsimonious and manageable. This is critical for model selection.

While the logistic regression technique will allow us to determine the characteristics (variables) that influence citizen participation and, more significantly, the magnitude of the effect (if any) of political trust on such participation behavior; more sophisticated machine learning approaches will assist us in validating -or not- such findings as well as help us obtain simplified models describing the relationship between citizen engagement and political trust in the region. Additionally, these techniques will help us in the search of a more detailed mechanism underlying the relationship between citizen involvement and trust, such as non-linear interactions between the explanatory variables.

4.1 Logistic regression

In regression analysis, the logistic regression model (logit model) consists of estimating the parameters of a model where the dependent variable is a binary variable which commonly takes the values of 0 or 1. The independent variables can be either continuous or discrete, having two or more classes, that is, either binary or ordinal explanatory variables can be used. The logistic regression model calculates the likelihood of an event occurring, such as participating or not participating in political activities. The dependent variable is then confined between 0 and 1 because the outcome is a probability:

$$p_i = P(y = 1|x) = F(x\beta)$$

F(.) is the logistic function, which is represented as follows:

$$F(x\beta) = \frac{e^{x\beta}}{1 + e^{x\beta}}$$

This is the cumulative density function (CDF) of a standard logistic distribution. The domain of this function F(.) is from negative infinity to positive infinity, and the range is from 0 to 1, which makes it extremely useful for interpreting probability. We acquire the model we'll estimate by applying a logit transformation on the odds—that is, the probability of success divided by the probability of failure:

$$ln(pi/(1 - pi)) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k$$

The beta coefficients in this model are commonly estimated via maximum likelihood estimation (MLE). The estimates of the parameters are obtained through maximizing the log-likelihood function:

$$l(\beta) = \sum_{i=1}^{n} (y_i log(\pi_i) + (1 - y_i) log(1 - \pi_i))$$

$$l(\beta) = \sum_{i=1}^{n} (y_i log(\frac{\pi_i}{1 - \pi_i}) + log(1 - \pi_i))$$

$$l(\beta) = \sum_{i=1}^{n} (y_i x_i \beta - log(1 + e^{x_i \beta}))$$

In addition, the beta coefficients must be interpreted as the predicted change in log odds as a result of a unit change in x. As a result, raising the predictor by one unit (or advancing from one level to the next) increases the odds of the outcome by e^{β}.

In the context of this study, the estimated logit model will be useful in determining the set of statistically significant independent variables relating to citizen involvement. Furthermore, given a set of individual attributes, the probability of involvement can be estimated. In this regard, the Bayes classifier can be used to predict whether such an individual will participate; that is, if the estimated probability is greater than 50%, we anticipate that the individual will participate; if it is less than 50%, we predict that she will not participate.

4.2 Lasso, Ridge and Elastic Net

When there is a binary dependent variable, the Logit model is widely utilized. However, when the number of correlated independent variables is high, there are some drawbacks. The estimator is consistent but has a high variance, implying that more sophisticated models are less biased but have a higher variance, inflating the prediction error. Alternative approaches such as Lasso logistic (Park and Casella, 2008; Tibshirani, 1996) and Ridge logistic regressions (Hoerl and Kennard, 1970; Le Cessie and Houwelingen, 1992; Tibshirani, 1996) -or the combination of the two: Elastic Net- can be quite effective in this situation since they regularize the coefficients by compensating for a modest increase in bias with a larger reduction in prediction variance. Ridge and Lasso are often characterized as 'shrinkage' approaches since the coefficients in the resulting regression are reduced or shrunk.

These techniques avoid overfitting, which might cause the model to fail to generalize. That is, the estimated model may appear to work well on the data used to train it, but its performance degrades when tested on a fresh set of data. As a result, the model's accuracy on new data can be improved by lowering the variance.

Ridge and Lasso regularization both work by including a new component to the log-likelihood function:

$$l(\beta) = \sum_{i=1}^{n} (y_i x_i \beta - log(1 + e^{x_i \beta}))$$

In the case of Lasso logit, a new term that represents the sum of the magnitudes of all the coefficients in the model is added to the log-likelihood function; this way regularization occurs by penalizing the excess of coefficients:

$$l_l(\beta) = \sum_{i=1}^{n}(y_i x_i \beta - log(1 + e^{x_i \beta})) - \lambda \sum_{j=1}^{p}(|\beta_j|)$$

Ridge logit follows a similar pattern, except that the penalty term is the squared sum of the coefficients (Duffy and Santner, 1989; Cessie and Houwelingen, 1992):

$$l_r(\beta) = \sum_{i=1}^{n}(y_i x_i \beta - log(1 + e^{x_i \beta})) - \lambda \sum_{j=1}^{p}(\beta_j^2)$$

In both cases, lambda is a tuning parameter that controls the size of the penalty. If we leave it at zero, we'll get a standard logit regression. To choose the best lambda value for the model, different approches may be employed. The classical approach, namely k-fold cross-validation, is commonly used (Hastie et al., 2009). The data is divided into k subsets of approximately the same size and one of the subsets becomes the validation set. The remaining k-1 subsets are used as training data. This procedure is repeated k times, each time with a different validation set, and the optimal value is estimated so as to maximize the cross-validated log-likelihood function (Goeman, 2010). Although cross-validation techniques are generally effective for prediction tasks and universally applicable, they are computationally expensive (Ahrens, Hansen and Schaffer, 2020). Other approaches include information criteria methods such as the Akaike information criterion (Zou et al. 2007; Zhang et al. 2010), or the Bayesian Information Criterion (Schwarz, 1978). A third approach is the rigorous penalization approach, which selects the penalization parameters in order to guarantee consistency in prediction and parameter estimation. Which approach is preferable depends on the type of data and the purpose of the study (Ahrens, Hansen and Schaffer, 2020).

As the penalty increases, the ridge coefficients will approach zero, but none of them will be exactly zero. When lambda = 0 the regularization term has no effect and the estimators will be equal to those of the logit model. As a result, Ridge does not select variables, it includes all of them in the model (James et al., 2013).

The addition of the extra penalty term effectively disincentivizes the addition of new regressors. A new regressor may assist in increasing the first term of the log-likelihood function, but it will also increase the penalty term. The gain of adding a coefficient is compared against the equivalent increase in the model's overall variance -given by lambda-, which is ultimately a balancing act.

Ridge and Lasso both operate selecting variables in a way that, characteristics that do not drive the regression's predictive power have their coefficients reduced, while more predictive variables have larger coefficients in spite of the penalty. Because ridge squares the coefficients in the penalty term, it tends to send coefficients on less important regressors close to zero, but not exactly to zero. Lasso, on the other hand, will send some coefficients all the way down to zero, 'selecting' regressors.

When the number of regressors p exceeds the number of observations n in the dataset, Lasso forces the model to select at most n regressors. Furthermore, when a set of variables is highly correlated, Lasso tends to pick one of them arbitrarily, forcing the coefficient of the other variables to zero. In contrast, Ridge tends to assign similar coefficients to highly correlated variables. In general, even when n>p and the independent variables are highly correlated, Ridge performs better in terms of the Mean Squared Error (MSE).

Elastic Net (Zou and Hastie, 2005), which combines Lasso and Ridge, appears as a solution to the difficulties mentioned above, especially when there are high correlations between predictors. Elastic Net regularizes the model while choosing correctly among highly correlated predictors. The log-likelihood function to be maximized in the case of Logistic Elastic Net is as follows:

$$l_{nen}(\beta) = \sum_{i=1}^{n}(y_i x_i \beta - log(1 + e^{x_i \beta})) - \lambda_1 \sum_{j=1}^{p}(\beta_j^2) - \lambda_2 \sum_{j=1}^{p}(|\beta_j|)$$

The coefficient obtained by maximizing the aforementioned function is known as the naïve elastic net coefficient. It should be noted that in practice, such a coefficient is rescaled to remove the double shrinkage effect. The elastic net coefficient is calculated as follows:

$$\hat{\beta_{en}} = \frac{1}{1+\lambda_1}\hat{\beta_{nen}}$$

We will employ these techniques to validate the factors that appear as significant when using logistic regression analysis and to 'polish' the variable selection to account for those qualities that are truly central in determining citizen engagement.

4.3 Random Forest (decision trees)

Random forest is a supervised learning method that can be used to do classification tasks as well as regression analyses (Breiman, 2001). Random forest models outperform linear regression in terms of prediction. This is because, whereas linearity simplifies model interpretation in linear regressions, it typically reduces predictive power. Random decision trees can easily adapt to nonlinearities in the data and hence outperform linear regression in prediction (Schonlau and Zou, 2020).

When there are more independent variables than observations in the data, random forest models are especially helpful. In this situation, the number of parameters that need to be estimated exceeds the number of observations, hence the logistic regression and linear regression methods cannot be used. Because not all predictor variables are employed at once, Random Forest is effective in this situation.

A random forest, as the name implies, is made up of several decision-tree models. In a tree-based model, the given dataset is recursively divided into two groups according to a certain criterion until a preset stopping condition is satisfied (see figure 12). The so-called leaf nodes or leaves are located at the base of decision trees. Decision trees have the problem of being prone to over-fitting, which causes the model to adhere too closely to the peculiarities of the test dataset and perform badly on a new dataset, i.e., the test data. Random forest deals with this difficulty by building many individual trees and averaging predictions over those individual trees. In turn, each tree is trained with a different random sample (bootstrapping) and produces a forecast. The randomization in the tree construction aims to reduce the correlation between the trees. When conducting a classification task, each decision tree in the random forest votes for one of the classes to which the input belongs. Once all of the trees have reached a conclusion, the random forest will count which class had the most votes, and this class will be the one that the random forest predicts. In the case of regression analyses, the random forest will average the outcomes of each decision tree rather than determining the most common class.

As mentioned, decision trees operate by dividing the data into distinct groups based on the data's characteristics. The decision trees will keep splitting the data into groups until there is just a limited amount of data that fits into one label (a classification). Based on a purity metric that quantifies information gain, the decision tree selects where to split the data. When it comes to classification, it uses the Gini index or entropy, and when it comes to regression, it uses the residual sum of squares. The main difference with the previous models (logit, lasso, ridge) is that the trees allow the different variables to interact with each other and condition the prediction.

To give an example, suppose we have a dependent variable y_i and a set of predictors x_1,x_2,..,x_k. The random forest algorithm will pick a predictor and partition the space on a given point. Afterwards, another partition will be made and so forth. This procedure will be repeated recursively until a stop point has been reached. Ultimately, the algorithm generates a set of relationships between the predictors and the dependent variable, similar to tree branches. Figure 12 below illustrates this procedure:

Universidad de San Andrés

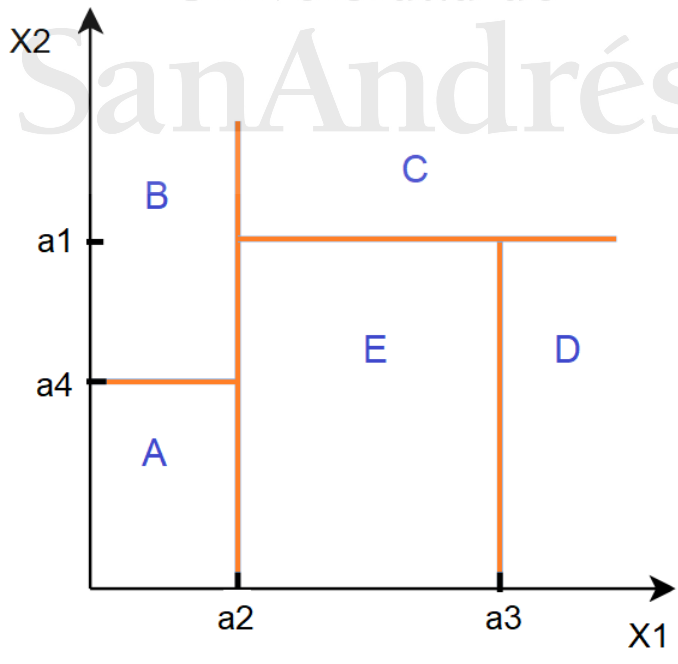


Figure 12: Random forest recursive partition

There are numerous advantages of using decision trees to classify or predict. For starters, they are simple to interpret since their results may be conveniently presented using a tree-branches scheme that clearly shows the relationships between the variables. However, because the outputs of multiple trees are aggregated in random forest techniques, this interpretability is lost. Second, tree-based models make no assumptions regarding the distribution of the data and they can employ both numerical and categorical predictors and are unaffected by outliers.

We will use decision trees to investigate the presence of nonlinearities in the characteristics influencing citizen participation. Additionally, we will compute the variable importance metric, which assesses each variable's relevance within the broader citizen engagement model.

5 Results and discussion

In this study we explore the relationship between trust and citizen participation in LAC. Trust variables used include: trust in the National government, trust in the Judiciary, trust in the Police, trust in the Parliament and trust in the National Electoral Institution. We, therefore, focus on institutional trust rather than generalized support for the system as a whole or confidence in specific leaders. We include also interpersonal trust as a measure of social trust.

Citizen engagement, on the other hand, is accounted for in this study via three distinct variables: i) signing a petition (at least once), ii) taking part in authorized demonstrations (at least once) and, iii) working for a problem that affects you or your community (frequently and very frequently). Because trust may interact differently with each type of engagement, the current paper looks at the relationship between trust and all three forms of participation.

The analyses conducted involve a set of control variables. These variables are further classified as demographic variables and perception variables. Age, gender, education level, income level (as perceived by the individual), social class (as perceived by the individual), subsidy recipient, employment status, ability to save money, house ownership, internet access, and sewage access are all among the variables in the first group. The second set of variables includes: political interest, freedom of expression and freedom to join any organization without fear (as viewed by the individual), discrimination encountered, victim of a crime, and food insecurity status. Annex A includes a table with a detailed description of the variables.

5.1 Logistic regressions

As a first step, we conduct a logistic regression analysis to identify the important determinants influencing citizen participation in LAC and to evaluate whether trust in governmental institutions has any impact on citizen engagement, and if so, what the sign of the relation is. In each model, the dependent variable is modeled as a function of the demographic set of variables and the perception variables. There is also a dummy variable for each country. An odds ratio is used to calculate the effects of relevant variables. A ratio greater than 1 indicates an increase in the likelihood of the dependent variable, whereas a value greater than 0 and less than 1 indicates a fall in the likelihood of the dependent variable. Table 1 presents the results of such analyses. For the sake of brevity, we have left out some of the control variables. The complete set of results are presented in Annex B. For the purpose of the estimation we employed the *logit* command in Stata 16.

In model 1, the dependent variable is signing a petition. As table 1 shows, trust in government has a significant and negative effect on signing a petition. The odds of signing a petition falls by a factor of 0.164 when trust in government rises by one standard deviation. This indicates that people who have trust in the government are roughly 15% less likely to sign a petition. Trust in the electoral system also has a significant but positive effect of signing a petition. In this case, as trust in government rises by one standard deviation, the odds of signing a petition increase by a factor of 0.14. This means that people who trust the government have 15% more odds of signing a petition than people who do not trust the government. Interpersonal trust – or social trust- also plays a role in determining the likelihood of signing a petition. In this regard, social trust increases the odds of signing a petition by 22%.

Patterns of petition signing are accounted for by several control variables. Higher income and education levels are shown to increase signing. Age, being employed, receiving a subsidy, having internet access at home, owning the home one lives in, and belonging to a lower socioeconomic class are all factors that increase the likelihood that someone will sign a petition. Unsurprisingly, being interested in politics makes someone more likely to sign a petition. Interestingly, having been a victim of a crime or having experienced discrimination at least once both enhance the likelihood of signing a petition. Contrarily, having experienced food insecurity and being a man have a negative impact on signing a petition.

In model 2, the dependent variable is participating in demonstrations. In this case, trust in the police and trust in the parliament along with social trust have a significant effect on participation. The odds of participating in demonstrations decreases by a factor of 0.25 when trust in police increases by one standard deviation. This indicates that people who have trust in the police have approximately 22% less odds of participating in demonstrations. By contrast, having trust in the parliament increases the odds of participating in demonstrations by 18%. Similarly, social trust increases the likelihood of participating by 19%. Like before, a higher income and education level increase the odds of participating. Age, being employed, belonging to a lower social class, having internet access as well as having an interest in politics all affect positively the likelihood of participation. Similar to signing a petition, having felt discriminated or having been the victim of a crime also prompts people to participate more, in this case, by taking part in demonstrations. It's interesting to note that having a strong belief in free speech—that is, that the right to say what one truly believes is guaranteed—decreases one's propensity to take part in demonstrations. However, believing that freedom to join any organization without fear is guaranteed boosts the likelihood of participation in all three models, showing that those who believe in political freedom engage more politically.

When it comes to working for a problem that affects the community, that is model 3, only trust in the judiciary has a significant effect on participation. In this case, having trust in the courts increases the odds of participating by almost 16%. Age and education, as well as being employed, receiving a subsidy, and owning a home, all raise the likelihood of working for a community problem. As in the previous models, having an interest in politics, feeling discriminated against, and having been a victim of a crime all increase the likelihood of participating. Notably, believing in freedom of speech as well as having experienced food insecurity, both boost the likelihood of working for a community problem. Contrary to the previous models, belonging to a lower social class decreases -although marginally- the likelihood of working for community problems. Moreover, being a man increases the odds of working for community problems by almost 25%.

From the above analyses, it emerges that there is no straightforward or simple relationship between political trust and citizen participation in LAC. While trust in government appears to decrease the tendency to sign petitions; or trust in police appears to reduce the odds of participating in demonstrations, the opposite is true for trust in courts and its positive effect on engagement in community problems. Such mixed results imply that reducing the tale to one theory triumphing over the other is not the best strategy to address the issue of civic engagement and political trust in LAC.

Citizens' participation appears to be impacted differently depending on how much they trust certain government institutions. Therefore, confining political trust to a single entity—such as the national government or the parliament—may obfuscate the issue and lead to incorrect conclusions. As a result, neither theory can be confirmed nor denied. We cannot claim that political trust reduces citizen engagement (the stealth democracy argument), nor can we claim the contrary (deliberative democracy theory). Conclusions must be drawn from an examination of the effect of trust in each government institution.

Interestingly, trust in the National government only has an effect on citizen participation when it comes to signing a petition. In other aspects, such as participation in demonstrations and working for community problems there is no significant effect.

One important limitation of this study is that we do not investigate the effect of political trust on voting, which is a crucial form of citizen involvement. The reason for this is that the Latinobarometro 2020 does not ask if the respondent voted in the most recent national or local elections. The only question in the survey is whether respondents believe voting is important for the development of the nation and which party they would vote for. However, the variables pertaining to voting in the Latinobarometro 2020 are not applicable for our study because we are evaluating actual participation or engagement, e.g., whether a respondent actually voted or signed a petition in the past or took part in a demonstration.

Table 1. Logistic regressions

Universidad de San Andrés

	(1)	(2)	(3)
	petition	demons	civic_part
main			
t_government	-0.164**	-0.0702	0.0119
	(-2.60)	(-1.01)	(0.21)
t_police	0.0224	-0.250***	-0.0734
	(0.43)	(-4.29)	(-1.59)
t_parliament	0.0864	0.168*	0.0890
	(1.35)	(2.41)	(1.57)
t_courts	0.0439	0.0176	0.147**
	(0.72)	(0.26)	(2.73)
t_elections	0.140*	0.109	0.0913
	(2.50)	(1.77)	(1.83)
t_people	0.199**	0.174*	0.0728
	(3.13)	(2.54)	(1.27)
int_politics	0.682***	0.874***	0.793***
	(14.34)	(16.88)	(18.67)
free_join	0.236***	0.250***	0.157***
	(4.78)	(4.58)	(3.62)
free_speak	0.00654	-0.238***	0.109*
	(0.13)	(-4.41)	(2.52)
discriminated	0.469***	0.490***	0.504***
	(9.00)	(8.78)	(10.84)
victim_crime	0.305***	0.338***	0.287***
	(6.53)	(6.67)	(6.88)
enough_food	-0.220***	-0.115	0.0979*
	(-3.94)	(-1.89)	(2.10)

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

QUAERERE VERUM
Universidad de San Andrés

5.2 Lasso regressions

One of the objectives of this research is to build a simple model that captures the important factors influencing the relationship between civic involvement and political trust. A simplified model, for example, can help policymakers identify the main variables that can serve as an instrument to reach and generate an impact on citizen participation in the region. Machine learning techniques such as lasso allow us to reduce model complexity through regularization while building a model that can also be used for prediction, however we do not seek to predict citizen participation in this study. For estimation purposes, we used the function *rlassologit* from the LASSOPACK package in Stata 16.

As explained in section 4, regularized techniques like lasso rely on tuning parameters that control the degree and type of penalization. In order to select these tuning parameters, namely λ, we employed the rigorous penalization approach, which estimates the penalty level using iterative algorithms. Controlling overfitting is given top priority in the rigorous approach, thus resulting in parsimonious models (Ahrens, Hansen and Schaffer, 2020). This significant emphasis on controlling overfitting is beneficial for selecting control variables in a model on both a practical and theoretical level. Although cross-validation techniques might outperform this approach for pure prediction tasks, because we are attempting to develop a model of citizen participation rather than predict participation, the rigorous approach is appropriate for our purpose.

After applying lasso to the three models of interest, the pool of covariates shrinks considerably. The number of independent variables in model 1 (signing a petition) was lowered from 23 to 15, thus decreasing the model's complexity. The number of variables in models 2 and 3 was reduced from 23 to 14. The resulting models are presented in tables 2-4.

The important variables identified by lasso, which are common across all three models are:

- Demographic variables: age, education, income and employment status;

- Perception variables: having felt discriminated, having been victim of a crime, having an interest in politics and believing freedom to join any organization without fear is guaranteed

The picture is more varied when it comes to trust variables. While in models 1 and 2 interpersonal trust plays a role, in model 3 it is not included as an important factor determining citizen participation (working for a community problem). All three models highlight the relevance of trust in elections. Moreover, trust in the parliament was included in model 1 (signing a petition) and in model 2 (participation in demonstrations), while trust in the judiciary was selected as an important factor in models 1 and 3.

As shown in tables 2-4, the pool of covariates in each model corresponds to a large extent - but not entirely - with the set of regressors that stood out as significant in the preceding section's logit analysis. Tables 2-4 also show post logit results, that is, the coefficients estimated using only the covariates chosen via lasso. As can be seen there, many of the coefficients resemble those estimated using the logistic regression in the preceding section.

Table 2. Lasso model 1

Model 1 – Signing a petition		
Selected	Logistic Lasso	Post logit
age	0.01	0.01
education	0.11	0.14
income	0.10	0.11
social_class	0.05	0.17
employed	0.01	0.15
internet	0.23	0.32
t_parliament	0.04	0.12
t_courts	0.00	0.09
t_elections	0.07	0.12
t_people	0.04	0.17
int_politics	0.61	0.66
free_join	0.17	0.26
discriminated	0.36	0.51
victim_crime	0.20	0.33
enough_food	-0.11	-0.26
_cons	-3.32	-4.48

Universidad de San Andrés

Table 3. Lasso model 2

Model 2 – Participating in demonstrations		
Selected	Logistic Lasso	Post logit
age	0.00	0.01
education	0.09	0.11
income	0.06	0.07
employed	0.03	0.20
internet	0.06	0.15
sewage	0.01	0.10
t_police	-0.05	-0.35
t_parliament	0.01	0.19
t_elections	0.03	0.17
t_people	0.01	0.18
int_politics	0.75	0.81
free_join	0.10	0.24
discriminated	0.35	0.52
victim_crime	0.17	0.30
_cons	-2.91	-3.77

Table 4. Lasso model 3

Model 3 – Working for a community problem		
Selected	Logistic Lasso	Post logit
age	0.00	0.01
sex	0.14	0.22
education	0.04	0.07
income	0.01	0.02
subsidy	0.03	0.17
employed	0.15	0.24
own_house	0.04	0.13
t_courts	0.06	0.14
t_elections	0.05	0.10
int_politics	0.75	0.79
free_join	0.11	0.15
free_speak	0.04	0.11
discriminated	0.34	0.47
victim_crime	0.16	0.27
_cons	-2.07	-2.83

As was already mentioned, when there are groups of correlated regressors, lasso typically chooses only one variable from each group, whereas ridge typically produces estimates of the coefficients for groups of correlated variables that are similar. Elastic net analysis can be used in this context to prevent the random selection of variables that happens when there are highly correlated covariates in lasso analyses. By applying a combination of lasso and ridge penalizations, elastic net conveniently integrates some of the advantages of lasso and ridge regression. In the context of our investigation, however, and after conducting a simple correlation analysis between the covariates (see figure 13), we conclude that the correlations are not strong enough to justify the usage of an elastic net and that lasso findings will be employed instead.

Pairwise correlations

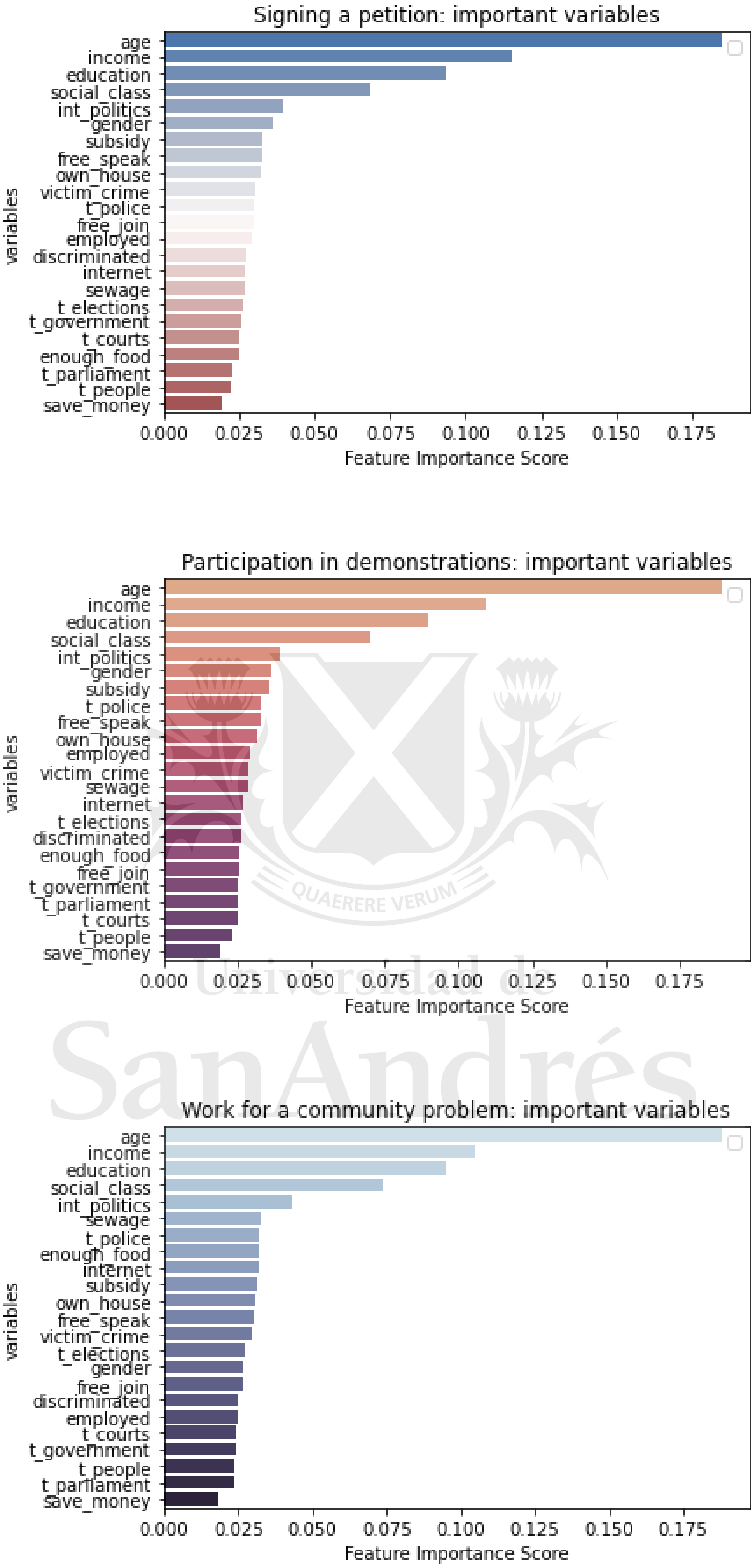
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) t_government	1.00											
(2) t_police	0.34*	1.00										
(3) t_parliament	0.44*	0.28*	1.00									
(4) t_courts	0.44*	0.35*	0.42*	1.00								
(5) t_elections	0.37*	0.31*	0.37*	0.45*	1.00							
(6) t_people	0.09*	0.07*	0.08*	0.07*	0.07*	1.00						
(7) int_politics	0.17*	0.12*	0.15*	0.15*	0.18*	0.09*	1.00					
(8) free_join	0.20*	0.17*	0.16*	0.17*	0.20*	0.06*	0.21*	1.00				
(9) free_speak	0.21*	0.18*	0.16*	0.19*	0.21*	0.06*	0.13*	0.37*	1.00			
(10) discriminated	-0.07*	-0.07*	-0.04*	-0.06*	-0.04*	-0.02*	0.04*	-0.05*	-0.09*	1.00		
(11) victim_crime	-0.04*	-0.03*	-0.02*	-0.01*	-0.02*	-0.01	0.08*	0.00	-0.02*	0.11*	1.00	
(12) enough_food	0.00	-0.06*	0.00	-0.02*	-0.04*	-0.03*	-0.03*	-0.07*	-0.06*	0.06*	0.04*	1.00

**** p<0.01, ** p<0.05, * p<0.1*

Figure 13: Correlation analysis

5.3 Random Forest

A random forest approach was used to study the presence of non-linearities in the data, specifically how interactions between the independent variables (i.e., attributes) could affect citizen engagement in LAC. Furthermore, we computed the variable importance score (see figure 14 below), which identifies the characteristics that are most important in determining citizen engagement. For the purpose of the estimation we employed the Scikit-Learn 1.1.1 library in Python 3.10.5, and used the function *RandomForestClassifier*.



QUAERERE VERUM
Universidad de
SanAndrés

Figure 14: Random forest: Variable importance

Age, education, income, social class, and having an interest in politics emerged as the most important variables in predicting citizen engagement in LAC in all three models. In general, these results are consistent with the previous logit and lasso models. There are, however, differences: For example, being employed was an important factor in determining engagement in its three forms (signing a petition, participating in demonstrations and working for community problems). However, in the case of the random forest analysis, being employed has just a limited impact.

The random forest analysis also reveals that political trust variables other than trust in police are of limited importance in determining citizen engagement in LAC. Moreover, the ability to save money appears to have little influence on citizen engagement in LAC, as was also the case in the logit and lasso analyses.

The use of tree-based models enables the visualization of non-linearities in the data, that is, interactions between independent variables that influence the outcomes of the dependent variable. This is important because the manner in which predictors interact with one another can greatly influence how the dependent variable behaves. Non-linearities, in this context, relate to variables that are only significant for a particular value or subset of the other explanatory variables.

Figures 15-17 depict the decision trees produced by the random forest algorithm when applied to the three models under consideration (signing a petition, participate in demonstrations and work for community problems). For explanatory purposes, only the relationships between a few variables are represented, however, the trees include and relate all the variables in the dataset.

Figure 17 illustrates the relationships between six predictor variables and how they interact to determine whether or not a person in LAC will work on a community problem. The algorithm begins by examining the individual's income group; if it is less than 5.5, the individual's trust in the government is assessed. If the individual has trust in the government, the algorithm checks to see if she or he receives a subsidy, and if so, it determines that the individual will participate (work for a community problem). It is crucial to note that the model contains non-linearities: receiving a subsidy only matters in terms of determining citizen engagement if the recipient has confidence in the government. Similarly, the gender of the individual, in particular, being a man, only matters when determining citizen engagement if the person has an interest in politics.

Similar non-linearities can be seen in the other models as well. For example, in model 2 (participation in demonstrations), trust in the parliament will play a role in determining whether or not an individual will participate only if she/he belongs to a very high-income group (more than 8.5) and has not been the victim of a crime. Similarly, in model 1, income dictates which variables are important in determining citizen engagement. In this regard, having been a victim of a crime and being older than 40.5 years will be important factors in the decision to sign a petition for those individuals from a low-income category. Other factors, such as political interest, will influence engagement among individuals with higher incomes (see figures 15-16).

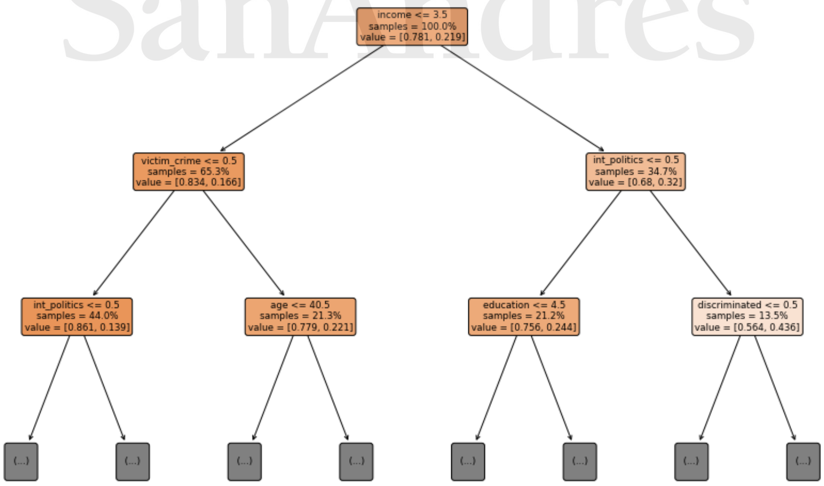


Figure 15: Decision tree: Signing a petition

Universidad de SanAndrés

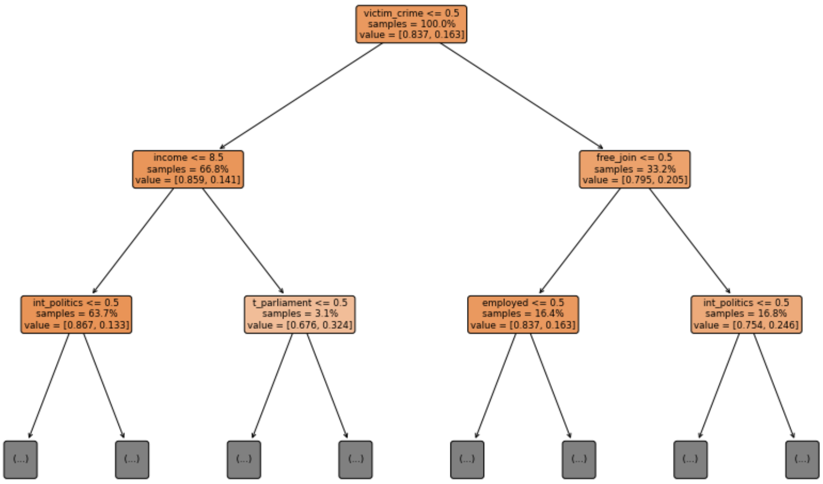
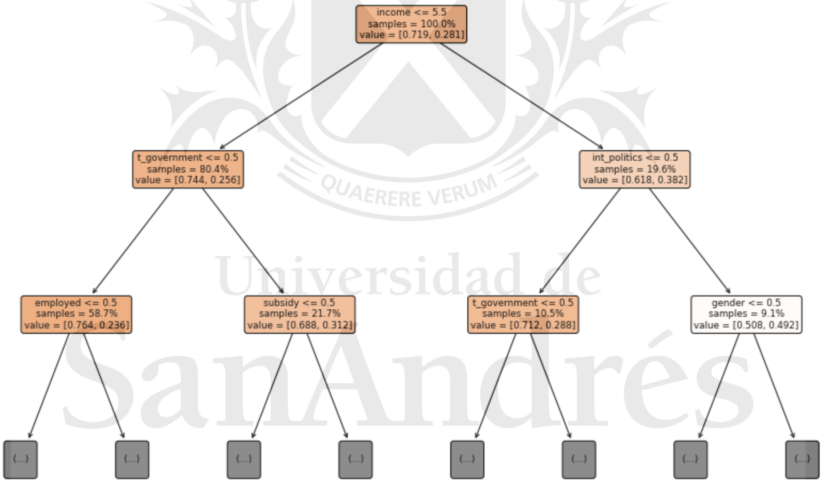


Figure 16: Decision tree: Participating in demonstrations



QUAERERE VERUM
Universidad de
SanAndrés

Figure 17: Decision tree: Work for community problems

6 Concluding remarks

In this final section, we will attempt to address the issues highlighted in the introduction. Our goal is to shed some light on the relationship between political trust and citizen engagement in LAC, an issue that has been poorly investigated from the citizen angle and where the use of micro-level data has been limited (Rizzo, 2021).

We began the paper by asking, "Is there a link between trust in government and citizen engagement in LAC?" If so, in which direction does the link operate? The quantitative analyses conducted throughout this work demonstrate the existence of a link, but the mechanism by which it operates is far from straightforward. We have found that trust in the national government has an effect on citizen participation when it comes to signing a petition but appears to have no effect on the other two types of engagement studied in this work (participating in demonstrations and working for community problems). A similar pattern emerges when trust in other governmental institutions is taken into account, such as trust in the police, which significantly influenced participation in demonstrations but not the other two types of citizen engagement, or trust in the judiciary, which only influences citizen engagement in the form of working to solve community problems.

Our findings show that there is a connection between political trust in general and citizen engagement, but that connection is nuanced in both its nature and how it works. There is evidence that trust in various government institutions affects citizen engagement, but neither the magnitude nor the direction of the effect are consistent among the three types of participation that were examined in this study. Moreover, non-linearity analysis in the data reveals a complex mix of interactions between the explanatory variables that drive their impact on citizen engagement.

At the outset of the study, we presented two competing theories on political trust and citizen engagement, hoping to ascertain which one prevails in the region. According to the stealth democracy theory, there is an inverse relationship between engagement and trust, although the deliberative theorists hold the opposite view. Given the heterogeneity of the effects observed in our analyses and the complexities of the relationships they suggest, we cannot say that one hypothesis is superior than the other in LAC.

While we found that trust in the national government has a significant negative impact on signing a petition or that trust in the police negatively affects participation in demonstrations, all of which support the stealth democracy theory, we also found that trust in the parliament has a positive impact on participation in demonstrations and that trust in the judiciary has a positive impact on working to address community problems, which ultimately supports the deliberative democracy theory. The fact that we are unable to draw a firm conclusion in favor of one theory or the other, as is the case in other related studies for the United States (see Lee and Schachter, 2019), is an important finding in and of itself, since it reveals the complexity of the relationship between political trust and citizen participation in the region, and how the latter is differently impacted by different types of political trust.

According to Lee and Schachter's (2019) research for the United States, people who have high levels of trust in the government are more inclined to sign petitions, which supports the deliberative democracy theory. However, their results are not comparable to ours because they constructed a measure of trust by averaging four World Values Survey questionnaires (trust in national government, Congress, the court, and civil servants), whereas we did not aggregate trust variables but rather used them separately. Nonetheless, their findings show that there are significant differences in how the relationship between political trust and citizen engagement operates in the United States and in Latin America.

Our results are in line with substantial prior studies that linked higher income, age, and education levels with more engagement. We also found that having an occupation boosts the likelihood of participating in all three types of citizen engagement. This study thus supports the notion of socially biased participation patterns. As in Lee and Schachter (2019), the impact of socioeconomic position on participation remains salient regardless of the engagement forum that is looked at or whether stealth or deliberative democracy theories seem to better explain a given engagement pattern.

Interestingly, being a woman increases the chances of signing a petition whereas being a man increases the probability of working for a community problem, suggesting that men and women have different inclinations for different types of engagement.

One intriguing finding is that certain unfavorable social life circumstances and experiences seem to influence willingness to engage. In this regard, we found that, regardless of the type of engagement taken into account, having been a victim of a crime and having ever felt discriminated against have a positive impact on participation.

The study's sole reliance on cross-sectional data is a significant drawback. We are unable to analyze causal evidence for political trust because unquantified macro events like political scandal, economic crises, and war almost surely have an impact on citizen participation. If these unmeasured events alter considerably the engagement pattern in a given period, it jeopardizes the validity of the conclusions. Moreover, cross-sectional data may not guarantee causality direction. As a result, it is very likely that citizen participation can predict political trust (Lee and Schachter, 2019).

Another limitation of the study is that voting, arguably the most significant form of citizen participation, was not taken into account. The reason for this is that the Latinobarometro 2020 survey only inquired about voting intentions rather than actual voting behavior (if the person voted or not in the previous elections). Since we are interested in actual behavior rather than intentions, we decided not to rely on such an indicator.

Future research on the linkage between political trust and citizen engagement should also consider other and new forms of citizen engagement like e-participation, that is, participation through the Internet. Neblo et al. (2010), for instance, finds that traditionally excluded groups like ethnic minorities, young people and those with lower incomes are more likely than others to interact with politicians through the Internet (Lee and Schachter, 2019).

This paper contributes to the understanding of the linkage between trust in government and citizen involvement in Latin America and the Caribbean by examining responses to the Latinobarometro 2020 survey. An incompatible view of why people participate is presented in earlier literature. Deliberative theorists state that higher levels of government trust boost greater involvement, whereas stealth theorists argue that lack of trust motivates participation. The findings in this study suggest that whether deliberative or stealth democracy is more effective in explaining engagement depends on the participation forum. There are more intricacies driving the linkage between political trust and citizen involvement than obvious straightforward effects.

QUAERERE VERUM
Universidad de
SanAndrés

Bibliography

Alesina, A. & Vacziarg, R. (2000). The Economies of Civic Trust. In S. Pharr and R. Putnam (eds.), *Disaffected Democracies* (149-173). Princeton: Princeton University press.

Ahrens, A., Hansen, C. & Schaffer, M. (2020). Lassopack: Model selection and prediction with regularized regression in Stata. *The Stata Journal*, 20(1), 176-235.

Arizti, P., Brumby, J., Manning, N., Senderowitsch, R. & Thomas T. (2010). *Results, Performance Budgeting, and Trust in Government.* Washington, DC: World Bank

Blind, P. (2007). Building Trust in Government in the Twenty-First Century: Review of Literature and Emerging Issues. UNDESA

Breiman, L. (2001). Random Forests. *Machine Learning*, 45, 5–32.

Caceres, L. (2019). Determinants of Trust in Government in Latin America. *Revista Mexicana de Economía y Finanzas*, 14(3), 329-351.

Catterberg, G. & Moreno, A. (2006). The Individual Bases of Political Trust: Trends in New and Established Democracies. *International Journal of Public Opinion Research*, 18(1), 31-48.

Chanley, V., Rudolph, T. & Rahn, W. (2000). The Origins and Consequences of Public Trust in Government: A Time-Series Analysis. *Public Opinion Quarterly*, 64, 239-56.

Cessie, S. & Van Houwelingen, J.C. (1992). Ridge Estimators in Logistic Regression. *Applied Statistics*, 41, 191-201.

Crozier, M., Huntington, S. & Watanuki, J. (1978). *The Crisis of Democracy: On the Governability of Democracies.* New York: New York University Press.

Dalton, R. J., Burklin, W. P. & Drummond, A. (2001). Public opinion and direct democracy. *Journal of Democracy*, 12 (4), 141–153.

Duffy, D. E., & Santner, T. J. (1989). On the small sample properties of norm-restricted maximum likelihood estimators for logistic regression models. *Communications in Statistics-Theory and Methods*, 18(3), 959-980.

Gastil, J., Black, L. W., Deess, E. P., & Leighter, J. (2008). From group member to democratic citizen: How deliberating with fellow jurors reshapes civic attitudes. *Human Communication Research*, 34(1), 137–169.

Goeman J. J., (2010). L1 and L2 Penalized Regression Models. Technical document for CRAN, http://cran.r-project.org/web/packages/penalized/penalized.pdf

Hastie, T., Tibshirani, R. & Friedman, J., (2009). *The Elements of Statistical Learning: Data Mining, Inference, and Prediction.* Second Edition. Springer.

Hetherington, M., & Husser, J. (2012). How trust matters: The changing political relevance of political trust. *American Journal of Political Science*, 56(2), 312–325.

Hibbing, J. R., & Theiss-Morse, E. (2002). *Stealth democracy: Americans' beliefs about how government should work.* Cambridge: Cambridge University Press.

Hoerl, A. E. & Kennard, R. W. (1970). Ridge regression: Biased estimation for nonorthogonal problems. *Technometrics*, 12(1), 55-67.

Iorio, F. & Kumagai, S. (2020). Building Trust in Government through Citizen Engagement. Washington, DC: World Bank.

James, G., Witten, D., Hastie, T. & Tibshirani, R. (2013). *An introduction to statistical learning.* New York: springer.

Khan, H. (2016). The Linkage Between Political Trust and the Quality of Government: An Analysis.*International Journal of Public Administration*,39(9), 665-675.

QUAERERE VERUM
Universidad de
SanAndrés

Le Cessie, S. & Van Houwelingen, J. C. (1992). ridge estimators in logistic regression. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, 41(1), 191-201.

Lee, Y. & Schachter, H. (2019). Exploring the Relationship between Trust in Government and Citizen Participation. *International Journal of Public Administration*, 42:5, 405-416.

Mullainathan, S. & Spiess, J. (2017). Machine learning: an applied econometric approach. *Journal of Economic Perspectives*, 31(2), 87-106.

Neblo, M. A., Esterling, K. M., Kennedy, R. P., Lazer, D. M. J., & Sokhey, A. E. (2010). Who wants to deliberate—And why? *American Political Science Review*, 104(3), 566–583.

Newman, B. J., Johnson, J., & Lown, P. L. (2014). The "Daily grind": Work, commuting, and their impact on political participation. *American Politics Research*, 42(1), 141–170

Park, T. & Casella, G. (2008). The bayesian lasso. *Journal of the American Association*, 103(482), 681-686.

Rizzo, T. (2021). Shaping Political Trust Through Participatory Governance in Latin America. IDB Technical Note 2079.

Schwarz, G. (1978). Estimating the Dimension of a Model. *The Annals of Statistics*, 6(2), 461–464.

Schonlau, M. & Zou, R. (2020). The Random Forest Algorithm for Statistical Learning. *The Stata Journal*, 20(1), 3-29.

Theiss-Morse, E., & Hibbing, J. R. (2005). Citizenship and civic engagement. *Annual Review of Political Science*, 8, 227–249.

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society: Series B (Methodological)*, 58(1), 267-288.

Van der Meer, T. & Zmerli, S. (2017). The Deeply Rooted Concern with Political Trust. In S. Zmerli and T.W.G. Van der Meer (eds), *Handbook on Political Trust* (1–16). Chelton, UK: Edward Elgar Publishing.

Verba, S., & Nie, N. H. (1987). *Participation in America: Political democracy and social equality.* Illinois, IL: University of Chicago Press.

Wagle, U. R. (2006). Political participation and civic engagement in Kathmandu: An empirical analysis with structural equations. *International Political Science Review*, 27(3), 301–322.

World Bank Group (2014). The World Bank Group Goals: End Extreme Poverty and Promote Shared Prosperity. Washington, DC: World Bank.

World Bank Group (2022). Social Sustainability Global Database 2022. Washington DC: World Bank.

Yang, K., & Pandey, S. K. (2011). Further dissecting the black box of citizen participation: When does citizen involvement lead to good outcomes? *Public Administration Review*, 71(6), 880–892.

Zack, P. & Knack, S. (2001). Trust and Growth. *Economic Journal*, 111, 295-321

Zhang, Y., Li, R. & Tsai, C.L. (2010). Regularization Parameter Selections via Generalized Information Criterion. *Journal of the American Statistical Association*, 105(489), 312-323.

Zou, H. & Hastie, T. (2005). Regularization and Variable Selection via the Elastic Net. *Journal of the Royal Statistical Society. Series B (Statistical Methodology)*, 67(2), 301-320.

Zou, H. (2006). The Adaptive Lasso and Its Oracle Properties. *Journal of the American Statistical Association*, 101(476), 1418-1429.

Zou, H., Hastie, T. & Tibshirani, R. (2007). On the degrees of freedom of the lasso. *Ann. Statist*, 35(5), 2173-2192.

Universidad de San Andrés

Annex A

Variables employed from the Latinobarometro 2020:

Demographic variables

- Age: Age of the respondent
- Sex: Gender of the respondent (1=male; 0=female)
- Education: Education level achieved
- Income: Subjective income group for household (1-10 from lowest to highest)
- Social_class: Subjective social class (from highest to lowest)
- Subsidy: Beneficiary of a subsidy from the state (yes)
- Employed: Has a job (self-employed, salaried work or temporarily out of work)
- Own_house: Owns the house in which lives in
- Internet: Has internet connection at home (yes)
- Sewage: Has sewage system (yes)

Perception variables

- int_politics: Has an interest in politics (yes)
- free_join: Believes freedom of political participation is guaranteed
- free_speak: Believes freedom of expression is guaranteed
- discriminated: Feels part of a discriminated group (yes)
- victim_crime: Was victim of a crime in the last 12 months
- enough_food: Has gone without enough food to eat in the last 12 months

Trust variables

- t_government: Has a lot or some confidence in the National government
- t_police: Has a lot or some confidence in the Police
- t_parliament: Has a lot or some confidence in the Parliament
- t_courts: Has a lot or some confidence in the Judiciary
- t_elections: Has a lot or some confidence in the National Electoral Institution
- t_people: Interpersonal trust (believes one can trust most people)

Dependent variables (citizen engagement)

- Petition: Sign a petition (have ever done)
- Demons: Take part in authorized demonstrations (have ever done)
- Civic_part: Work for a problem that affects you or your community (Frequently)

Universidad de San Andrés

Annex B

Table B1. Logistic regression results

	(1) petition	(2) demons	(3) civic_part
main			
t_government	-0.164**	-0.0702	0.0119
	(-2.60)	(-1.01)	(0.21)
t_police	0.0224	-0.250***	-0.0734
	(0.43)	(-4.29)	(-1.59)
t_parliament	0.0864	0.168*	0.0890
	(1.35)	(2.41)	(1.57)
t_courts	0.0439	0.0176	0.147**
	(0.72)	(0.26)	(2.73)
t_elections	0.140*	0.109	0.0913
	(2.50)	(1.77)	(1.83)
t_people	0.199**	0.174*	0.0728
	(3.13)	(2.54)	(1.27)
age	0.0122***	0.00600***	0.00958***
	(8.18)	(3.66)	(7.21)
sex	-0.133**	-0.0237	0.221***
	(-2.89)	(-0.47)	(5.40)
education	0.148***	0.114***	0.0847***
	(9.21)	(6.43)	(6.01)
income	0.0700***	0.0606***	0.0128
	(6.67)	(5.29)	(1.33)
social_class	0.0963***	0.0693*	-0.0477*
	(3.66)	(2.42)	(-2.16)
subsidy	0.180***	0.0797	0.137**
	(3.56)	(1.45)	(3.09)
employed	0.196***	0.182**	0.247***
	(3.87)	(3.26)	(5.52)
save_money	0.0334	0.0871	0.0617
	(0.47)	(1.11)	(0.95)
own_house	0.113*	0.0323	0.138**
	(2.19)	(0.58)	(3.07)
internet	0.182***	0.168**	0.0349
	(3.34)	(2.80)	(0.74)
sewage	0.123*	0.0746	-0.135**
	(2.21)	(1.21)	(-2.83)
int_politics	0.682***	0.874***	0.793***
	(14.34)	(16.88)	(18.67)
free_join	0.236***	0.250***	0.157***
	(4.78)	(4.58)	(3.62)
free_speak	0.00654	-0.238***	0.109*
	(0.13)	(-4.41)	(2.52)
discriminated	0.469***	0.490***	0.504***
	(9.00)	(8.78)	(10.84)
victim_crime	0.305***	0.338***	0.287***
	(6.53)	(6.67)	(6.88)
enough_food	-0.220***	-0.115	0.0979*
	(-3.94)	(-1.89)	(2.10)
N	14283	14400	14366

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Universidad de San Andrés

Universidad de
SanAndrés