CENTRO DE INVESTIGAÇÃO INTERDISCIPLINAR EM JUSTIÇA

Exploring how corruption affects voter turnout in Portuguese mayoral elections: A fuzzy-set Qualitative Comparative Analysis

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Literature review and empirical study: explaining voter-turnout in local elections

- **Relevant conditions identified in literature – reasons to vote**
  - Corruption (mostly social motivation, individual damages are unknown)
  - Education (social motivation)
  - Inequality (selfish and social motivation)
  - Government efficacy (mostly selfish motivation - local governments have limited powers in key policy areas)
- **Empirical study**
  - A fuzzy-set Qualitative Comparative Analysis
  - Sample: 149 municipalities were included in the analysis (48.4% of 308 Portuguese municipalities)

Corruption and voter-turnout

- **Corruption**: “misuse of public office for private gains” (Stockemer, 2013: 190)
- **TWO OPPOSITE EFFECTS**
- ***Demobilizing effect*** (Školník, 2020: 91)
    - Corruption weakens the voice of citizens by transferring power and resources from the public to the private sphere.
    - If citizens perceive political leaders as corrupt, they often prefer not to vote, because they believe that their voices cannot change the corrupt environment.

Corruption and voter-turnout

- ***Mobilizing Effect*** (Školník, 2020: 91): Corruption can provoke political mobilization, which can act in two ways:
  - Firstly, elections represent an opportunity to punish the politicians involved in corruption by supporting alternative candidates.
  - Secondly, voters can also choose to intentionally vote for corrupt candidates because of electoral clientelism in which politicians exchange votes for public goods.

Corruption and voter-turnout – Empirical results in local elections

- **Both the *demobilizing effect* and the *mobilizing effect* find empirical support in local elections**
- For example, studies by Chong et al. (2015), Costas-Perez (2014), Giommoni (2021), Jiménez and Garcia (2018), Johnson (2024), Sundström & Stockemer (2013) confirm the *demobilizing effect*.
- Studies by Escalera et al. (2012), Karahan, Coats & Shughart II (2006), Lacombe et al. (2016), Neskkova & Kalesnikaite (2019), Rundlett (2018), Stockemer and Calca (2013) find support for the *mobilizing effect*.
- *For the local election in Portuguese municipalities, Stockemer and Calca (2013) find "corruption to be a rather strong mobilizing agent." (Stockemer & Calca, 2013, p. 535)*

Education and voter-turnout

- **TWO OPPOSITE EFFECTS**
- ***The Absolute Education Model***
  - Education increases civic skills, political knowledge and political interest.
  - Education increases citizens' beliefs that they can effectively play a role in the political process.
  - Thus, the higher the level of education of the population, the higher the voter turnout.

Education and voter-turnout

- ***The Relative Education Model***
  - Individuals with high social status are exposed to networks that encourage participation.
  - Education should be seen as a 'positional good', i.e. something that is 'valuable to some people only on condition that others do not have it':
    - As more people obtain higher education, the social status of a college diploma is reduced (more competition leads to qualified individuals moving down the job hierarchy).
    - The loss of social status leads to lower political participation.
- Thus, the increase in the percentage of the population with higher education may dampen aggregate political participation**.**

Education and voter-turnout

- ***The relationship between education and voter turnout at the level of local elections in different countries***
  - Some studies found a positive relationship supporting the ***absolute education model*** (Bhatti et al, 2019; Haman & Školník, 2020; Helliwell & Putnam, 1999; Lappie & Marschall, 2018; Tavares & Raudla, 2018).
  - However, a negative relationship was also found in accordance with the ***relative education model*** (Harka & Rocco, 2022)
  - There are also several studies that indicate that the relationship is not statistically significant (Lindgren, Oskarsson & Persson, 2019; Freire, Martins & Meirinho, 2012; Magalhães, 2001; Tavares, Raudla & Silva, 2020).

Inequality and voter-turnout

- **TWO OPPOSITE EFFECTS**
- ***The Relative Power Theory***
  - "inequality reduces electoral participation (…) [because] as economic power becomes more unequal, the poor reduce their political participation, because it becomes too difficult for them to have the issues they care about addressed by the political process." (Stockemer & Scruggs, 2012: 765).
- ***The Conflict Theory***
  - Predicts mobilization – "increased inequality may increase participation as individuals with fewer resources head to the polls to protest" (Wilfrid, 2020: 320)

Inequality and voter-turnout

- **Empirical results in local elections - The effect of inequality on voter-turnout is inconclusive**
  - Kouba, Van Holm (2018) and Szewczyk and Crowder-Meyer (2022) show that local income inequality increases political participation – ***conflict theory***.
  - Schäfer and Schwander (2019, p. 407) conclude that there is "a consistently negative effect of income inequality on turnout." – ***relative power theory***
  - Cancela & Geis (2016) and Novák and Strnad (2021) found that the influence of income inequality on voter turnout is almost irrelevant.

Efficacy of government and voter-turnout

- ***If high efficacy increases turnout, this suggests that voters want to re-elect competent leaders.***
- ***If low efficacy increases turnout, this suggests that voters want to punish incumbents.***
- ***Empirical results for local elections***
  - Hansen (1994) and McDonnel (2020) found that perceived efficacy increases participation.
  - Wang (2016) suggests that low efficacy mobilize voters.

Fuzzy-set Qualilative Comparative Analysis (fsQCA)

(Ragin, 2000, 2008)

- **Empirical Study - fsQCA**
  - The fsQCA uses Boolean logic to establish necessary and sufficient conditions.
  - Computer algorithms developed by electrical engineers in the 1950s provide techniques for simplifying this type of data.
  - In this study the data was computed using the software package fsQCA 3.0 developed by Charles Ragin and Sean Davey, which uses the **Quine-McCluskey algorithm.**

Advantages and limitations of fsQCA

- **ADVANTAGES**
  - **Asymmetry** - the cause of the negative outcome is not seen as the inverse of the cause of the positive outcome.
  - **Conjunctural causation -** combinations of conditions, rather than just a single condition, lead to the presence of outcome.
  - **Equifinality** – there may be multiple causal configurations of conditions, or pathways, that lead to the outcome.
- **LIMITATIONS**
  - The impossibility of generalizing the results to any set of municipalities other than those included in the sample, because the analysis is qualitative, i.e., based on cases.
  - The fsQCA uses the term 'causation' within Boolean logic. What is evaluated is to what extent a given set is contained or contains the other set. They are not statistical tests of causation.

Fuzzy-set QCA – see Ragin (2000).

- FsQCA allows for gradations in set membership (mix of qualitative and quantitative methodology)
- **Variable data is calibrated in the range between zero and one, using as thresholds percentiles 95 (full membership), 50 (central point); 5 (full non-membership):**
  - Values higher than 0.5 mean membership in a given set: the more closer to percentile 95, the higher the degree of membership in the set;
  - Values lower than 0.5 mean low membership in a given set (variable): the more closer to percentile 5, the higher the degree of membership in the "negation (~)" (logical complement) of the set.
  - Values near percentile 50 are points of maximum ambiguity

Necessary conditions

- Condition A is **necessary** for outcome K if in each case the degree of membership in A is consistently **greater than or equal** to the degree of membership in K. (K is a subset of A)
    - For example, “high education" will be a necessary condition for "high voter-turnout" if, taking into account all cases (municipalities), membership in the condition “high education” is consistently **greater or equal** to level of membership in "high voter-turnout".
  - **Consistency** indicates the degree to which cases that are members of a given condition are also members of the outcome.
  - To consider that a condition is a necessary condition, the consistency of this condition must be **at least 90% (0.9)** (Fiss, 2011). - **[Σ(min(Ai,Ki))/Σ(Ki) ≥ 0.9]**

Sufficient conditions

- Condition A (or a set of conditions, for example B and C) is **sufficient** for K if in all cases the membership in condition A (or set of conditions B and C) is consistently **less than or equal** to the membership in K. (A is a subset of K)
  - To consider that a condition (or a combination of conditions) is a **sufficient condition, the consistency of this condition must be at least 80% (0.8).** - **[Σ(min(Ai,Ki))/Σ(Ai) ≥ 0.8]**

Note – why in the study of necessary conditions combinations of conditions are not considered: logical ***and*** (combination of conditions) is obtained by taking the minimum membership score of each case in the sets that are combined – that´s why in the study of necessary conditions, combinations of conditions are not incorporated – If no single condition is a necessary condition, none of their combinations will be.

What affects local levels of voter-turnout?

- MODELS
  - *~Abstention = g(Corruption; Education; Inequality; Efficacy of Government) – (~ means negation – **high voter turnout model**);*
  - *Abstention = f(Corruption; Education; Inequality; Efficacy of Government) – (**low voter turnout model**).*

(2 models, because asymmetry is possible)

Measures

ABST - Abstention is measured by the average of the percentage of abstention in two Portuguese municipal elections (2013 and 2017) .

PRCO – Prevention of corruption (*corruption is reversed – the lower the prevention of corruption, the higher the risk of corruption*) is measured by "Dimension E – Rule of Law and Prevention" of Corruption" - of the Local Democracy Quality Index (IQDL) by Tavares et. al. (2018). According to the authors, this dimension of the index measures "The Rule of Law and the absence of corruption" (Tavares et. al., 2018, p. 82). The data refer to the period 2013 to 2016.

EDUC - Education is measured by the percentage of the resident population aged 15 or older who have completed secondary education (average of 2011 and 2021 Census values).

INEQ - Inequality is measured by the municipal Gini coefficient for 2017.

EFFI - Efficacy of the government is measured by "Dimension C – Governmental Efficacy" - of the Local Democracy Quality Index (IQDL) by Tavares et. al. (2018). According to the authors, this dimension of the index comprises "Criteria that capture the quality of public services, the absence of political patronage, and the quality and credibility of policies formulated and implemented" (Tavares et al., 2018, p. 39). The data refer to the period 2013 to 2016.

Groups of municipalities

- There are major organizational, socio-cultural, and other differences between populous urban municipalities and municipalities with low population density and small numbers of inhabitants.
  - Combining such different municipalities in one and the same case group would violate the homogeneity principles of the fsQCA.
- 4 groups divided on the basis of the statistical distribution of the municipality's population size and population density (degree of urbanization)

Groups of municipalities

- i) VS (VERY SMALL) – population and population density in the first quartile - 35 municipalities (VS ≤ 6250 inhabitants; VS ≤ 25 inhabitants per km^2).
- ii) S (SMALL) - population and population density between the first quartile and the median - 25 municipalities (6250 inhabitants < S ≤13747 inhabitants; 25 inhabitants per km^2 < S ≤ 66 inhabitants per km^2);
- iii) M (MEDIUM) - population and population density between median and average - 43 municipalities (13747 inhabitants < M ≤33581 inhabitants; 66 inhabitants per km^2 < M ≤ 292.5 inhabitants per km^2);
- iv) L (LARGE) - - population and population density above the average - 46 municipalities (L > 33581 inhabitants; L > 292.5 inhabitants per km^2).

NECESSARY CONDITIONS

SETS	Outcome: HIGH VOTER TURNOUT - Consistency				Outcome: LOW VOTER TURNOUT - Consistency			
	VS	S	M	L	VS	S	M	L
High PRCO	0.61	0.57	0.69	0.68	0.73	0.59	0.72	0.67
Low PRCO	0.72	0.68	0.59	0.63	0.60	0.66	0.58	0.63
High EDUC	0.71	0.67	0.49	0.46	0.57	0.45	0.69	0.83
Low EDUC	0.57	0.55	0.77	0.85	0.71	0.76	0.59	0.46
High INEQ	0.50	0.47	0.60	0.53	0.71	0.75	0.61	0.69
Low INEQ	0.76	0.76	0.67	0.75	0.56	0.48	0.69	0.58
High EFFI	0.59	0.68	0.59	0.61	0.65	0.69	0.69	0.69
Low EFFI	0.67	0.60	0.68	0.64	0.62	0.57	0.61	0.55

None of the values is equal to or higher than 0.9, thus, none of the sets is a necessary condition for a high or low voter turnout.

SUFFICIENT CONDITIONS – HIGH VOTER-TURNOUT (low abstention)

GROUP	Sufficient conditions (pathways)	Consistency	Nr. of municip.	Frequency cut-off	Consistency cut-off	Solution consistency	Solution coverage
VS	~INEQ ^EDUC^ ~EFFI	0.909706	5	-------	-------	-------	-------
	~INEQ ^ EDUC ^ ~PRCO	0.906358	4	2	0.915556	0.902256	0.540541
S	~INEQ ^ EDUC	0.835869	8	-------	-------	-------	-------
	~INEQ ^ ~EFFI	0.856474	4	-------	-------	-------	-------
	~INEQ^~PRCO	0.806162	4	1	0.828423	0.78508	0.718699
M	~EDUC ^ ~EFFI	0.836218	8	-------	-------	-------	-------
	~INEQ ^ EFFI ^ ~PRCO	0.879245	2	1	0.847568	0.831549	0.656292
L	~EDUC ^ ~EFFI	0.888039	9	-------	-------	-------	-------
	~EDUC^~INEQ	0.916201	12				
	~EDUC^~PRCO	0.89410	8	1	0.860029	0.878365	0.820018

SUFFICIENT CONDITIONS – LOW VOTER-TURNOUT (high abstention)

GROUP	Sufficient conditions (pathways)	Consistency	Nr. of municip.	Frequency cut-off	Consistency cut-off	Solution consistency	Solution coverage
VS	INEQ ^ ~EDUC	0.827712	6	-------	-------	-------	-------
	INEQ ^ PRCO	0.872266	7	2	0.885756	0.812261	0.614849
S	INEQ ^ PRCO	0.884498	2	-------	-------	-------	-------
	INEQ ^ EFFI	0.858855	4	1	0.850498	0.84289	0.57874
M	~INEQ ^ EDUC	0.824365	8	-------	-------	-------	-------
	PRCO^EDUC	0.839399	6				
	~ PRCO^INEQ^EFFI	0.832962	4	1	0.84957	0.781664	0.719161
L	EDUC	0.850195	17	-------	-------	-------	-------
	INEQ ^ PRCO	0.902422	8	1	0.907035	0.841387	0.910202

Conclusions

- ***Corruption*** – **low corruption prevention mobilize voters** in all community groups**.**
- ***Education*** has mixed effects depending on the size of the municipality.
  - In very small and small municipalities, high education is associated with high voter turnout, which supports the *absolute education model*.
  - In medium and large municipalities, high education is associated with lower voter turnout, which supports the *relative education model*.

Conclusions

- ***Inequality*** **- demobilizes voters (**the results support *relative power theory).*
- ***Government efficacy*** – **voters are mobilized when governance is poor.**

Policy implications

The findings emphasize the importance of reducing inequality, improving corruption prevention, and ensuring government efficacy to increase voter turnout at the local level.

FINAL COMMENTS

- This study provides evidence that voters behave rationally, challenging the rational voter paradox.
- Voter turnout is shaped by multiple causal configurations, with corruption and poor governance acting as mobilizing factors.
- Findings suggest that the local political system in Portugal is responding to citizen preferences, with electoral participation serving as a response to governance failures and corruption.

Data and calibrated data from Very Small municipalities.

Municipalities	ABST	PRCO	INEQ	EDUC	EFFI	cABST	cPRCO	cINEQ	cEDUC	cEFFI
Alandroal	24.35	-70.3307	19.3	18.8	18.3508	0.07	0.06	0.02	0.59	0.27
Alfândega da Fé	30.95	37.8622	27.5	18.3	-26.7637	0.65	0.67	0.97	0.5	0.04
Aljezur	39.6	-60.9701	25.4	24.8	-6.48657	0.95	0.07	0.88	0.99	0.09
Almeida	35.5	53.7759	23.5	16.7	25.3373	0.86	0.82	0.66	0.21	0.34
Alter do Chão	27.75	-14.8538	21.6	19.1	64.976	0.38	0.24	0.23	0.65	0.91
Arronches	20.25	80.1987	21.6	20	19.4713	0.01	0.95	0.23	0.79	0.28
Avis	27.7	15.0884	21	20.7	39.3358	0.37	0.43	0.13	0.86	0.52
Boticas	46.55	39.3824	25.9	14.4	75.7424	0.99	0.69	0.92	0.04	0.96
Carrazeda de Ansiães	37.3	104.947	26.8	16.3	44.9522	0.91	0.99	0.95	0.16	0.64
Castelo de Vide	26.5	27.5502	22.9	20.5	52.6712	0.22	0.54	0.55	0.84	0.77
Crato	23.75	19.3015	20.4	17	56.4232	0.05	0.46	0.07	0.25	0.82
Fig. de Castelo Rodrigo	26.15	-43.4625	25.6	15.3	64.9467	0.18	0.12	0.9	0.08	0.91
Freixo de Espada à Cinta	24.35	3.07368	22.7	16.9	-61.8738	0.07	0.35	0.52	0.24	0.01
Fronteira	23.65	-2.56686	24.7	20.5	-2.51968	0.05	0.31	0.82	0.84	0.11
Gavião	30.75	-25.9098	21.1	16.7	72.7306	0.64	0.18	0.14	0.21	0.95
Góis	27.05	11.5597	21.7	19.6	-10.0453	0.28	0.41	0.26	0.73	0.08
Marvão	24.9	24.7342	20.9	16.9	33.8931	0.09	0.5	0.12	0.24	0.45
Mêda	33.5	57.6213	24.9	14.7	-18.5926	0.78	0.85	0.84	0.05	0.05
Mértola	26.95	46.519	22	19	63.7996	0.27	0.76	0.33	0.63	0.9
Monchique	28.55	10.2771	22.9	20.4	28.3251	0.5	0.4	0.55	0.83	0.38
Mora	39.1	86.4595	21.2	17	20.4376	0.94	0.96	0.16	0.25	0.29
Nisa	30.9	54.4464	22.6	17.9	48.0012	0.65	0.83	0.5	0.42	0.7
Oleiros	28.1	24.4154	22.9	15.5	49.2299	0.43	0.5	0.55	0.09	0.72
Ourique	24.6	-91.6753	23.6	20.8	11.8279	0.08	0.03	0.67	0.87	0.21
Pampilhosa da Serra	33.55	-23.9729	20.1	14.7	43.1626	0.79	0.19	0.05	0.05	0.6
Penamacor	28.95	-146.016	21.6	17.4	38.1875	0.53	0.01	0.23	0.32	0.5
Portel	29.1	36.7344	21	22	66.2445	0.54	0.65	0.13	0.94	0.91
São Roque do Pico	31.15	6.03192	26.2	21.7	147.313	0.66	0.37	0.93	0.93	1
Sousel	26.3	37.2114	21.8	19.6	-2.89213	0.2	0.66	0.28	0.73	0.11
Viana do Alentejo	35.1	20.8353	22.3	22.7	46.8322	0.85	0.47	0.41	0.97	0.68
Vidigueira	33.45	-47.5421	22.8	21	16.9732	0.78	0.11	0.54	0.89	0.25
Vila de Rei	27.1	32.5105	20.1	18.7	25.4175	0.29	0.6	0.05	0.58	0.34
Vila Flor	35.9	55.7364	26.7	17.6	38.8793	0.87	0.84	0.95	0.36	0.51
Vila Velha de Ródão	27.55	54.4802	20	17.7	13.7028	0.35	0.83	0.04	0.38	0.22
Vimioso	41.05	53.445	25.5	14.9	39.7973	0.96	0.82	0.89	0.06	0.53

Data and calibrated data from Small municipalities.

Municipalities	ABST	PRCO	INEQ	EDUC	EFFI	cABST	cPRCO	cINEQ	cEDUC	cEFFI
Alijó	35.9	31.3526	25.4	17.2	-92.1236	0.4	0.51	0.84	0.11	0.01
Arganil	35.35	61.3102	21.9	20.8	5.23791	0.31	0.96	0.1	0.76	0.44
Campo Maior	32.25	55.7043	21.1	25	45.504	0.04	0.94	0.04	0.98	0.89
Castro Daire	38.95	24.6852	25.1	16.5	53.4426	0.7	0.45	0.79	0.05	0.93
Celorico da Beira	34.95	-59.362	23.4	17.6	-53.8632	0.25	0.04	0.39	0.17	0.05
Ferreira do Zêzere	32.1	32.49	21.6	20.1	9.79847	0.04	0.54	0.07	0.67	0.49
Gouveia	41.75	21.1988	24.5	17	5.75479	0.86	0.42	0.67	0.09	0.44
Madalena	33.4	-1.33443	23.2	21.7	50.5134	0.1	0.25	0.33	0.85	0.91
Melgaço	55.35	-48.4955	24.8	16.6	16.2798	1	0.06	0.74	0.06	0.58
Moimenta da Beira	44.4	13.0841	26.7	18.9	-17.9879	0.94	0.35	0.95	0.5	0.21
Mondim de Basto	42.25	-7.68153	25.4	18.2	-56.1549	0.88	0.21	0.84	0.3	0.05
Mortágua	40.2	31.5585	23.8	16.7	23.5465	0.78	0.52	0.5	0.07	0.68
Oliveira de Frades	35.55	59.1991	22.3	21.8	28.8497	0.34	0.96	0.15	0.85	0.74
Paredes de Coura	36.45	-13.3365	23.1	19.4	9.74445	0.5	0.18	0.31	0.58	0.49
Penacova	41.35	34.3292	21.9	18.3	79.8556	0.84	0.59	0.1	0.33	0.98
Penalva do Castelo	36.5	-0.71633	24.7	15.6	23.5582	0.5	0.25	0.72	0.02	0.68
Ponte da Barca	39.65	31.1133	25.7	21.3	-9.2987	0.75	0.5	0.88	0.81	0.29
São João da Pesqueira	34.8	-139.228	27.3	16.5	9.87049	0.23	0	0.97	0.05	0.49
Sátão	45.5	39.0295	25.2	19	37.7074	0.96	0.71	0.81	0.52	0.83
Tábua	35.1	3.68129	21.6	20.2	-19.9276	0.27	0.28	0.07	0.69	0.2
Vendas Novas	41.45	37.6928	22	23.6	27.2109	0.85	0.68	0.11	0.95	0.73
Vieira do Minho	33.25	30.9447	25.6	18.3	-7.61688	0.09	0.5	0.87	0.33	0.3
Vila Pouca de Aguiar	43.65	45.7747	26.7	16.4	39.646	0.92	0.83	0.95	0.05	0.85
Vila Viçosa	32.7	-21.8026	20.8	23.9	63.158	0.06	0.14	0.03	0.95	0.96
Vouzela	33.35	32.4845	22.3	19.2	10.9399	0.09	0.54	0.15	0.55	0.5

Data and calibrated data from Medium-sized municipalities.

Municipalities	ABST	PRCO	INEQ	EDUC	EFFI	cABST	cPRCO	cINEQ	cEDUC	cEFFI
Albergaria-a-Velha	40.65	35.9274	22.3	22.9	11.1047	0.26	0.83	0.08	0.59	0.5
Alcochete	45.7	-224.002	28.2	28	31.5364	0.64	0	0.96	0.98	0.75
Almeirim	51.6	10.3553	24.2	22.7	32.3879	0.95	0.46	0.52	0.55	0.76
Amares	37.65	-17.218	24.7	23.6	-26.5419	0.13	0.28	0.62	0.7	0.18
Anadia	45.3	29.6987	24.4	20.5	21.0586	0.6	0.75	0.56	0.16	0.63
Arruda dos Vinhos	39.6	4.67437	25.5	24.8	29.6144	0.2	0.42	0.75	0.85	0.73
Azambuja	45.95	7.29209	22.6	25.4	-7.72145	0.67	0.43	0.11	0.89	0.32
Baião	35.2	36.2659	24.1	18.7	3.80506	0.07	0.84	0.5	0.04	0.43
Batalha	44.6	45.1278	21.9	22.8	54.8378	0.53	0.92	0.05	0.57	0.92
Caminha	35.7	8.62423	27.4	23	-10.3748	0.08	0.44	0.93	0.61	0.3
Cantanhede	48.4	56.2947	25.2	20.1	37.9819	0.85	0.96	0.7	0.11	0.81
Cartaxo	47	-56.7284	23.2	25.1	-115.821	0.75	0.11	0.22	0.87	0.01
Castelo de Paiva	25.3	-5.26753	22.4	19.8	-51.2293	0	0.35	0.09	0.09	0.08
Celorico de Basto	36.1	56.7761	24.1	19.3	-8.5665	0.08	0.97	0.5	0.06	0.31
Cinfães	33.9	52.6426	25.8	18.2	5.45495	0.05	0.95	0.79	0.02	0.44
Condeixa-a-Nova	44.3	11.8558	23.5	23.3	33.3342	0.5	0.47	0.3	0.66	0.77
Estarreja	49.5	50.1031	23.5	22	18.8512	0.9	0.94	0.3	0.41	0.6
Horta	37.95	30.9859	26.4	22.6	65.066	0.14	0.77	0.86	0.54	0.95
Lagoa	50.6	7.42827	26.6	25.8	50.9752	0.93	0.44	0.88	0.92	0.9
Lagos	53.45	39.6303	25.8	26.8	-8.3923	0.98	0.87	0.79	0.96	0.31
Lamego	37.1	-15.4782	28.3	20.5	-25.3383	0.11	0.29	0.96	0.16	0.19
Lourinhã	45.95	-6.05329	25.6	22.9	-34.3087	0.67	0.35	0.76	0.59	0.14
Lousã	46.45	34.5493	22.9	25.6	41.9567	0.71	0.82	0.16	0.91	0.84
Machico	43.9	-93.3498	24.1	19.8	-65.3091	0.47	0.04	0.5	0.09	0.05
Mangualde	42.95	22.1696	23.7	19.7	25.01	0.4	0.61	0.37	0.08	0.68
Mealhada	49.05	51.6239	23.1	22.7	72.8223	0.88	0.95	0.2	0.55	0.97
Monção	40.35	44.6723	24.8	20.5	-16.3005	0.24	0.91	0.63	0.16	0.25
Montemor-o-Velho	38.6	-69.2316	22.1	22.4	-51.6262	0.16	0.08	0.06	0.5	0.08
Nazaré	50.1	-193.654	23.4	22.6	-119.439	0.92	0	0.28	0.54	0.01
Oliveira do Bairro	46.8	33.782	23.1	23.1	14.7778	0.74	0.81	0.2	0.62	0.55
Oliveira do Hospital	33.8	33.9947	21.6	20.3	69.5147	0.04	0.81	0.03	0.13	0.96
Peso da Régua	40.2	1.73714	26.5	21.2	-27.8435	0.23	0.4	0.87	0.26	0.17
Porto de Mós	41	30.4323	21.5	22	11.0419	0.28	0.76	0.03	0.41	0.5
Póvoa de Lanhoso	35.65	13.8745	23.7	19.9	66.456	0.07	0.48	0.37	0.1	0.95
Ribeira Grande	45.65	16.7276	28	19	53.9852	0.64	0.5	0.95	0.05	0.91
Rio Maior	41.9	-23.9338	23	24.3	-0.07635	0.33	0.24	0.18	0.79	0.39
Salvaterra de Magos	51.95	47.6015	23.2	22.4	20.7744	0.96	0.93	0.22	0.5	0.63
Sines	45.5	-0.35542	25.2	26.7	-21.4037	0.62	0.38	0.7	0.96	0.21
Tondela	41.25	-52.1709	23.6	19.7	26.2045	0.29	0.13	0.33	0.08	0.69
Torres Novas	46.4	22.8285	23.6	23.6	-9.78581	0.71	0.63	0.33	0.7	0.3
Vagos	46.6	27.2833	24.1	21.4	-17.441	0.72	0.71	0.5	0.29	0.24
Vale de Cambra	36.05	28.4643	22.8	19.3	-29.9723	0.08	0.73	0.14	0.06	0.16
Vil. Praia da Vitória	50.4	-7.16031	24.8	20.4	32.1878	0.93	0.34	0.63	0.14	0.76

Data and calibrated data from Large municipalities.

Municipalities	ABST	PRCO	INEQ	EDUC	EFFI	cABST	cPRCO	cINEQ	cEDUC	cEFFI
Albufeira	59.85	47.6629	25.4	29.4	31.3592	0.96	0.86	0.61	0.96	0.8
Almada	57.65	41.0274	26.2	26.9	-5.07608	0.93	0.79	0.72	0.84	0.41
Amadora	58.25	16.4901	24.9	27.1	68.3174	0.94	0.47	0.53	0.86	0.96
Aveiro	50.95	-125.722	25.9	23.7	-56.8748	0.67	0.06	0.68	0.47	0.11
Barcelos	29.6	21.5396	22	21.5	-4.1189	0.04	0.49	0.06	0.11	0.42
Barreiro	52.3	23.6557	23	27.7	64.2064	0.75	0.52	0.15	0.89	0.96
Braga	41.25	-54.2817	26.5	24.1	18.304	0.23	0.19	0.76	0.53	0.66
Cascais	59.25	-15.8865	29.9	27	61.9956	0.96	0.32	0.97	0.85	0.95
Coimbra	48.55	26.947	27.7	22.1	20.5318	0.51	0.58	0.87	0.17	0.69
Esposende	40.75	-52.981	26.3	22.1	63.4243	0.22	0.19	0.74	0.17	0.95
Faro	54.5	-1.06569	26.4	26.4	-37.9559	0.85	0.39	0.75	0.8	0.19
Felgueiras	34.15	13.2956	20.9	20.5	26.2302	0.08	0.46	0.02	0.05	0.75
Funchal	48.4	-8.22704	27.4	23.4	-19.7931	0.5	0.36	0.85	0.4	0.3
Gondomar	46.7	25.2707	24.4	25.1	-70.4803	0.43	0.55	0.42	0.67	0.07
Guimarães	36.4	11.3459	22.3	21.2	-42.0787	0.12	0.45	0.08	0.09	0.17
Ílhavo	58.1	49.5205	25.2	23.3	21.4983	0.94	0.88	0.58	0.38	0.7
Lisboa	51.85	30.7285	32.2	21.1	-20.7242	0.72	0.64	0.99	0.08	0.29
Loures	49.1	51.3194	24.2	26.4	54.3222	0.54	0.89	0.37	0.8	0.93
Lousada	29.8	66.6559	21.8	20.5	-12.4038	0.04	0.96	0.05	0.05	0.35
Mafra	48.95	48.1008	26.6	26.8	45.9201	0.53	0.86	0.77	0.84	0.89
Maia	46.45	35.025	26.1	25	-32.2662	0.42	0.71	0.71	0.65	0.22
Matosinhos	49	-38.8737	26.9	23.3	16.4102	0.54	0.24	0.8	0.38	0.64
Moita	58.45	-1.72743	21.8	28.1	58.0212	0.94	0.39	0.05	0.91	0.94
Odivelas	55.2	-4.75081	24.1	26.8	31.6021	0.87	0.37	0.35	0.84	0.8
Oeiras	48.75	29.642	27.8	25.2	49.9948	0.52	0.62	0.88	0.68	0.91
Olhão	57.25	-15.4333	24.5	25.7	-26.1971	0.92	0.33	0.45	0.74	0.26
Oliveira de Azeméis	42.3	34.2814	22.4	21.1	-17.6821	0.26	0.7	0.08	0.08	0.31
Ovar	46.65	73.8293	24.2	23.8	38.728	0.42	0.98	0.37	0.49	0.85
Paços de Ferreira	33.45	-113.978	21.9	19.6	-34.2731	0.08	0.07	0.05	0.02	0.21
Paredes	32.6	-136.589	24.9	22.2	17.168	0.07	0.05	0.53	0.19	0.65
Penafiel	28.45	-57.6861	23.9	22.2	-14.2311	0.03	0.18	0.3	0.19	0.34
Portimão	58.2	-164.384	25.1	27.1	-68.7212	0.94	0.03	0.56	0.86	0.07
Porto	46.85	34.9912	31	20.9	31.5175	0.43	0.71	0.98	0.07	0.8
Póvoa de Varzim	50.5	24.6372	26.8	22.6	53.6686	0.64	0.54	0.79	0.25	0.93
Santa Cruz(Madeira)	42.95	-31.4147	24.4	27	-86.6608	0.28	0.26	0.42	0.85	0.04
Santa Maria da Feira	43.65	85.133	23.7	21.7	-33.3385	0.31	0.99	0.26	0.13	0.21
Santo Tirso	35.85	56.0255	22.4	20.2	-20.5128	0.11	0.92	0.08	0.04	0.29
Seixal	58.9	-17.128	23.6	28.9	-0.46322	0.95	0.32	0.24	0.94	0.45
Setúbal	59.1	-151.478	25.3	27.2	-21.9718	0.95	0.03	0.6	0.86	0.28
Sintra	58.65	31.9827	24.4	30.8	2.87582	0.95	0.66	0.42	0.98	0.48
Trofa	33.95	47.4235	22.4	22.7	-95.2472	0.08	0.86	0.08	0.26	0.03
Valongo	47.7	50.5914	23.9	25	7.30965	0.47	0.88	0.3	0.65	0.53
Vila do Conde	40.6	5.96167	25.5	22.1	25.4314	0.21	0.42	0.63	0.17	0.74
Vila Franca de Xira	53.7	44.2473	22.4	29.8	35.2285	0.81	0.83	0.08	0.96	0.83
Vil. Nova de Famalicão	35.75	27.7643	22.3	23	45.6234	0.11	0.59	0.08	0.32	0.89
Vila Nova de Gaia	47.25	12.8449	26.3	23.9	-86.6977	0.45	0.45	0.74	0.51	0.04

Sets and fsQCA calibration thresholds

Groups	SETS	Full membership – percentile 95	Central point- percentile 50	Full non-membership – percentile 5
VS	ABS	40.035	28.550	23.720
	PRCO	82.07691549	24.41542017	-76.73409583
	EDUC	22.21	18.3	14.7
	INEQ	26.73	22.6	20.07
	EFFI	73.634	38.187	-21.044
S	ABS	45.280	36.450	32.340
	PRCO	58.50015394	30.94465769	-57.18871837
	EDUC	23.84	18.9	16.42
	INEQ	26.7	23.8	21.2
	EFFI	61.215	10.940	-55.697
M	ABS	51.500	44.300	34.030
	PRCO	52.54073884	16.72762053	-90.93800753
	EDUC	26.61	22.4	19.03
	INEQ	27.94	24.1	21.92
	EFFI	66.317	11.042	-63.941
G	ABS	59.050	48.475	30.500
	PRCO	63.9983338	22.59762796	-133.8724337
	EDUC	29.275	23.85	20.5
	INEQ	29.375	24.7	21.825
	EFFI	63.067	5.093	-82.616

CENTRO DE INVESTIGAÇÃO
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Thank You /Obrigado!

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