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## The Front National vote and its sectorial support

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#### Introduction

The French Front national, the country's main populist New Right party (Kitschelt, 1995), was described by the litterature, when it first electorally emerged in 1983-1984, as a petty-bourgeois, Poujadist party (Mayer and Perrineau, 1996). Then, after 1995, a consensus was reached on the working-class electoral basis of the party, even though a fierce controversy began regarding the interpretation of it, between those arguing that former left-wing voters changed their allegiance to the FN (Perrineau, 1995) and those underlining that if the FN electorate was predominantly working-class, it didn't mean that these blue-collars previously voted for the left (Mayer, 2002) – even though some definitely did (Evans, 2000).

Since then, most of the debates, both in the (at least French) academic litterature and in the larger audience, have dwelt on the extent to which the FN electorate is composed of blue collar workers. What could be a rather simple empirical debate has been complicated by methodological difficulties (the FN voters are notoriously underrepresented in opinion polls and surveys (Lehingue, 2003); to which extent does this underrepresentation lead to a bias? One could for example imagine that the FN vote is more understated by non-blue collars than by blue-collars) and political arguments (for the academic version of the political argument, see Collovald (2004)). However, a consensus has probably been reached by now on the fact that the working class constitutes the core of the FN electorate.

Since its election at president of the FN in 2011, Marine Le Pen has steered the party according to the so-called 'dédiabolisation' (de-demonization) strategy. Along with a distanciation with some of the most controversial tenets of the party's ideology and style (e.g. negationnism, antisemitism), Marine Le Pen has put forward some supposedly left-wing economic and social positions (for a detailed assessment of the party's positions on this issues, see Ivaldi (2013)). One may then speculate on the effects that these supply-side developments may have on the social basis of the FN electorate.

This paper aims at presenting some figures about the sociology of the FN electoral basis over the last ten years – from 21 April, 2002, the acme of Jean-Marie Le Pen's career, to 2012, when Marine Le Pen represented, for the first time, the FN at the presidential election.

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Our main hypothesis is that the FN electoral support has been shifting from its original petty-bourgeois basis to a much more proletarian basis since, at least, 1995. Recent developments, such as the 'dédiabolisation' strategy or the impact of the 2008 crisis, haven't fundamentally altered this dynamic. However, the structuration of political offer may alter this social basis. In particular, in 2007 Nicolas Sarkozy, candidate for the center-right party UMP, made a strategic move towards the FN, especially along the cultural dimension and on issues such as immigration, law and order, etc. This move resulted in a high score for Sarkozy, at the expenses of Jean-Marie Le Pen, who got 10.4 % of the votes cast – a historically low performance for the FN (Mayer, 2007). Another hypothesis is that, if the FN vote is fundamentally a proletarian vote, the level of inequalities interfere with the political alignments of different social groups (for a first assessment of this hypothesis, see Gombin and Rivière (2013)). Indeed, if people vote in line with their subjective social position, this perception may be influenced by the local social configuration one lives in, and especially by the level of inequality.

#### 1 Data

This paper relies on aggregate data. This strategy has drawbacks (all usual limitations about ecological inference apply, some variables are difficult or impossible to test with aggregate data), but it also has definite value in the case of the Fn.

The Front national electoral support is indeed notoriously underestimated by opinion polls and academic surveys (for a close study of bias in French polls, see Arzheimer and Evans (2013)), and there is no way of knowing for sure to what extent it alters the underlying structure. Furthermore, the sociodemographic data offered by such surveys are often relatively poor: either the categories used are not detailed enough to allow for a thorough analysis, or the size of the groups gets so small that the estimations become very uncertain. Last but not least, in the French case, the surveys seldom allow for proper contextual and/or multilevel analysis (Gombin, 2013b).

By contrast, aggregate data are 'real', unbiased figures. In the French context, they are (relatively) easy – and free – to get, and they are usually available at the *commune* level, which gives the researcher over 36,000 statistical individuals to play with. The researcher may also use purely contextual variables – variables that cannot be measured at the individual level (e.g., the level of income inequalities). One of the drawbacks of this kind of data is the strongly skewed distribution of the *communes* size, and hence of the implicit variance of aggregate variables, when they measure aggregated attributes, as is often the case. There is no clear 'best' strategy ot deal with this: either one doesn't use weigths in statistical procedures, thus running the risk of having some (possibly large) heteroskedasticity, or one uses weights, but at the risk of having the weight of large cities overdetermining the estimations of quantities of interest. Another issue is that when the quantities of interest (e.g. regression coefficients) differ along the unit size, the average estimate will be biased towards the value of the parameter in small units. As we will see, some of these concerns can be taken care of by appropriate methodological choices. At any rate, aggregate data seems valuable to assess the FN social basis.

#### 1.1 Election returns

We use election returns by *communes* for the 2002, 2007 and 2012 presidential elections. In 2002, at the first round, two far-right candidates ran, Jean-Marie Le Pen (FN) and Bruno Mégret (MNR). So our dependant variable is the sum of both scores (see table 1 for a summary of these variables). Furthermore, Jean-Marie Le Pen made it through the second round, so his results at the second round are considered as well (see table 2 for summary statistics).

	Weighted mean	Unweighted mean	Weighted sd	Unweighted sd	N
Le Pen	12.09	12.75	4.11	5.14	36538
Mégret	1.68	1.82	0.96	1.45	36538
Far right	13.77	14.56	4.73	5.74	36538

Table 1: Summary statistics onf the far-right electoral results at the first round of the 2002 presidential election. Source: French Ministry for Home Affairs.

Weighted mean		Unweighted mean Weighted sd		Unweighted sd	N
Le Pen	13.81	15.33	4.80	5.79	36538

Table 2: Summary statistics of Le Pen's electoral results at the second round of the 2002 presidential election. Source: French Ministry for Home Affairs.

Tables 3 and 4 show summary statistics about the 2007 and 2012 results of, resp., Jean-Marie and Marine Le Pen. All results are expressed as a share of registered voters.

Weighted mean		Unweighted mean Weighted sd		Unweighted sd	N
Le Pen	8.85	10.74	3.65	4.60	36573

Table 3: Summary statistics of Le Pen's electoral results at the first round of the 2007 presidential election. Source: French Ministry for Home Affairs.

#### 1.2 Census results for sociodemographic data

Our data regarding demographics comes from the census brought out by France's national statistics institute, the INSEE. Until the 1999 census, the data relative to the socio-professionnal category was very finely detailed (in 42 categories). After 1999, though, the census' methodology changed, and the data is released in 8 large categories only. In one file from the 2008 census, however, a 24-point classification scheme is used. As the exploration of the FN social basis requires as detailed data as possible, we chose to use the 24-point classification scheme, with 1999 data matched to the 2002 election, and 2008 data matched with the 2007 and 2012 elections<sup>1</sup>.

<sup>&</sup>lt;sup>1</sup>Unfortunately, the 2009 data is not available and the 2010 data won't be released for a few more weeks.

	Weighted mean	Unweighted mean	Weighted sd	Unweighted sd	N
Le Pen	14.62	17.70	5.47	5.93	36558

Table 4: Summary statistics of Le Pen's electoral results at the first round of the 2012 presidential election. Source: French Ministry for Home Affairs.

The French Pcs (professions et catégories socioprofessionnelles) classification scheme uses several criteria to classify individuals along their socio-professional category: employed (categories 3 to 6 – even though some in the category 3 may be self-employed professionnals) vs self-employed (categories 1 and 2); the education level and the 'cadre' status (category 3 vs categories 4 and 5); blue collars vs white collars (category 5 vs category 6); public sector vs private sector; etc. Table 5 presents the 24 categories (with the French labels and a temptative translation) and some summary statistics for the 1999 census, whereas the results of the 2008 census are displayed in table 6.

Code	PCS	Translation	Weighted mean	Unweighted mean	Weighted sd	Unweighted sd	N
10	Agriculteurs exploitants	Farmers	1.26	5.39	2.76	6.21	36604
21	Artisans	Crafters	1.56	1.98	0.95	2.07	36604
22	Commerçants et assimilés	Shopkeepers	1.53	1.54	0.91	2.05	36604
23	Chefs d'entreprise de 10 salariés ou plus	Businessmen	0.37	0.32	0.40	0.80	36604
31	Professions libérales et assimilés	Professionnals liberal professions	0.80	0.43	0.71	0.96	36604
32	Cadres de la fonction publique, professions intellectuelles et artistiques	Managers in the public sector Intellectuals and artists	2.89	1.60	2.26	2.19	36604
36	Cadres d'entreprise	Managers in the private sector	3.47	1.68	3.38	2.26	36604
41	Professions intermédiaires de l'enseignement, de la santé, de la fonction publique et assimilés	Technicians and associate professionals in teaching, health and public service	5.01	4.38	1.76	3.51	36604
46	Professions intermédiaires administratives et commerciales des entreprises	Commercial associate professionals and clerks – private sector	3.96	2.65	1.98	2.54	36604
47	Techniciens	Technicians	1.95	1.65	1.02	1.87	36604
48	Contremaîtres, agents de maîtrise	Foremen	1.17	1.23	0.76	1.51	36604
51	Employés de la fonction publique	Public sector employees (white collar)	5.89	5.27	2.03	3.59	36604
54	Employés administratifs d'entreprise	Private sector employees (white collar)	4.55	3.45	1.70	2.81	36604
55	Employés de commerce	Commercial employees	2.31	1.78	0.93	1.89	36604
56	Personnels des services directs aux par- ticuliers	Personal services staff	3.46	3.08	1.21	2.58	36604
61	Ouvriers qualifiés	Skilled workers	8.42	9.16	3.18	4.60	36604
66	Ouvriers non qualifiés	Non-skilled workers	5.28	5.73	2.98	4.24	36604
69	Ouvriers agricoles	Agricultural workers	0.59	1.44	1.22	2.52	36604
71	Anciens agriculteurs exploitants	Retired farmers	2.12	7.61	4.09	8.04	36604
72	Anciens artisans, commerçants, chefs d'entreprise	Retired self-employed	1.95	2.18	1.35	2.72	36604
73	Anciens cadres et professions intermédiaires	Retired managers and technicians and associates	4.80	3.75	2.35	3.81	36604
76	Anciens employés et ouvriers	Retired workers	13.09	12.70	4.18	6.71	36604
81	Chômeurs n'ayant jamais travaillé	Unemployed who have never worked	0.74	0.45	0.64	0.95	36604
82	Inactifs divers (autres que retraités)	Other inactives	22.84	20.55	4.75	6.84	36604

Table 5: Summary statistics of the socio-professional category of people over 15 in the 1999 census. Source: INSEE.

Code	PCS	Translation	Weighted mean	Unweighted mean	Weighted sd	Unweighted sd	N
10	Agriculteurs exploitants	Farmers	0.83	3.62	1.97	5.03	36719
21	Artisans	Crafters	1.31	1.83	0.91	2.06	36719
22	Commerçants et assimilés	Shopkeepers	1.23	1.34	0.79	1.90	36719
23	Chefs d'entreprise de 10 salariés ou plus	Businessmen	0.29	0.27	0.31	0.68	36719
31	Professions libérales et assimilés	Professionnals liberal professions	0.86	0.51	0.80	1.08	36719
32	Cadres de la fonction publique, professions intellectuelles et artistiques	Managers in the public sector Intellectuals and artists	2.87	1.69	2.27	2.10	36719
36	Cadres d'entreprise	Managers in the private sector	4.22	2.29	3.88	2.63	36719
41	Professions intermédiaires de l'enseignement, de la santé, de la fonction publique et assimilés	Technicians and associate professionals in teaching, health and public service	4.91	4.56	1.61	3.30	36719
46	Professions intermédiaires administratives et commerciales des entreprises	Commercial associate professionals and clerks – private sector	4.15	3.10	1.85	2.61	36719
47	Techniciens	Technicians	1.95	1.90	0.98	1.99	36719
48	Contremaîtres, agents de maîtrise	Foremen	0.96	1.09	0.63	1.38	36719
51	Employés de la fonction publique	Public sector employees (white collar)	5.18	5.03	1.87	3.34	36719
54	Employés administratifs d'entreprise	Private sector employees (white collar)	3.42	2.92	1.18	2.33	36719
55	Employés de commerce	Commercial employees	2.44	2.01	0.91	1.89	36719
56	Personnels des services directs aux par- ticuliers	Personal services staff	3.43	3.18	1.10	2.47	36719
61	Ouvriers qualifiés	Skilled workers	6.72	7.87	2.64	4.23	36719
66	Ouvriers non qualifiés	Non-skilled workers	4.39	4.90	2.39	3.69	36719
69	Ouvriers agricoles	Agricultural workers	0.46	1.09	0.94	2.15	36719
71	Anciens agriculteurs exploitants	Retired farmers	1.58	5.59	3.10	6.67	36719
72	Anciens artisans, commerçants, chefs d'entreprise	Retired self-employed	1.92	2.28	1.37	2.66	36719
73	Anciens cadres et professions intermédiaires	Retired managers and technicians and associates	5.72	5.02	2.67	4.19	36719
76	Anciens employés et ouvriers	Retired workers	12.82	12.82	4.62	6.65	36719
81	Chômeurs n'ayant jamais travaillé	Unemployed who have never worked	0.58	0.27	0.79	0.77	36719
82	Inactifs divers (autres que retraités)	Other inactives	27.75	24.83	4.98	6.69	36719

Table 6: Summary statistics of the socio-professional category of people over 15 in the 2008 census. Source: INSEE.

#### 1.3 More contextual data: tax statistics

In order to evaluate the level of economic inequality, we use some figures released each year by the Budget Ministry. Several indicators of inequality are released (inter-quartile and interdecile range, standard deviation, etc.). We use the Gini coefficient, as it uses the whole distribution of incomes rather than just a part of it. The income upon which the Gini coefficient is computed are pre-tax incomes that are declared to the tax administration. They are standardized by 'consumption unit', so as to take into account the size and the composition of the household.

Since the Gini coefficient is not computed on geographical units under 2,000 inhabitants, we chose to use Gini coefficients at the *département* level. This seems relevant, since people are probably influenced by the social structure of a space that goes beyond the *commune* in which they live.

For the 2002 presidential election, 2002 tax data is used. For the 2007 election, 2007 tax data is used, and for the 2012 election, 2011 tax data (the most recently released) is used. Some summary statistics on these variables are presented in tables 7, 8 et 9.

	Unweighted mean	Unweighted sd	N
Gini coefficient	0.34	0.03	96

Table 7: Summary statistics of income inequalities in 2002, by *départements*. Source: French Ministry of Budget.

	Unweighted mean	Unweighted sd	N
Gini coefficient	0.34	0.03	96

Table 8: Summary statistics of income inequalities in 2007, by *départements*. Source: French Ministry of Budget.

	Unweighted mean	Unweighted sd	N
Gini coefficient	0.34	0.03	96

Table 9: Summary statistics of income inequalities in 2011, by *départements*. Source: French Ministry of Budget.

## 2 Methodology

In this section, we lay out our methodology. We analyse data through multilevel analysis.

#### 2.1 Data preparation and structure

Election results have been used as such. They could have been centered around their unweighted mean, so that regression coefficients would only be determined by the relative structure of the results, not by their levels. This is especially useful to compare coefficients obtained from regressions on different elections results. However, we wanted to have raw coefficients, with the possibility to transform them in various ways once they are estimated. In particular, one useful transformation is to withdraw the average FN score from coefficients, thus leading to coefficients that reflects only the particular structure of an election, not the absolute level reached by the FN. But it seemed more convenient to perform this transformation post-estimation rather than to transform the data itself.

Sociodemographic data are not transformed and are used such as.

Since the Gini coefficient is not very significant in itself, we have centered it around its unweighted mean, and divided by two standard deviations, so that coefficients and values can be easily interpreted. A change of 1 in the transformed variable thus corresponds to a change from the mean minus one sd to the mean plus one sd.

#### 2.2 Modelisation

Our substantial interest being the social basis of the FN and its evolution across the last decade, several questions arise.

First, should we model independantly each election, and then compare the coefficients (or quantities derived from the coefficients)? Or should we build a growth model, thus integrating all elections in a single model? A growth model may seem intellectually more relevant. However, it draws attention on the dynamics of a party's electoral results rather than on their structure. Moreover, a growth model may quickly become quite complex and thus its results difficult to interpret. And when the considered growth model is multilevel, its estimation may become computationally very intensive, even in some cases challenging. Therefore, in this paper, we opted for a simpler approach: each election is modelled independantly. Since the election results are centered, coefficients can be compared without caring for the varying levels of support the FN got across time; indeed, it is the relative strength of the FN vote in each social group that we are interested in.

The second question regards the choice of the model itself. Since we are primarily interested in the propensity of each social group to vote for the FN, rather than in the spatial variation of this propensity, ole regression may seem as the logical choice. However, since we have a large number of *communes*, which are clustered and spatially autocorrelated, and since the estimations may be biased by the skewed distribution of teh *communes* by size, it seems wise to use a multilevel (also called 'hierarchical' or 'mixed model') strategy. Multilevel models tend to provide more accurate estimations. Of course, they also allow to assess the degree of spatial variability of each coefficient, that is to assess to what extent the propensity of a social group to support the FN varies across space. Level-2 predictors can then be introduced in order to try to mimimize the (unexplained) *département*-level variance. We therefore make use of the nested nature of our data to improve its understanding. In an arguably somewhat arbitrary manner, we choose the *département* as the level-2 unit – standing on the shoulders of giants

indeed (Derivry and Dogan, 1971, 1986).

Thirdly, as we are modeling a proportion, it may be advisable to either transform the response variable (e.g. with the logit), or perform a beta regression, thus modelling the response variable with a beta distribution (Ferrari and Cribari-Neto, 2004). However, there is at the moment no implementation of multilevel beta-regression models in R (R Core Team, 2012), the statistical package we use. We would therefore need to set up a full-fledge Bayesian implementation in a software such as Bugs, Jags or Stan – a task that would be computationally very intensive. Moreover, tests we have run with simple one-level models show that the added value of beta regression, in this case, is unclear – at the costs of getting coefficients that are less straightforward in their interpretation. At any rate, none of our (Gaussian) models produce fitted values that are out of range (i.e. inferior to 0 or superior to 1). Therefore, we decided to stick with classical Gaussian modelisation.

We thus estimate both OLS and multilevel models for the same variables, and compare the results. Since few summary statistics allow to compare the goodness of fit of OLS linear models and multilevel models, we use the standard-deviation of residuals (thereafter called sigma) as such a statistics. In all models, there is no intercept (that is, it is fixed at o). Indeed, since all FN voters necessarily belong to one of the social categories, the idea of an intercept (the value the response variable takes when all preditors are set to zero) doesn't make any sense. Therefore, the coefficient for a given social category can be directly interpreted as the predicted FN vote in an imaginary *commune* where all voters would belong to this social category.

For each election, six OLS models  $(M_1 \text{ to } M_6)$  and six corresponding models  $(H_1 \text{ to } H_6)$  are built.

- Models  $M_1$  only have the broad social categories CS1 to CS8 as predictors<sup>2</sup>. Models  $H_1$  have the same predictors, but the coefficients are allowed to vary at the *département* level (random slope model).
- Models  $M_2$  replace CS<sub>4</sub> (intermediate professions) in  $M_1$  with its breakdown into CS<sub>41</sub>, CS<sub>46</sub>, CS<sub>47</sub> and CS<sub>48</sub>. Models  $H_2$  have the same predictors, but the coefficients are allowed to vary at the *département* level (random slope model).
- Models  $M_3$  replace CS<sub>5</sub> (employees/white collar workers) with its breakdown into CS<sub>51</sub>, CS<sub>54</sub>, CS<sub>55</sub> and CS<sub>56</sub>. Models  $H_3$  have the same predictors, but the coefficients are allowed to vary at the *département* level (random slope model).
- Models  $M_4$  replace CS6 (blue collar workers) with its breakdown into CS61, CS66 and CS69. Models  $H_4$  have the same predictors, but the coefficients are allowed to vary at the *département* level (random slope model).
- Models  $M_5$  replace CS7 (pensioners) with its breakdown into CS71, CS73 and CS76. Models  $H_5$  have the same predictors, but the coefficients are allowed to vary at the *département* level (random slope model).

 $<sup>^2</sup>$ Social category CS2, for example, corresponds to the sum of all socio-professional categories starting with a 2 in tables 5 and 6 – that is, CS21, CS22 and CS23.

• Models  $M_6$  use all broken-down categories from models  $M_2$  to  $M_5$ . Thus, categories CS<sub>1</sub>, CS<sub>2</sub>, CS<sub>3</sub> and CS<sub>8</sub> are not broken down, whereas CS<sub>4</sub>, CS<sub>5</sub>, CS<sub>6</sub> and CS<sub>7</sub> are broken down. Furthermore, it adds interaction effects with the level of inequalities (measured by the Gini coefficient of pre-tax incomes per consumption unit, observed at the *département* level). Models  $H_6$  have the same predictors, but the coefficients are allowed to vary at the *département* level (random slope model). Interaction effects, however, involve data measured at the departement level, so allowing them to vary by *département* would lead to overfitting; therefore, these coefficients are not allowed to vary<sup>3</sup>.

#### 3 Results

The detailed results of all models are presented in the final Appendix.

#### 3.1 Sociological and sectorial support for the FN

Figure 1 displays the coefficients (centered around the unweighted mean of the FN vote) from models  $M_1$ , and coefficients from hierarchical models  $H_1$  are displayed on figure 2. The results, although a bit different, are consistent4. The propensity to vote for the FN of a commune is directly and strongly related to its sociodemographic composition; and the upper one goes on the social scale, the lower is the FN vote, and vice versa. In particular, higher managerial and professional positions (CS3) are strongly negatively associated with the FN vote, whereas blue collars (CS6) are strongly positively associated with it. Somewhere in between, technicians and associate professionals (CS4) are slightly less associated to the FN vote than the average, whereas wwhite collar workers can't be distinguished from the average. Even if the coefficients associated to CS4 and CS5 have slighty raised since 2002 (2nd round), this has been very limited - and even hardly statistically significant. So far, then, there is little support for the 'squeezed middle' thesis. Quite the opposite, actually: in 2012 particularly, a stronger social polarisation can be observed, at both ends of the social ladder: the upper class (CS<sub>3</sub>) voted significantly less for the FN than in previous elections, whereas the blue-collar workers' basis got reinforced. In terms of electoral geography, this translated by a shift of the party's electoral map from the South-East towards the North-East (Gombin, 2013a).

Another lesson to be learned from these graphics is that coefficients estimates from hierarchical models, by comparison with OLS models, are 'schrinked' towards the average. There are also more conservatives, with larger standard errors and confidence intervals. For these reasons, and those stated earlier, we trust the multilevel models estimate more, and in the analysis of other models we will focus on multilevel models.

Now, it may be that CS<sub>4</sub> and CS<sub>5</sub> are too agregated and heterogeneous categories. The same could be said of CS<sub>6</sub> (blue-collar workers), since skilled and non-skilled workers should probably be distinguished, the latter being more exposed to precarious work conditions than

<sup>&</sup>lt;sup>3</sup>It has been checked that the introduction of interaction effects with the level of inequality does not significantly alter other fixed effects. This is achieved thanks to the centering of the Gini coefficient.

<sup>&</sup>lt;sup>4</sup>Since coefficients have been centered, they are to be interpreted as relative propensity to vote for the FN, compared to the average.

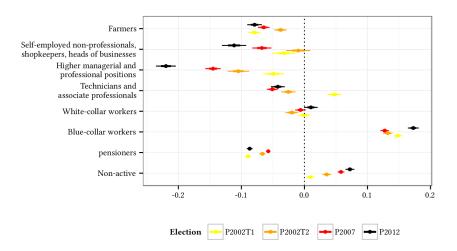


Figure 1: Coefficients for the 8-position socio-professional scale, from 2002 to 2012, model  $M_1$ . The points represent coefficient estimates, while the lines range over the mean  $\pm$  one (resp. two) standard-error.

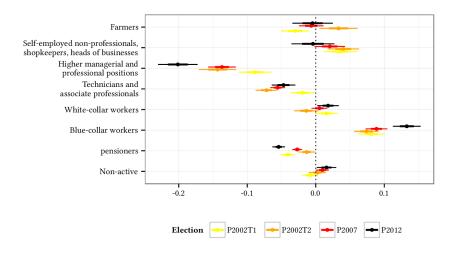


Figure 2: Coefficients for the 8-position socio-professional scale, from 2002 to 2012, model  $H_1$ . The points represent coefficient estimates of the fixed effects, while the lines range over the mean  $\pm$  one (resp. two) standard-error.

the former. CS7 (pensioners) should also be broken down according to the retiree's former socioprofessional position.

Models  $H_2$  to  $H_5$  do exactly that. The comparison of the models' output shows that, despite the concerns one might have about colinearity, especially in model  $H_6$ , the coefficients estimates are actually quite stable. This is probably due to the large number of units in the dataset, and the multilevel modelling strategy. Furthermore, adding an interaction effect with the level of inequalities (model  $H_6$ ) doesn't significantly modify the coefficients either. Therefore, we can focus on the results of model  $H_6$ .

Figure 3 displays coefficients estimates for broken-down socioprofessional categories, from 2002 to 2012.

Both CS4 and CS5 appear to be indeed heterogeneous, from the point of view of the propensity to vote for the Fn. On the one hand, those technicians and associate professionals who work in the teaching, health, or public service (CS41) are almost as negatively associated to the Fn vote as the CS3. On the other hand, associate professionals and clerks working in the private sector (CS46) tend to behave as the average voter, and more and more so: if in 2002 (first round) they voted more than average for Le Pen, this is no longer true in 2007 and 2012. Technicians are also associated with a close-to-average propensity to vote Fn, but the dynamics seem to go the other way: since the second round of the 2002 presidential election, the coefficient goes up. Finally, foremen are consistently associated with a high Fn vote, at a level comparable with the level of blue-collar workers. In this category, the trend has clearly been upward since the second round of the 2002 election. Generally speaking, among the intermediate professions, the Fn vote was quite high at the first round of the 2002 election, and only in 2012 did it return at such a (relative) high level – and only for those subcategories that are the most associated with the Fn vote.

The white-collar workers social category is subdivided into four subcategories: public sector employees (CS51), private sector (administrative) employees (CS54), commercial employees (CS55) and personal services staff (CS56). Except for commercial employees, all categories exhibit a close-to-average behaviour. Commercial employees, on the other hand, are consistently consistently associated with an above average vote for the Fn. At the first round of the 2002 presidential election, private sector employees and commercial employees were the subcategories with the highest coefficients among all employees. Since then, however, only the commercial employees single out; in 2012, public sector employees may even have been more strongly associated with the Fn vote than private sector employees. One should remain cautious, though, for the confidence intervals of the coefficients largely overlap. At any rate, since the second round of 2002, the various subcategories of employees – except for the personal services staff – are increasingly prone to vote for the far-right party.

If one goes down the social ladder and turns towards blue-collar workers, one finds a more homogeneous situation. The CS6 is subdivided into three subcategories: skilled workers (CS61), unskilled workers (CS66) and agricultural workers (CS69). The three of them have exhibited, at least since 2007, equivalent levels of support for Le Pen's party. In 2002, at the first round, agricultural workers were less associated then others with the FN vote, but this should be taken with some care, since agricultural workers are a social category that is particularly hard to enumerate (among other reasons, because many of them have seasonal jobs).

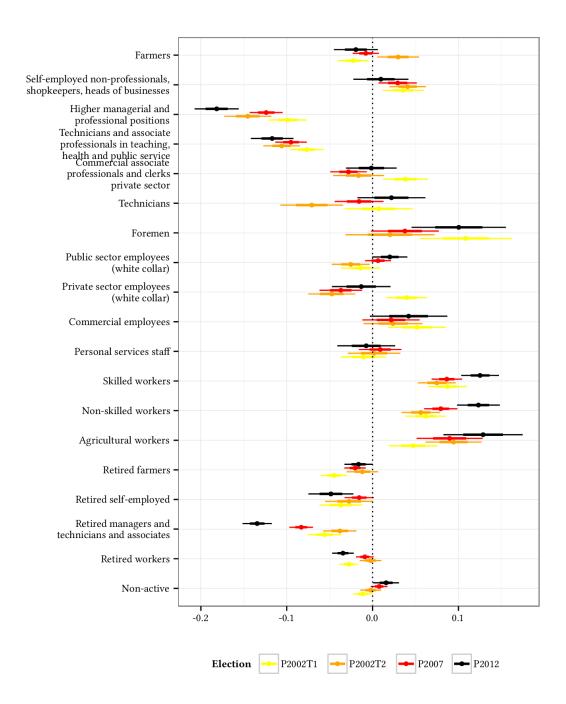


Figure 3: Coefficients for detailed socio-professional categories, from 2002 to 2012, model  $H_6$ . The points represent coefficient estimates of the fixed effects, while the lines range over the mean  $\pm$  one (resp. two) standard-error.

Furthermore, this group is very small in size, so standard errors of the coefficients are quite large.

The interesting point here is the pattern of rise of the coefficients from 2002 to 2012. This is particularly clear in 2012: blue-collar workers are, by far, the social groups the most closely associated with the far right vote.

It is possible, however (and other analysis, not displayed here, point in this direction), that the skilled vs unskilled distinction is not the most relevant with regards to the FN vote. It is likely in particular that the distinction between workers working in industrial settings and those working in non-industrial settings may be more relevant. Indeed, factors that could restrain the workers' propensity to vote for the FN are more powerful in industrial settings – for example, workers parties and unions. Unfortunately, testing this hypothesis is impossible here, since the 42-categories detailed census data that would allow to do this is unavailable for censuses after 1999.

Overall, the results of our analysis underline the increasing social polarisation underpinning the FN vote. Over the past ten years, and even though patterns are not always unequivocal, the categories that vote the least for the FN went voting even less in favour of this party, whereas the categories that vote the most for it increased their propensity to do so. And these categories find themselves at each end of the social ladder: professionals and managers on one side, blue-collar workers on the other. However, during the last ten years, the threshold below which the FN vote becomes more likely than average has decreased. Some categories, such as employees or technicians, consequently crossed this threshold. The story here, then, is not that the FN social basis has shifted from blue-collar to white-collar workers, or from the industry sector to the service sector, but rather that as this vote becomes increasingly socially polarised, some groups find themselves more prone to lean towards the FN. It is to be underlined, though, that blue-collar workers and other industrial workers still, and actually increasingly so, provide the strongest support for the Front national. Educated workers of the public or para-public sector, on the other hand, tend to behave the same way as professionals and managers, albeit with less intensity.

#### 3.2 Inequalities and propensities to vote FN

How do inequalities, such as measured at a local level, influence the propensities to vote in favour of the Fn? The interaction effect in models  $H_6$  allow to measure that. Since the inequelity measure (Gini coefficient of the pre-tax incomes per *département*) has been centered around its mean, and divided by two standard deviations, the coefficients can be interpreted as the difference in a propensity to vote Fn between two *départements* with Gini coefficients respectively equal to the mean minus one standard deviation and the mean plus one standard deviation. For example, for the first round of the 2002 election, for the CS55 (commercial employees), the value of the fixed effect of this variable is 0.197: this is its value in a *département* where the inequality takes its mean value. The value of the interaction effect is 0.162, meaning that for a Gini coefficient equal to its mean minus one s.d., the fixed effect associated with CS55 is equal to 0.197 - 0.162/2 = 0.116, whereas for a Gini coefficient of its mean plus one s.d., this effect is 0.197 + 0.162/2 = 0.278. It should be noted here that, the model being quite complex with a fairly large number of parameters, the combination of coefficients, in particular of random

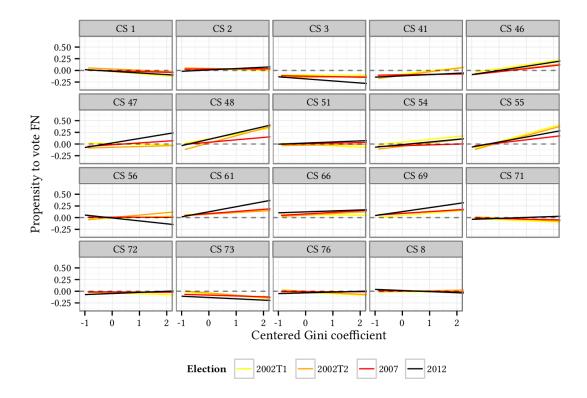


Figure 4: Propensity to vote for the FN for each social category in function of the level of inequality . *Note for the reader*: The propensity values are centered, so a value of o indicates that this social group has an average propensity to vote FN. For example, at low levels of inequality, the CS55 is associated to an average level of FN vote; but its propensity to vote FN rises along with the level of inequalities, at each election.

effects parameters, can lead to sometimes negative values and should therefore not be read litteraly – even though it should also be underlined that fitting the models to the real values of the variables (i.e. to the original data) never leads to out-of-range predictions.

Looking at the values of the interaction effect show that, if they are not always significantly different from zero, there is a clear pattern. Most of the coefficients are positive, meaning that the propensity of voting for the Front national of these social groups rise as inequalities are higher. However, for a few social groups, the relationship is reversed: their propensity to vote for the Fn decreases when the inequalities are higher. This applies to groups whose average propensity to vote for the far right party is low, such as professionals and managers, but also pensioners (former professionals, managers and intermediate professions, but also former workers) or, in 2002 (first round), farmers. Figure 4 displays the propensity to vote for the Fn for each social category as a function of the level of inequality. Except for CS56 (personal services staff), all social categories we are interested in, from CS41 to CS69, have higher propensities to support the Fn when the level of inequality is higher. This pattern is particularly strong for

CS46, CS47 and CS48, CS55 and CS61 and CS69. These categories have in common that they mostly work in the private sector, and are exposed to international competition, and therefore may be fragilised by the impacts of globalisation. In particular, social groups that are connected to industry are more affected by this pattern.

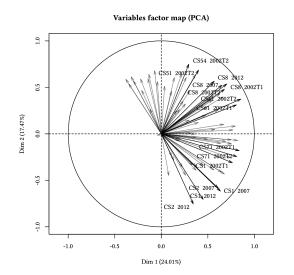
## 3.3 Spatial variability of propensities to vote FN: the geography of the 'squeezed middle' shifting towards the FN

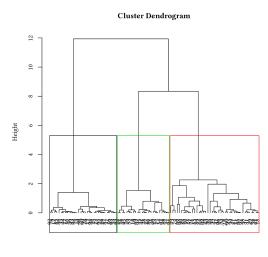
Our models being hierarchical models, they allow for some variation in the values of coefficients across *départements*. The amount of variation (that is, the standard deviation of the distribution of the coefficients) is estimated from the data. Therefore, each variable, each cofficient (except for the interaction coefficient, who are only defined as fixed effects) has a geography of its own. Looking at the spatial variation of each coefficient is not so interesting in itself; moreover, even though some of them have very clear spatial patterns (but even so, there are not easy to interpret – maps not reproduced here), most don't.

The interesting point is that some coefficients have a quite high spatial variability, going well beyond random variation. There is information here, that needs to be used. If the analysis of each coefficient does not help, there might be an underlying structure. In order to try to uncover it, we perform a principal component analysis (PCA) over a matrix whose rows are the *départements* and whose columns are all the random coefficients for the four elections analysed (from  $H_6$  models). This matrix therefore has 96 rows and 76 columns. The first factorial plan of this PCA is displayed on figure 5a. A hierarchical clustering on principal components (HCPC) is then fitted on this PCA. The dendogram resulting from this analysis is displayed on figure 5b. Clearly, three clusters appear. The individual points (i.e., the *départements*) are plotted on the first factorial plan and coloured according to the cluster they belong to (figure 5c). Finally, clusters are represented on a geographical map (figure 5d).

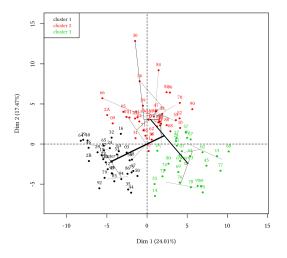
The result is surprisingly geographically organised, if one remembers that no geographic ingredient entered into the recipe that led to this map. Moreover, if one compares the map (figure 5d) and the first factorial plan of individuals (figure 5c), it can be seen that some apparent outliers (such as the Pas-de-Calais *département*, coded 62) are actually very close to being classified in another cluster (i.e. it is 'almost' green rather than red). Other 'isolated' *départements*, however, are quite differentiated from their neighbours. This is particularly the case for *départements* hosts to a large metropolis, such as the Bouches-du-Rhône (Marseilles), the Gironde (Bordeaux), the Rhône (Lyon), etc.

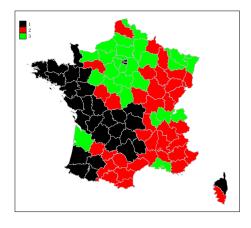
How do these clusters differ from each other? Table 10 describes the three clusters along the variables that were used in the PCA. Cluster 1 is characterised by its negative coefficients: in *départements* belonging to this cluster, in average, all social groups tend to vote less for the FN than they do elsewhere. This explains that these *départements* tend to be clustered in the Greater West, where the Front national vote, on the long run, is quite low. Unsurprisingly, the size of the difference is larger for the social groups which, on average, vote the most for the FN, especially blue-collar workers. Cluster 3 si different from cluster 2 on the behaviour of farmers, present and former: farmers tend to vote much more in *départements* from cluster 3 than in cluster 2. The same goes for independant workers (craftsmen, shopkeepers and businessmen) from the CS2. On the other hand, unskilled workers (at least in 2002) are more prone to vote for





- (a) First factorial plan from the PCA. Only the 15 highest contributions are labelled.
- (b) HCPC tree. Three clusters are selected.





- (c) The  $\emph{d\'epartements}$  in the first factorial plan from the PCA, coloured by their cluster.
- (d) Map of the *département* clusters.

Figure 5: A configurational analysis. PCA and HCPC analysis on the matrix of coefficients from the multilevel models.

the FN in cluster 2 than in cluster 3. Surprisingly, the situation is reversed for skilled workers: their propensity to vote in favour of the Front national is higher in cluster 3.

It might be useful to describe those clusters with supplementary variables. Table 11 provides these summaries. Unsurprisingly, cluster 1 is the most rural of all, but also – more surprisingly – the most urban, if not by much. It is actually the periurban inhabitants who are seldom in cluster 1. Cluster 1 is also characterised by the highest proportion of farmers, both active and retired, but also by the highest proportion of professionals and managers, both active and retired. On the other hand, it has the lowest rate of inactives (other than pensioners). It also has the highest average of immigrants, but this is very likely to be due to the contribution of Paris and the 'petite couronne', which have very high rates of immigrants.

Cluster 2 is characterised by its low share of urban dwellers, its high proportion of independent workers (active and retired), its particularly low share of professionals and managers and its high proportion of retired blue-collar workers. Hollande and Bayrou got low scores at the first round of the 2012 presidential election, and Le Pen performed (significantly) best in this cluster.

Finally, cluster 3 has the highest rate of periurban inhabitants, and a very low percent of rural dwellers. Consequently, farmers and other independent workers are very seldom, whereas social groups linked to the industry and the private sector are overrepresented (CS46, CS47, CS48, CS54, CS55, CS61, CS69). It is also in this cluster that the inactives are the most abundant. Politically, abstention and FN vote are overrepresented, whereas the left-wing vote is rather weak.

Overall, one could say it is three different relationships to the globalisation process that are underlying these three clusters. Cluster 1 allies the strenghts of large metropolis, such as Paris, or Western and central regional urban areas, with an educated workforce, and of residential territories, with a preserved quality of life and a low degree of urbanisation. The 'old' political right has an average audience, but the new radical right significantly underperforms in this cluster. Cluster 2 reprensents the less urbanised part of the country, at the fringes of the most economically dynamic regions. But, even though many areas in this cluster have been quite demographically attractive, they don't have the same ability as cluster 1 to take advantage of the residential economy. It is probably in this cluster that the effects of the globalisation process have been the hardest to most people. Finally, cluster 3 is the France of large metropolis, and its counterpart, periurbanisation. It is strongly connected to the global economy, of which it can, to a certain point, take profit. The metropolisation/periurbanisation processes, however, induces great tensions and inequalities that put territories and people under a great lot of strain – the level of unequality is maximum in this cluster, and would be without any doubt higher if Paris and its suburbs were included in this cluster.

In a way, then, the 'squeezed middle' that some argue is the new basis of radical right parties is not so much composed of defined social groups as characterised by a certain relationship to the globalisation process and, therefore, a certain kind of territorial configuration.

		Cluster 1	Cluster 2	Cluster 3
CS61	2002T2	-0.095	0.040	0.058
CS61	2002T1	-0.093	0.037	0.060
CS1	2007	-0.010	-0.030	0.055
CS8	2002T1	-0.045	0.024	0.020
CS8	2002T2	-0.047	0.024	0.024
CS8	2007	-0.037	0.021	0.015
CS71	2002T2	-0.046	-0.015	0.078
CS71	2007	-0.036	0.006	0.036
CS71	2002T1	-0.039	-0.007	0.059
CS66	2007	-0.057	0.029	0.028
CS1	2002T2	-0.054	-0.021	0.097
CS2	2007	-0.020	-0.035	0.076
CS76	2007	-0.034	0.017	0.016
CS61	2007	-0.051	0.008	0.051
CS66	2002T2	-0.066	0.042	0.019
CS1	2002T1	-0.033	-0.015	0.062
CS1	2012	-0.003	-0.059	0.089
CS2	2012	0.008	-0.076	0.101
CS76	2002T1	-0.029	0.005	0.029
CS8	2012	-0.051	0.035	0.012
CS71	2012	-0.039	-0.002	0.050
CS66	2002T1	-0.072	0.042	0.028
CS76	2002T2	-0.034	0.005	0.034
CS54	2002T2	-0.053	0.056	-0.017
CS2	2002T2	-0.021	-0.017	0.050
CS76	2012	-0.034	0.018	0.016
CS51	2002T2	-0.050	0.043	-0.001
CS61	2012	-0.049	0.002	0.058
CS2	2002T1	-0.033	-0.016	0.064

Table 10: Description of the three clusters by the variables used in the PCA. These were random effects, so there are centred, and must be interpreted as variations around the grand mean/fixed effect. Variables are ordered by decreasing order of their Eta<sup>2</sup> association with the clustering.

	Cluster 1	Cluster 2	Cluster 3
Urbans	66.98	62.10	66.61
Periurbans	18.18	24.50	27.38
Rurals	14.84	13.40	6.00
CS1	1.21	0.99	0.54
CS <sub>2</sub>	2.93	3.17	2.50
CS <sub>3</sub>	9.12	5.68	7·45
CS <sub>41</sub>	4.83	4.91	4.96
CS46	4.32	3.47	4.38
CS47	1.82	1.91	2.22
CS48	0.86	1.00	1.09
CS51	5.07	5.30	5.28
CS <sub>54</sub>	3.34	3.13	3.69
CS <sub>55</sub>	2.37	2.46	2.54
CS56	3.58	3.36	3.28
CS61	6.40	7.09	7.16
CS66	4.09	4.69	4.78
CS69	0.50	0.55	0.40
CS71	2.48	1.79	0.99
CS72	2.11	2.28	1.65
CS <sub>73</sub>	6.03	5.97	5.30
CS76	12.59	14.42	12.62
CS8	26.34	27.82	29.18
Income inequality	0.34	0.34	0.35
Immigrants	6.97	4.91	5.80
Turnout	82.30	81.96	80.18
Sarkozy	21.55	21.44	21.76
Hollande	25.63	20.99	21.13
Le Pen	10.65	17.49	15.49
Mélenchon	9.42	9.06	8.66
Bayrou	8.39	6.66	7.05
Sarkozy 2	35.00	38.88	38.53
Hollande 2	43.83	37.89	37.57

Table 11: Description of the three clusters by supplementary variables.

#### 4 Discussion

Several points of our analysis deserve some amount of discussion.

The first issue is the use of ecological data. Robinson's (1950) shadow looms large over every political scientist who resort to ecological analysis methods. Howerver, we are arguing that quality ecological data allied with a sensible analysis strategy can be as valuable as, or even more valuable than individual data. The conclusions we've reached in this paper could not be reached with ordinary survey data. Furthermore, ecological data can also be contextual data, and they can provide very valuable insights that individual data cannot: we believe that this is the case of the income inequality variable, for example. We also think that adequate multilevel modelling overcomes most obstacles to ecological analysis.

Another point of discussion relates to the modelisation strategy. As we've stated it earlier, there can be some discussion as to the relative merits of cross-section and growth models. In this paper, our main concern was not the *level* reached by the FN vote, but rather its underlying social structure. Using a growth model would have led us to focus more on the determinants of the growth rather than on the structures themselves. An interesting possiblity would be to compare raw coefficients rather than centered coefficients: this would shed more light on the (absolute) evolution of the propensity of each social group to vote FN.

The choice of territorial units – *communes* and *départements* – could also be discussed. *Départements* are arguably not the most relevant reference space, for they don't necessarily make much political or social sense. Urban areas may appear more relevant, since they have a real economic and geographical existence. However, both substantial and technical arguments plead for our choice. At a substantial level, *départements* are an essential reality of the French political life since the French Revolution. The political offer in particular is partly elaborated at the *département* level. Moreover, citizens often identify themselves to the *département* they live in (or come from). On a more technical note, this choice allows to have a balanced design for multilevel analyses: 36000+ *communes* nested in 96 *départements*. Using urban areas would lead to ignore rural communes which are not part of an urban area – a small loss in terms of total number of inhabitants, but a big loss in terms of statistical information carried on by this very large number of units.

More profoundly, lies the question of the operationalisation of the 'squeezed middle' theory. As interesting as this line of argument sounds, where exactly is this squeeze middle? The question falls back to that of the social stratification. Unfortunately, this question cannot be solved independently from the cognitive and administrative tools elaborated by such actors as national statistics institute. It is less than obvious that the categories proposed by the French national institute, the Insee, are adapted to the purpose of studying how social position relates to political behaviour. For example, the census categories 'Intermediate professions' (CS4) and 'employees' (CS5) are actually very heterogeneous with regards to their electoral behaviour. So their use (as always happens with survey data, since hardly any survey provides data more detailed than this) obfuscates the relationship between social position and voting behaviour rather than it enlightens it. A task of upmost interest for electoral studies would then be to elaborate (or, at least, identify) a relevant socioprofessional classification scheme. At a time of social polarisation, of declining blue-collar workforce and of increasing job insecurity, classi-

fications elaborated at a time of the triumphing middle class, strong working class and lifetime jobs might not be very well suited.

#### Conclusion

In this paper, we have analysed the socioprofessional and sectorial electoral support of the Front national at presidential elections from 2002 to 2012. We have shown that working class support remains essential to the success of the Fn until today. The social basis of the far right party is indeed increasingly socially polarised. Moreover, the level of inequality acts as a catalyst, increasing this polarisation. Finally, we've explored the spatial variations in the relationship between the Fn and its social basis, and laid out three different configurations, related to three relationships to the globalisation process. This process indeed pushes some social groups, neither prolétaires nor bourgeois, in the Fn arms, but through complex social, political and territorial processes.

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### **Appendix**

	$M_1$	$M_2$	$M_3$	$M_4$	$M_5$	$M_6$
CS1	0.066***	0.071***	0.066***	0.074***	0.098***	0.111***
CS <sub>2</sub>	$(0.005) \\ 0.113***$	$(0.005) \\ 0.116***$	$(0.005) \\ 0.110***$	$(0.005) \\ 0.115***$	$(0.005) \\ 0.122^{***}$	(0.005) 0.119***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
CS <sub>3</sub>	0.097*** (0.008)	0.084***	0.087*** (0.008)	0.097*** (0.008)	0.097*** (0.008)	0.069***
CS <sub>4</sub>	0.193***	(0.008)	0.185***	0.189***	0.192***	(0.008)
	(0.005)	0.105***	(0.005)	(0.005)	(0.005)	
CS <sub>5</sub>	0.145*** $(0.005)$	0.137*** (0.005)		0.140*** (0.005)	$0.140*** \\ (0.005)$	
CS6	0.294***	0.282***	0.292***	(0.000)	0.288***	
CS <sub>7</sub>	$(0.004) \\ 0.056***$	$(0.004) \\ 0.063***$	$(0.004) \\ 0.060***$	0.057***	(0.004)	
.57	(0.003)	(0.003)	(0.003)	(0.002)		
CS8	0.155***	0.154***	0.157***	0.154***	0.149***	0.141***
S41	(0.003)	$(0.003) \\ 0.073***$	(0.003)	(0.003)	(0.003)	(0.003) $0.068***$
		(0.008)				(0.008)
S46		0.276*** (0.012)				0.251*** (0.012)
S <sub>47</sub>		0.274***				0.261***
C .0		(0.016)				(0.015) $0.451***$
CS48		$0.475^{***}$ $(0.019)$				(0.019)
CS51		,	0.112***			0.102***
CS <sub>54</sub>			$(0.008) \\ 0.242***$			$(0.008) \\ 0.201***$
			(0.010)			(0.010)
CS <sub>55</sub>			$0.180*** \\ (0.015)$			0.151*** (0.015)
CS <sub>5</sub> 6			0.086***			0.080***
			(0.011)	0.202***		(0.011)
CS61				0.323*** (0.006)		0.314*** (0.006)
CS66				0.281***		0.274***
CS69				$(0.007) \\ 0.206***$		(0.007) $0.166***$
3509				(0.011)		(0.012)
CS71					0.015***	0.035***
CS72					$(0.004) \\ 0.015$	$(0.004) \\ 0.031**$
CS <sub>73</sub>					$(0.010) \\ 0.041^{***}$	(0.010) 0.060***
6673					(0.007)	(0.007)
CS <sub>7</sub> 6					0.100*** (0.004)	0.113*** $(0.004)$
$CS_1 \times Gini coef.$					(0.001)	0.029* (0.012)
CS2 × Gini coef.						0.048* (0.019)
$CS_3 \times Gini coef.$						$-0.034^*$ $(0.016)$
$CS_{41} \times Gini \ coef.$						0.010) 0.093*** (0.017)
CS46 × Gini coef.						0.017 $0.115***$

	$M_1$	$M_2$	$M_3$	$M_4$	$M_5$	$M_6$
						(0.026)
$CS_{47} \times Gini coef.$						-0.029
OC 10 M Obil 1 and						(0.034)
$CS_{48} \times Gini coef.$						0.140** (0.044)
CS51 × Gini coef.						0.037*
cogr // chin coch						(0.015)
CS <sub>54</sub> × Gini coef.						0.082**
						(0.023)
$CS_{55} \times Gini coef.$						0.221**
00 ( 0) (						(0.033)
$CS_{56} \times Gini coef.$						0.093** (0.024)
CS61 × Gini coef.						0.052**
C501 × Gilli C6Ci.						(0.013)
CS66 × Gini coef.						-0.010
						(0.015)
CS69 × Gini coef.						0.178**
						(0.025)
CS71 $\times$ Gini coef.						0.024**
00 0: :						(0.009)
CS72 × Gini coef.						$0.071^{**}$ $(0.021)$
CS <sub>73</sub> × Gini coef.						-0.064**
C5/3 × GIII C0CI.						(0.014)
CS76 × Gini coef.						-0.049**
•						(0.007)
$CS8 \times Gini coef.$						-0.053**
						(0.006)
$R^2$	0.879	0.881	0.879	0.879	0.880	0.884
adj. $\mathbb{R}^2$	0.879	0.881	0.879	0.879	0.880	0.884
sigma	0.054	0.054	0.054	0.054	0.054	0.053
F	33132.789	24471.940	24197.449	26573.515	24288.816	7337.523
p	0.000	0.000	0.000	0.000	0.000	0.000
Log-likelihood	54469.025	54718.729	54537.427	54510.610	54597.975	55297.443
Deviance AIC	108.427 $-108920.049$	106.955 $-109413.459$	108.022 $-109050.853$	108.180 $-108999.219$	107.664 $-109171.949$	103.619 $-110516.885$
BIC	-108920.049 $-108843.496$	-109415.459 $-109311.387$	-109030.833 $-108948.782$	-108999.219 $-108905.654$	-109171.949 $-109069.878$	-110316.883 $-110185.153$
DIC	100049.430	-103311.307	-100340.102	-100300.004	-103003.010	-110100.100
N N	36532	36532	36532	36532	36532	36532

Table 12: textscols models for the far-right vote at the first round of the 2002 presidential election.

	$H_1$	$H_2$	$H_3$	$H_4$	$H_5$	$H_6$
CS1	0.115***	0.118***	0.116***	0.119***	0.120***	0.123***
	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)	(0.009)
CS2	0.182***	0.181***	0.181***	0.181***	0.184***	0.181***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
CS <sub>3</sub>	0.057***	0.054***	0.052***	0.055***	0.058***	0.047***
	(0.012)	(0.011)	(0.012)	(0.012)	(0.012)	(0.011)
CS <sub>4</sub>	0.126***		0.123***	0.125***	0.128***	
	(0.009)		(0.009)	(0.009)	(0.009)	
CS <sub>5</sub>	0.161***	0.157***		0.159***	0.159***	
	(0.008)	(0.008)		(0.008)	(0.008)	
CS6	0.227***	0.221***	0.225***		0.225***	
00	(0.010)	(0.009)	(0.010)	0.105***	(0.009)	
CS <sub>7</sub>	0.105***	0.107***	0.106***	0.105***		
000	(0.005)	(0.005)	(0.005)	(0.005)	0.196***	0.194***
CS8	0.137***	0.136***	0.138***	0.137***	0.136***	0.134***
2 00	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$\sigma_{Dpt}^2$ CS1	0.007	0.007	0.007	0.008	0.006	0.005
2 00	(0.086)	(0.083)	(0.086)	(0.088)	(0.077)	(0.069)
$\sigma_{Dpt}^2$ CS2	0.007	0.007	0.007	0.007	0.007	0.007
	(0.084)	(0.081)	(0.085)	(0.085)	(0.083)	(0.084)
$\sigma_{Dpt}^2$ CS3	0.007	0.006	0.007	0.007	0.007	0.006
	(0.086)	(0.081)	(0.084)	(0.085)	(0.084)	(0.076)
$\sigma_{Dpt}^2$ CS4	0.005		0.005	0.005	0.005	
	(0.071)		(0.072)	(0.068)	(0.072)	
$\sigma_{Dpt}^2$ CS5	0.005	0.005		0.004	0.004	
	(0.068)	(0.068)		(0.066)	(0.067)	
$^2_{Dpt}$ CS6	0.007	0.007	0.007	, ,	0.007	
	(0.086)	(0.083)	(0.085)		(0.083)	
$\sigma_{Dpt}^2$ CS7	0.002	$0.002^{'}$	0.002	0.002	` ,	
	(0.046)	(0.044)	(0.044)	(0.045)		
$\sigma_{Dpt}^2$ CS8	$0.002^{'}$	$0.002^{'}$	$0.002^{'}$	$0.002^{'}$	0.002	0.002
Dpt	(0.047)	(0.045)	(0.048)	(0.046)	(0.047)	(0.046)
$\sigma^2_{Residual}$	0.002	0.002	0.002	0.002	0.002	0.002
Residual	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.042)
CS41	(010 20)	0.066***	(0.0.20)	(0.0 = 0)	(0.0.20)	0.069***
1-		(0.011)				(0.010)
CS46		0.190***				0.184***
1		(0.014)				(0.013)
CS47		0.162***				0.153***
17		(0.021)				(0.020)
CS48		0.267***				0.254***
<u>.</u>		(0.028)				(0.027)
$\sigma^2_{Dpt}$ CS41		0.006				0.004
Dpt		(0.076)				(0.065)
$\sigma^2_{Dpt}$ CS46		0.008				0.006
Dpt Co40		(0.092)				(0.079)
$\sigma_{Dpt}^2$ CS47		0.020				0.017
$\sigma_{Dpt}$ C547		(0.141)				(0.131)
-2 CC.0		0.045				0.038
$\sigma_{Dpt}^2$ CS48						
CS=1		(0.213)	0.126***			(0.195)
CS <sub>5</sub> 1			0.136***			0.132***
CS=4			$(0.011) \\ 0.201***$			(0.011) $0.185***$
CS54			0.∠01			0.185

		$H_1$	$H_2$	$H_3$	$H_4$	$H_5$	$H_6$
CS56         0.145***         0.135*** $\sigma_{Dpt}^2$ CS51         0.007         0.038 $\sigma_{Dpt}^2$ CS54         0.008         0.008 $\sigma_{Dpt}^2$ CS54         0.008         0.000 $\sigma_{Dpt}^2$ CS55         0.022         0.011           0.08         0.008         0.008           0.008         0.008         0.008           0.008         0.008         0.008           0.008         0.008         0.008           0.008         0.008         0.008           0.008         0.008         0.008           0.008         0.008         0.008           0.008         0.008         0.008           0.009         0.009         0.009           0.009         0.001         0.009           0.001         0.002         0.001           0.002         0.001         0.009           0.003         0.009         0.007           0.004         0.009         0.007           0.005         0.009         0.007           0.007         0.009         0.007           0.008         0.009         0.007           0.009         0.009	00						
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	2855						
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	CS56						0.135***
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$							, ,
$2^{2}_{Dyt}$ CS54         0.008         0.006 $7^{2}_{Dyt}$ CS55         0.022         0.011 $7^{2}_{Dyt}$ CS56         0.008         0.008           CS61         0.008         0.008           CS66         0.008         0.242***         0.23***           CS66         0.217****         0.208**         0.008**           CS69         0.010**         0.010**         0.001**           CS69         0.013***         0.019**         0.001**           CS69         0.019***         0.001**         0.001**           CS69         0.010***         0.001**         0.009**           CS70         0.010***         0.009**         0.009**           CPpt***         0.000***         0.009**         0.009**           CS71         0.000***         0.009***         0.008**           CS72         0.000***         0.009***         0.008**           CS73         0.000***         0.000***         0.009***           CS72         0.004***         0.009***         0.008***           CS73         0.004***         0.00***         0.00***           CS72         0.004***         0.00***         0.00***	$\sigma_{Dpt}^2$ CS51						
	$\sigma_{\rm D}^2$ , CS54						
$\vec{v}_{Dpt}$ CS55         0.022         0.011 $\sigma^2_{Dpt}$ CS66         0.008         0.008           CS61         0.008         0.008           CS66         0.012****         0.233***           CS66         0.217****         0.208***           CS69         0.012**         (0.012)           CS69         0.013***         0.193*** $\sigma^2_{Dpt}$ CS61         0.010         0.009 $\sigma^2_{Dpt}$ CS66         0.009         0.009 $\sigma^2_{Dpt}$ CS66         0.009         0.009 $\sigma^2_{Dpt}$ CS69         0.009         0.009 $\sigma^2_{Dpt}$ CS69         0.009         0.009           CS71         0.009***         0.009***           CS72         0.009***         0.009***           CS73         0.008***         0.009***           CS72         0.008***         0.009***           CS73         0.008***         0.009***           CS72         0.008***         0.001***           CS73         0.008***         0.001***           CS74         0.006***         0.006***           CS75         0.006***         0.001***           CS70         0.006*** </td <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td>							
2°Date CS56         0.008         0.008           CS61         (0.089)         (0.087)           CS66         0.242***         0.233***           CS66         0.217***         0.208***           CS69         (0.012)         (0.012)           CS69         (0.013****         (0.012)           2°Date CS61         (0.010         0.009           2°Date CS66         (0.000         0.009           2°Date CS66         (0.099)         (0.095)           CS72         (0.095)         (0.092)           CS73         (0.092)         (0.088)           CS74         (0.008)         (0.098)           CS75         (0.008)         (0.091)           CS76         (0.008)         (0.008)           CS77         (0.008)         (0.008)           CS78         (0.008)         (0.008)           CS79         (0.008)         (0.007)           CS71         (0.008)         (0.008)           CS72         (0.008)         (0.008)           CS73         (0.008)         (0.008)           CS79         (0.006)         (0.005)           CS79         (0.006)         (0.007)	$\sigma_{Dpt}^2$ CS55						0.011
$ \begin{array}{c} (0.089) \\ (0.012) \\ (0.012) \\ (0.012) \\ (0.012) \\ (0.012) \\ (0.012) \\ (0.012) \\ (0.012) \\ (0.012) \\ (0.012) \\ (0.013) \\ (0.013) \\ (0.013) \\ (0.013) \\ (0.013) \\ (0.014) \\ (0.012) \\ (0.095) $	-2 oc-(						` /
CS61       0.242***       0.233***         CS66       0.217***       0.208***         CS69       (0.012)       (0.012) $q^2_{Dpt}$ CS61       (0.015)       (0.014) $q^2_{Dpt}$ CS62       (0.009)       (0.009) $q^2_{Dpt}$ CS66       (0.009)       (0.009) $q^2_{Dpt}$ CS69       (0.009)       (0.009***         CS71       (0.009)       (0.009***         CS72       (0.009***       (0.008***)         CS73       (0.008***       (0.008***)         CS74       (0.010***)       (0.010***)         CS75       (0.010***)       (0.010***)         CS76       (0.010***)       (0.008***)         CS76       (0.010***)       (0.008***)         CS76       (0.006***)       (0.007***)         CS77       (0.000***)       (0.000***)         CS79       (0.000***)       (0.000***)         CS79       (0.000***)       (0.001***)         CS79       (0.000***)       (0.001***)         CS79       (0.000***)       (0.000***)         CS79       (0.000***)       (0.000***)         CS79       (0.000***)       (0.000***)         CS79 </td <td><math>\sigma_{Dpt}^2</math> CS56</td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td>	$\sigma_{Dpt}^2$ CS56						
$\begin{array}{c} (0.012) \\ (0.012) \\ (0.012) \\ (0.012) \\ (0.012) \\ (0.012) \\ (0.013) \\ (0.015) \\ (0.015) \\ (0.010) \\ (0.009) \\$	CS61			(0.003)	0.242***		
$\begin{array}{c} \text{CS} \\ \text{CS} \\$							(0.011)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	2S66						
	CS60						
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\sigma_{Dpt}^2$ CS61						
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	2 0044						
$ \sigma_{Dpt}^2 \text{CS69} & 0.009 & 0.007 \\ (0.092) & (0.086) & (0.086) \\ (0.008) & (0.008) & (0.008) \\ (0.008) & (0.008) & (0.008) \\ (0.008) & (0.008) & (0.008) \\ (0.012) & (0.012) & (0.012) \\ (0.012) & (0.012) & (0.012) \\ (0.012) & (0.012) & (0.012) \\ (0.012) & (0.012) & (0.012) \\ (0.012) & (0.012) & (0.012) \\ (0.012) & (0.012) & (0.012) \\ (0.012) & (0.012) & (0.012) \\ (0.012) & (0.012) & (0.012) \\ (0.012) & (0.012) & (0.012) \\ (0.006) & (0.012) & (0.018) \\ (0.006) & (0.005) & (0.005) \\ (0.006) & (0.005) & (0.006) \\ (0.006) & (0.005) & (0.006) \\ (0.007) & (0.066) & (0.007) \\ (0.079) & (0.082) & (0.070) & (0.066) \\ (0.070) & (0.066) & (0.018) \\ (0.018) & (0.018) & (0.018) \\ (0.023) & (0.023) & (0.023) \\ (0.024) & (0.024) & (0.020) \\ (0.024) & (0.024) & (0.026) \\ (0.026) & (0.026)$	$\sigma_{Dpt}^2$ CS66						
$\begin{array}{c} \text{CS71} & (0.092) & (0.086) \\ 0.099^{***} & 0.101^{***} \\ (0.008) & (0.008) \\ (0.008) & (0.008) \\ (0.012) & (0.012) \\ (0.012) & (0.012) \\ (0.012) & (0.012) \\ (0.010) & (0.010) \\ (0.010) & (0.010) \\ (0.010) & (0.010) \\ (0.006) & (0.005) \\ 0.007 \\ 0.006 & (0.005) \\ 0.007 \\ 0.006 & (0.007) \\ 0.007 \\ 0.007 \\ 0.007 \\ 0.007 \\ 0.008 \\ 0.007 \\ 0.009 \\ 0.008 \\ 0.007 \\ 0.009 \\ 0.008 \\ 0.007 \\ 0.008 \\ 0.009$	$\sigma_{D=4}^2$ CS69						
$\begin{array}{c} \text{CS72} & (0.008) & (0.008) \\ 0.107^{***} & 0.109^{***} \\ (0.012) & (0.012) \\ (0.012) & (0.012) \\ (0.012) & (0.012) \\ (0.012) & (0.012) \\ (0.010) & (0.006^{***}) \\ (0.006) & (0.006) \\ (0.006) & (0.005) \\ (0.006) & (0.005) \\ (0.006) & (0.006) \\ (0.006) & (0.006) \\ (0.006) & (0.006) \\ (0.006) & (0.006) \\ (0.0079) & (0.082) \\ (0.079) & (0.082) \\ (0.079) & (0.082) \\ (0.079) & (0.066) \\ (0.079) & (0.066) \\ (0.079) & (0.066) \\ (0.079) & (0.066) \\ (0.079) & (0.066) \\ (0.079) & (0.066) \\ (0.079) & (0.066) \\ (0.018) & (0.041) \\ (0.018) & (0.019) \\ (0.023) \\ \text{CS4} \times \text{Gini coef.} & (0.020) \\ \text{CS4} \times \text{Gini coef.} & (0.026) \\ \text{CS4} \times Gin$							
CS72 $0.107^{***}$ $0.109^{***}$ CS73 $(0.012)$ $(0.012)$ CS76 $0.117^{***}$ $0.118^{***}$ $\sigma_{Dpt}^2$ CS71 $(0.006)$ $(0.005)$ $\sigma_{Dpt}^2$ CS72 $(0.006)$ $(0.002)$ $\sigma_{Dpt}^2$ CS73 $(0.005)$ $(0.005)$ $\sigma_{Dpt}^2$ CS76 $(0.002)$ $(0.002)$ CS1 × Gini coef. $(0.048)$ $(0.041)$ CS2 × Gini coef. $(0.048)$ $(0.019)$ CS3 × Gini coef. $(0.020)$ CS41 × Gini coef. $(0.020)$ CS41 × Gini coef. $(0.020)$ CS47 × Gini coef. $(0.026)$	CS71						0.101***
CS73       (0.012)       (0.012)         CS76 $0.084^{***}$ $0.090^{**}$ $\sigma_{Dpt}^2$ CS71 $(0.006)$ $(0.005)$ $\sigma_{Dpt}^2$ CS72 $(0.066)$ $(0.062)$ $\sigma_{Dpt}^2$ CS73 $(0.079)$ $(0.082)$ $\sigma_{Dpt}^2$ CS76 $(0.070)$ $(0.066)$ CS1 × Gini coef. $(0.048)$ $(0.041)$ CS2 × Gini coef. $(0.048)$ $(0.048)$ CS3 × Gini coef. $(0.023)$ $(0.023)$ CS41 × Gini coef. $(0.020)$ $(0.023)$ CS44 × Gini coef. $(0.029)$ $(0.029)$ CS46 × Gini coef. $(0.019)$ $(0.019)$ CS47 × Gini coef. $(0.026)$ $(0.019)$ CS47 × Gini coef. $(0.026)$ $(0.026)$ CS48	CSE2						
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	55/2						
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	CS73						0.090***
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	00. (						
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	JS76						
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\sigma_{Dnt}^2$ CS71						
$\begin{array}{cccccccccccccccccccccccccccccccccccc$						(0.066)	
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\sigma_{Dpt}^2$ CS72						
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\sigma^2$ CS72						
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\sigma_{Dpt}$ C5/3						
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	$\sigma_{Dvt}^2$ CS76						
$\begin{array}{c} \text{CS2} \times \text{Gini coef.} & (0.018) \\ \text{CS3} \times \text{Gini coef.} & (0.023) \\ \text{CS3} \times \text{Gini coef.} & (0.020) \\ \text{CS41} \times \text{Gini coef.} & (0.019) \\ \text{CS46} \times \text{Gini coef.} & (0.026) \\ \text{CS47} \times \text{Gini coef.} & (0.026) \\ \text{CS47} \times \text{Gini coef.} & (0.026) \\ \text{CS47} \times \text{Gini coef.} & (0.041) \\ \end{array}$	-					(0.048)	
$\begin{array}{c} \text{CS}_2 \times \text{Gini coef.} & -0.019 \\ & (0.023) \\ \text{CS}_3 \times \text{Gini coef.} & -0.002 \\ & (0.020) \\ \text{CS}_{41} \times \text{Gini coef.} & 0.065^{***} \\ & (0.019) \\ \text{CS}_{46} \times \text{Gini coef.} & 0.083^{**} \\ & (0.026) \\ \text{CS}_{47} \times \text{Gini coef.} & -0.013 \\ & (0.041) \end{array}$	CS1 × Gini coef.						
$\begin{array}{c} \text{CS}_3 \times \text{Gini coef.} & (0.023) \\ -0.002 & (0.020) \\ \text{CS}_{41} \times \text{Gini coef.} & (0.019) \\ \text{CS}_{46} \times \text{Gini coef.} & (0.083^{**} \\ \text{CS}_{47} \times \text{Gini coef.} & (0.026) \\ \text{CS}_{47} \times \text{Gini coef.} & (0.041) \end{array}$	CS2 × Gini coef.						
$\begin{array}{c} (0.020) \\ \text{CS}_{41} \times \text{Gini coef.} \\ (0.019) \\ \text{CS}_{46} \times \text{Gini coef.} \\ (0.026) \\ \text{CS}_{47} \times \text{Gini coef.} \\ \end{array}$							(0.023)
$\begin{array}{c} \text{CS}_{41} \times \text{Gini coef.} & 0.065^{***} \\ & (0.019) \\ \text{CS}_{46} \times \text{Gini coef.} & 0.083^{**} \\ & (0.026) \\ \text{CS}_{47} \times \text{Gini coef.} & -0.013 \\ & (0.041) \end{array}$	$CS_3 \times Gini coef.$						
$\begin{array}{c} (0.019) \\ \text{CS}_{46} \times \text{Gini coef.} \\ (0.026) \\ \text{CS}_{47} \times \text{Gini coef.} \\ \end{array}$	CS41 × Gini coef						
$\begin{array}{c} \text{CS}_{46} \times \text{Gini coef.} & 0.083^{**} \\ & (0.026) \\ \text{CS}_{47} \times \text{Gini coef.} & -0.013 \\ & & (0.041) \end{array}$	041 / Omi toti.						
$ ext{CS}_{47}  imes  ext{Gini coef.}                                    $	CS <sub>4</sub> 6 × Gini coef.						0.083**
(0.041)	CS in V Cini and						
	C347 X GIIII COEI.						
	CS48 × Gini coef.						

	$H_1$	$H_2$	$H_3$	$H_4$	$H_5$	$H_6$
						(0.054)
$CS_{51} \times Gini coef.$						-0.026
000:						(0.021)
$CS_{54} \times Gini coef.$						0.060* $(0.024)$
CS55 × Gini coef.						0.162***
cojj × cim coci.						(0.034)
CS <sub>5</sub> 6 × Gini coef.						0.020
						(0.026)
CS61 $\times$ Gini coef.						0.030
_						(0.021)
$CS66 \times Gini coef.$						-0.005
0000 1000						(0.023)
CS69 × Gini coef.						0.048 $(0.028)$
CS71 × Gini coef.						-0.023
co/1 // cim cocii						(0.015)
CS72 × Gini coef.						$-0.019^{'}$
						(0.024)
$CS_{73} \times Gini coef.$						-0.044*
_						(0.018)
$CS76 \times Gini coef.$						-0.027**
CS8 × Gini coef.						(0.010) $-0.000$
C58 × Gilli coel.						(0.010)
	0.048	0.049	0.049	0.049	0.048	
sigma	0.043 $62625.727$	0.043 $62782.628$	0.043 $62701.093$	0.043 $62684.482$	0.043 $62705.146$	0.042 $62971.416$
Log-likelihood Deviance	-125251.454	-125565.256	-125402.185	-125368.963	-125410.292	-125942.833
AIC	-125251.454 $-125161.454$	-125409.256	-125402.185 $-125246.185$	-125368.963 -125236.963	-125410.292 $-125254.292$	-125942.833 $-125444.833$
BIC	-124778.686	-124745.792	-124582.722	-124675.571	-124590.828	-123326.853
DIC	-125376.747	-125727.919	-125567.298	-125521.657	-125581.388	-126446.312
N	36532	36532	36532	36532	36532	36532
Groups	96	96	96	96	96	96

Table 13: Multilevel models for the far-right vote at the first round of the 2002 presidential election.

	$M_1$	$M_2$	$M_3$	$M_4$	$M_5$	$M_6$
CS1	0.115***	0.119***	0.115***	0.110***	0.148***	0.150***
CS <sub>2</sub>	$(0.005) \\ 0.143***$	$(0.005) \\ 0.143***$	$(0.005) \\ 0.142^{***}$	$(0.005) \\ 0.142^{***}$	$(0.005) \\ 0.154***$	$(0.005) \\ 0.147^{***}$
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)
CS <sub>3</sub>	0.048*** (0.008)	0.038*** (0.009)	0.045*** (0.009)	$0.047^{***}$ $(0.008)$	0.049*** (0.009)	0.027** (0.009)
CS <sub>4</sub>	0.128***	()	0.125***	0.128***	0.127***	(====)
CS <sub>5</sub>	$(0.006) \\ 0.133***$	0.128***	(0.006)	$(0.006) \\ 0.133***$	$(0.006) \\ 0.128***$	
	(0.005)	(0.005)		(0.005)	(0.005)	
CS6	0.285*** (0.004)	0.277*** (0.004)	$0.285^{***}$ $(0.004)$		0.279*** (0.004)	
CS <sub>7</sub>	0.087***	0.091***	0.088***	0.087***	(0.002)	
CS8	(0.003) $0.189***$	$(0.003) \\ 0.188***$	$(0.003) \\ 0.189^{***}$	$(0.003) \\ 0.188***$	0.182***	0.156***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
CS <sub>4</sub> 1		0.040*** (0.008)				0.035*** (0.008)
CS46		0.222***				0.210***
CS47		(0.012) $0.126***$				(0.012) $0.151***$
		(0.016)				(0.016)
CS <sub>4</sub> 8		0.345*** (0.020)				0.343***
CS51		(0.020)	0.122***			$(0.019) \\ 0.110***$
			(0.008)			(0.008)
CS <sub>54</sub>			0.165*** (0.011)			0.132*** (0.011)
CS <sub>55</sub>			0.159***			0.132***
CS <sub>5</sub> 6			$(0.016) \\ 0.107***$			(0.015) $0.113***$
			(0.011)	0.00=444		(0.011)
CS61				0.297*** (0.006)		0.312*** (0.006)
CS66				0.260***		0.278***
CS69				$(0.007) \\ 0.341***$		(0.007) $0.290***$
				(0.012)		(0.012)
CS71					$0.045^{***} (0.004)$	0.070*** (0.004)
CS <sub>72</sub>					0.031**	0.045***
CS <sub>73</sub>					(0.011) 0.070***	(0.010) 0.080***
CS76					(0.008) 0.134***	(0.008) 0.148***
$CS_1 \times Gini \ coef.$					(0.004)	(0.004) 0.041**
CS <sub>2</sub> × Gini coef.						(0.013) 0.056**
$\text{CS}_3 \times \text{Gini coef.}$						(0.019) $-0.030$
$CS_{41} \times Gini \ coef.$						(0.016) 0.090*** (0.017)
$CS_{46} \times Gini \ coef.$						0.070**

	$M_1$	$M_2$	$M_3$	$M_4$	$M_5$	$M_6$
						(0.027)
$CS_{47} \times Gini coef.$						-0.007
00 0 0: :						(0.034)
$CS_{48} \times Gini coef.$						0.193**
CS <sub>51</sub> × Gini coef.						(0.044) 0.063**
Cosi × Onn coci.						(0.015)
CS <sub>54</sub> × Gini coef.						0.057*
						(0.023)
$CS_{55} \times Gini coef.$						0.244**
_						(0.034)
$CS_{56} \times Gini coef.$						0.105**
CS61 × Gini coef.						(0.024) $0.100**$
C561 × Gilli coei.						(0.014)
CS66 × Gini coef.						0.075**
cooo // chii cocii						(0.015)
CS69 × Gini coef.						0.159**
						(0.025)
$CS_{71} \times Gini coef.$						0.019*
_						(0.010)
$CS_{72} \times Gini coef.$						0.074**
CS <sub>73</sub> × Gini coef.						$(0.022) \\ -0.081**$
C5/3 × Gilli coei.						(0.014)
CS76 × Gini coef.						-0.064**
cojo // chii coci.						(0.007)
CS8 × Gini coef.						-0.032**
						(0.006)
$R^2$	0.883	0.884	0.883	0.883	0.884	0.890
adj. $\mathbb{R}^2$	0.883	0.884	0.883	0.883	0.884	0.890
sigma	0.056	0.056	0.056	0.056	0.056	0.054
F	34445.638	25268.221	25063.571	27585.628	25263.482	7798.024
p	0.000	0.000	0.000	0.000	0.000	0.000
Log-likelihood	53441.500	53581.908	53450.676	53459.418	53578.880	54631.221
Deviance AIC	114.714 $-106865.001$	113.835 $-107139.816$	114.656 $-106877.353$	114.601 $-106896.836$	113.854 $-107133.759$	$107.480 \\ -109184.442$
BIC	-106865.001 $-106788.447$	-107139.816 $-107037.744$	-106877.353 $-106775.281$	-106896.836 $-106803.270$	-107133.759 $-107031.687$	-109184.442 $-108852.710$
DIC	-100100.441	-101031.144	-100775.201	100005.270	-101031.031	-100002.710
N N	36533	36533	36533	36533	36533	36533

Table 14: textscols models for the Le Pen vote at the second round of the 2002 presidential election.

	$H_1$	$H_2$	$H_3$	$H_4$	$H_5$	$H_6$
CS1	0.186***	0.189***	0.186***	0.184***	0.187***	0.183***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)	(0.012)
CS <sub>2</sub>	0.193***	0.192***	0.196***	0.192***	0.196***	0.194***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
CS <sub>3</sub>	0.010	0.007	0.012	0.009	0.012	0.008
	(0.014)	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)
CS <sub>4</sub>	0.081***		0.082***	0.081***	0.083***	
	(0.008)	0.40	(0.008)	(0.008)	(0.008)	
CS <sub>5</sub>	0.140***	0.137***		0.139***	0.139***	
004	(0.009)	(0.009)	0.004***	(0.008)	(0.009)	
CS6	0.227***	0.224***	0.226***		0.226***	
00-	(0.009)	(0.009)	(0.009)	0.140***	(0.009)	
CS <sub>7</sub>	0.140***	0.141***	0.140***	0.140***		
CS8	$(0.006) \\ 0.155***$	$(0.006) \\ 0.155***$	$(0.006) \\ 0.155***$	$(0.006) \\ 0.155***$	0.155***	0.151***
CS8						
-2 CS:	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$\sigma_{Dpt}^2$ CS1	0.015	0.015	0.014	0.014	0.011	0.010
-2 oc-	(0.121)	(0.122)	(0.120)	(0.118)	(0.105)	(0.102)
$\sigma_{Dpt}^2$ CS2	0.005	0.004	0.005	0.005	0.005	0.004
2 00	(0.073)	(0.066)	(0.071)	(0.073)	(0.069)	(0.062)
$\sigma_{Dpt}^2$ CS $_3$	0.011	0.010	0.010	0.011	0.011	0.011
2	(0.103)	(0.101)	(0.101)	(0.105)	(0.103)	(0.103)
$\sigma_{Dpt}^2$ CS4	0.003		0.003	0.003	0.004	
0	(0.059)		(0.056)	(0.056)	(0.062)	
$\sigma_{Dpt}^2$ CS5	0.005	0.006		0.005	0.005	
0	(0.074)	(0.075)		(0.070)	(0.072)	
$\sigma_{Dpt}^2$ CS6	0.006	0.006	0.006		0.006	
2	(0.078)	(0.076)	(0.079)		(0.076)	
$\sigma_{Dpt}^2$ CS7	0.003	0.003	0.003	0.003		
	(0.052)	(0.052)	(0.050)	(0.052)		
$\sigma_{Dpt}^2$ CS8	0.003	0.003	0.003	0.002	0.003	0.003
	(0.050)	(0.050)	(0.051)	(0.050)	(0.050)	(0.050)
$\sigma^2_{Residual}$	0.002	0.002	0.002	0.002	0.002	0.002
	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.044)
CS41		0.043***				0.047***
		(0.011)				(0.011)
CS46		0.134***				0.137***
		(0.015)				(0.015)
CS47		0.086***				0.082***
00		(0.019)				(0.018)
CS <sub>4</sub> 8		0.174***				0.174***
2 00		(0.027)				(0.026)
$\sigma_{Dpt}^2$ CS41		0.007				0.005
2 00 1		(0.081)				(0.070)
$\sigma_{Dpt}^2$ CS46		0.009				0.009
2		(0.094)				(0.093)
$\sigma^2_{Dpt}$ CS47		0.012				0.011
0		(0.111)				(0.106)
$\sigma^2_{Dpt}$ CS48		0.035				0.030
		(0.187)				(0.174)
			0.4004444			0.100***
CS51			0.132***			0.128***
CS <sub>51</sub>			$0.132^{***}$ $(0.011)$ $0.117^{***}$			(0.011) 0.106**

	$H_1$	$H_2$	$H_3$	$H_4$	$H_5$	$H_6$
00			(0.015)			(0.014)
CS <sub>55</sub>			0.180*** (0.020)			0.177*** (0.017)
CS <sub>5</sub> 6			0.159***			0.155***
			(0.016)			(0.015)
$\sigma_{Dpt}^2$ CS51			0.006			0.006
$\sigma^2_{Dpt}$ CS <sub>54</sub>			$(0.080) \\ 0.013$			$(0.080) \\ 0.009$
			(0.115)			(0.094)
$\sigma^2_{Dpt}$ CS55			0.021			0.010
			(0.145)			(0.102)
$\sigma_{Dpt}^2$ CS56			0.013			0.011
CS61			(0.114)	0.236***		(0.106) $0.228***$
C301				(0.012)		(0.011)
CS66				0.217***		0.209***
				(0.011)		(0.011)
CS69				0.248***		0.248***
$\sigma_{Dpt}^2$ CS61				$(0.017) \\ 0.009$		$(0.016) \\ 0.008$
$O_{Dpt}$ Coor				(0.096)		(0.090)
$\sigma_{Dpt}^2$ CS66				0.008		0.007
				(0.089)		(0.085)
$\sigma_{Dpt}^2$ CS69				0.012		0.011
CC				(0.111)	0.142***	(0.105)
CS71					(0.009)	0.141*** (0.009)
CS72					0.125***	0.126***
					(0.013)	(0.014)
CS <sub>73</sub>					0.113***	0.115***
CS76					(0.010) $0.153***$	(0.010) 0.151***
C3/0					(0.007)	(0.006)
$\sigma_{Dpt}^2$ CS71					0.006	0.006
					(0.079)	(0.077)
$\sigma_{Dpt}^2$ CS72					0.008	0.009
$\sigma_{Dpt}^2$ CS73					$(0.090) \\ 0.005$	(0.097)
$\sigma_{Dpt}$ C3/3					(0.068)	0.004 $(0.064)$
$\sigma_{Dpt}^2$ CS76					0.003	0.002
Dpt					(0.054)	(0.049)
$CS_1 \times Gini coef.$					, ,	-0.026
00 01 0						(0.023)
CS <sub>2</sub> × Gini coef.						-0.012 $(0.021)$
CS <sub>3</sub> × Gini coef.						0.006
						(0.024)
CS <sub>41</sub> × Gini coef.						0.075***
CS46 × Gini coef.						$(0.021) \\ 0.066*$
C540 A GIIII COCI.						(0.030)
CS <sub>47</sub> × Gini coef.						0.017
						(0.038)
$CS_{48} \times Gini coef.$						0.157**

					(0.054) 0.008 (0.020) 0.070** (0.027) 0.158**
					(0.020) 0.070** (0.027) 0.158**
					0.070** (0.027) 0.158**
					(0.027) $0.158**$
					0.158**
					(0.036)
					0.052
					(0.031)
					0.034
					(0.020) $0.031$
					(0.021)
					0.032
					(0.031)
					$-0.027^{'}$
					(0.018)
					0.001
					(0.027)
					-0.047** (0.018)
					$-0.032^{**}$
					(0.011)
					0.013
					(0.011)
0.045	0.045	0.045	0.045	0.045	0.044
60950.358	61037.881	61014.584	61008.626	61040.073	61235.157
					-122470.314
					-121972.314
					-119854.327 $-122961.341$
					-122961.341 $36533$
					30333 96
	$60950.358 \\ -121900.715 \\ -121810.715 \\ -121427.947 \\ -122023.852 \\ 36533 \\ 96$	$\begin{array}{cccc} 60950.358 & 61037.881 \\ -121900.715 & -122075.763 \\ -121810.715 & -121919.763 \\ -121427.947 & -121256.297 \\ -122023.852 & -122234.671 \\ 36533 & 36533 \\ 96 & 96 \end{array}$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$

Table 15: Multilevel models for the Le Pen vote at the second round of the 2002 presidential election.

	$M_1$	$M_2$	$M_3$	$M_4$	$M_5$	$M_6$
CS1	0.043***	0.046***	0.043***	0.042***	0.062***	0.067***
CS2	$(0.005) \\ 0.040***$	$(0.005) \\ 0.044***$	$(0.005) \\ 0.040***$	$(0.005) \\ 0.040***$	$(0.005) \\ 0.050***$	(0.005) 0.057***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)
CS <sub>3</sub>	-0.038*** $(0.006)$	-0.037*** $(0.006)$	-0.039*** $(0.006)$	-0.038*** $(0.006)$	-0.026*** $(0.006)$	-0.020** (0.006)
CS <sub>4</sub>	0.056***	(0.000)	0.055***	0.057***	0.059***	(0.000)
CS <sub>5</sub>	$(0.004) \\ 0.101***$	0.097***	(0.004)	$(0.004) \\ 0.102***$	$(0.004) \\ 0.096***$	
	(0.004)	(0.004)		(0.004)	(0.004)	
CS6	0.235*** (0.003)	0.231*** (0.003)	0.235*** (0.003)		0.226*** (0.003)	
CS <sub>7</sub>	0.050***	0.052***	0.050***	0.050***	,	
CS8	(0.002) $0.165***$	$(0.002) \\ 0.165***$	$(0.002) \\ 0.165***$	(0.002) $0.165***$	0.162***	0.147***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
CS41		-0.003 $(0.007)$				-0.001 $(0.007)$
CS46		0.064***				0.068***
CS <sub>47</sub>		$(0.009) \\ 0.118***$				(0.009) 0.128***
		(0.012)				(0.011)
CS <sub>4</sub> 8		0.208*** (0.017)				0.209** <sup>*</sup> (0.016)
CS51			0.101*** (0.007)			0.095***
CS <sub>54</sub>			0.116***			(0.006) 0.095***
CS <sub>55</sub>			$(0.010) \\ 0.107***$			(0.010) 0.098***
			(0.012)			(0.012)
CS56			0.085*** (0.009)			0.075** <sup>*</sup> (0.009)
CS61			(0.000)	0.224***		0.238***
CS66				$(0.005) \\ 0.247^{***}$		(0.005) 0.260***
				(0.006)		(0.006)
CS69				$0.241^{***}$ $(0.011)$		0.199** <sup>*</sup> (0.011)
CS71				( /	0.023***	0.042***
CS72					$(0.004) \\ 0.020*$	(0.004) 0.028***
					$(0.008) \\ -0.020***$	(0.008)
CS <sub>73</sub>					(0.005)	$-0.017^{**}$ (0.005)
CS <sub>7</sub> 6					0.102***	0.104** <sup>*</sup> (0.003)
CS1 × Gini coef.					(0.003)	-0.006
CS2 × Gini coef.						(0.011) $0.020$
						(0.016)
$CS_3 \times Gini coef.$						-0.066** (0.009)
$CS_{41} \times Gini \ coef.$						0.052** <sup>*</sup> (0.014)

	$M_1$	$M_2$	$M_3$	$M_4$	$M_5$	$M_6$
						(0.020)
$CS_{47} \times Gini coef.$						0.020
						(0.025)
$CS_{48} \times Gini coef.$						0.071
CS51 × Gini coef.						(0.037) $0.003$
C351 × GIIII coei.						(0.014)
CS <sub>54</sub> × Gini coef.						0.019
51						(0.022)
CS <sub>55</sub> × Gini coef.						0.115*
						(0.027)
$CS_{56} \times Gini coef.$						0.022
						(0.020)
$CS61 \times Gini coef.$						0.090*
						(0.012)
$CS66 \times Gini coef.$						0.086*
004-14-01-1-1						(0.014)
CS69 × Gini coef.						0.225* (0.026)
CS71 × Gini coef.						0.046*
co/1 × onn coci.						(0.009)
CS72 × Gini coef.						0.031
, , , , , , , , , , , , , , , , , , , ,						(0.017)
CS <sub>73</sub> × Gini coef.						$-0.022^{*}$
						(0.010)
CS76 $\times$ Gini coef.						$-0.018^*$
						(0.006)
$CS8 \times Gini coef.$						$-0.011^*$
						(0.005)
$R^2$	0.862	0.862	0.862	0.862	0.863	0.869
adj. $\mathbb{R}^2$	0.862	0.862	0.862	0.862	0.863	0.869
sigma	0.043	0.043	0.043	0.043	0.043	0.042
F	28452.532	20811.763	20694.977	22765.446	20972.927	6392.030
p	0.000	0.000	0.000	0.000	0.000	0.000
Log-likelihood	62798.264	62889.950	62801.252	62801.493	63011.652	63839.309
Deviance AIC	69.066 $-125578.527$	68.720 $-125755.900$	69.054 $-125578.503$	69.053 $-125580.986$	68.264 $-125999.303$	$ 65.243 \\ -127600.618 $
BIC	-125578.527 $-125501.963$	-125755.900 $-125653.815$	-125978.503 $-125476.418$	-125380.986 $-125487.408$	-125999.303 $-125897.218$	-127600.618 $-127268.843$
DIC	-120001.000	-120000.010	-120410.410	-120401.400	-120091.210	-121200.043
N	36573	36573	36573	36573	36573	36573

Table 16: textscols models for the Le Pen vote at the first round of the 2007 presidential election.

	$H_1$	$H_2$	$H_3$	$H_4$	$H_5$	$H_6$
CS1	0.101***	0.102***	0.104***	0.100***	0.097***	0.099***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)
CS2	0.128***	0.131***	0.129***	0.129***	0.130***	0.137***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
CS <sub>3</sub>	-0.030**	-0.029**	-0.028**	-0.030**	-0.019	-0.017
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
CS <sub>4</sub>	0.052***		0.053***	0.051***	0.054***	
	(0.005)		(0.005)	(0.005)	(0.005)	
CS <sub>5</sub>	0.113***	0.110***		0.113***	0.111***	
	(0.006)	(0.006)		(0.006)	(0.006)	
CS6	0.196***	0.195***	0.196***		0.191***	
00	(0.008)	(0.008)	(0.008)	0.000***	(0.008)	
CS <sub>7</sub>	0.080***	0.081***	0.080***	0.080***		
000	(0.004)	(0.003)	(0.003)	(0.003)	0.115***	0.115***
CS8	0.117***	0.117***	0.116***	0.117***	0.117***	0.115***
2 00	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$\sigma_{Dpt}^2$ CS1	0.005	0.005	0.005	0.005	0.004	0.003
2	(0.071)	(0.068)	(0.070)	(0.068)	(0.064)	(0.055)
$\sigma_{Dpt}^2$ CS2	0.007	0.006	0.007	0.007	0.006	0.007
0	(0.081)	(0.080)	(0.082)	(0.083)	(0.080)	(0.082)
$\sigma_{Dpt}^2$ CS3	0.006	0.006	0.005	0.006	0.005	0.005
	(0.077)	(0.076)	(0.073)	(0.075)	(0.073)	(0.070)
$\sigma_{Dpt}^2$ CS4	0.001		0.001	0.001	0.001	
	(0.034)		(0.034)	(0.032)	(0.036)	
$\sigma_{Dpt}^2$ CS5	0.002	0.002		0.001	0.002	
	(0.040)	(0.042)		(0.037)	(0.039)	
$\sigma_{Dpt}^2$ CS6	0.005	0.005	0.005	, ,	0.004	
	(0.068)	(0.068)	(0.067)		(0.065)	
$\sigma_{Dpt}^2$ CS7	0.001	0.001	0.001	0.001	` ,	
	(0.029)	(0.028)	(0.028)	(0.029)		
$\sigma_{Dpt}^2$ CS8	0.001	0.001	0.001	0.001	0.002	0.002
Dpt	(0.038)	(0.037)	(0.038)	(0.038)	(0.039)	(0.039)
$\sigma^2_{Residual}$	0.001	0.001	0.001	0.001	0.001	0.001
Residual	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.035)
CS41	(0.000)	0.007	(01000)	(0.000)	(0.000)	0.012
1-		(0.009)				(0.009)
CS46		0.075***				0.079***
1.		(0.011)				(0.011)
CS47		0.088***				0.092***
17		(0.015)				(0.014)
CS48		0.147***				0.145***
1.		(0.021)				(0.020)
$\sigma_{Dpt}^2$ CS41		0.004				0.004
Dpt		(0.060)				(0.062)
$\sigma^2_{Dpt}$ CS46		0.005				0.004
$O_{Dpt}$ CO40		(0.073)				(0.064)
$\sigma^2_{Dpt}$ CS47		0.010				0.004)
$O_{Dpt}$ CS4/						(0.087)
-2 CC .0		(0.101)				\ /
$\sigma_{Dpt}^2$ CS48		0.020				0.015
00		(0.141)	0.115444			(0.121)
CS <sub>51</sub>			0.115***			0.114***
00			(0.007)			(0.008)
CS <sub>54</sub>			0.081***			0.070***

	$H_1$	$H_2$	$H_3$	$H_4$	$H_5$	$H_6$
00			(0.013) 0.140***			(0.012)
CS <sub>55</sub>			(0.018)			0.129*** (0.017)
CS <sub>5</sub> 6			0.123***			0.116***
2			(0.012)			(0.012)
$\sigma_{Dpt}^2$ CS51			0.002			0.002
$\sigma^2_{Dpt}$ CS <sub>54</sub>			$(0.044) \\ 0.007$			$(0.045) \\ 0.007$
			(0.086)			(0.081)
$\sigma_{Dpt}^2$ CS55			0.016			0.014
-2 00-6			(0.128)			(0.117)
$\sigma_{Dpt}^2$ CS56			0.007 $(0.082)$			0.007 $(0.084)$
CS61			(0.082)	0.197***		0.194***
				(0.009)		(0.009)
CS66				0.197***		0.187***
CS69				(0.010) $0.199***$		(0.010) 0.197***
C369				(0.020)		(0.019)
$\sigma_{Dpt}^2$ CS61				0.006		0.005
				(0.075)		(0.069)
$\sigma_{Dpt}^2$ CS66				0.006		0.005
				(0.080)		(0.070)
$\sigma_{Dpt}^2$ CS69				0.021 $(0.144)$		(0.140)
CS71				(0.144)	0.088***	(0.140) 0.087***
25/1					(0.006)	(0.006)
CS72					0.089***	0.092***
00					(0.009)	(0.009)
CS <sub>73</sub>					$0.023^{***}$ $(0.007)$	0.024*** (0.007)
CS76					0.101***	0.098***
					(0.005)	(0.005)
$\sigma_{Dpt}^2$ CS71					0.002	0.002
-2 00					(0.043)	(0.047)
$\sigma_{Dpt}^2$ CS72					0.002 $(0.042)$	0.002 $(0.040)$
$\sigma_{Dpt}^2$ CS <sub>73</sub>					0.002	0.002
					(0.045)	(0.044)
$\sigma_{Dpt}^2$ CS76					0.002	0.002
					(0.041)	(0.040)
$CS_1 \times Gini coef.$						-0.016 (0.016)
CS2 × Gini coef.						0.004
						(0.022)
$CS_3 \times Gini coef.$						-0.011
CS41 × Gini coef.						(0.014) $0.008$
C341 × Gilli coei.						(0.019)
CS46 × Gini coef.						0.065**
						(0.022)
$CS_{47} \times Gini coef.$						0.039
CS <sub>4</sub> 8 × Gini coef.						$(0.030) \\ 0.052$
						0.002

	$H_1$	$H_2$	$H_3$	$H_4$	$H_5$	$H_6$
						(0.042)
$CS_{51} \times Gini coef.$						0.012
00 01 1 0						(0.016)
$CS_{54} \times Gini coef.$						0.018
CS55 × Gini coef.						$(0.026)$ $0.068^*$
CS55 × Gini coei.						(0.034)
CS56 × Gini coef.						-0.001
Co50 × Gilli coei.						(0.026)
CS61 × Gini coef.						0.045*
CD01 × GIII COCI.						(0.018)
CS66 × Gini coef.						0.034
						(0.020)
CS69 × Gini coef.						0.038
						(0.041)
CS71 × Gini coef.						-0.013
						(0.013)
$CS_{72} \times Gini coef.$						-0.002
						(0.017)
$CS_{73} \times Gini coef.$						-0.018
_						(0.013)
CS76 $\times$ Gini coef.						-0.001
000 01						(0.009)
$CS8 \times Gini coef.$						-0.010
						(0.009)
sigma	0.036	0.036	0.036	0.036	0.036	0.035
Log-likelihood	69201.731	69324.579	69294.766	69249.342	69362.626	69579.230
Deviance	-138403.463	-138649.158	-138589.533	-138498.684	-138725.252	-139158.460
AIC	-138313.463	-138493.158	-138433.533	-138366.684	-138569.252	-138700.460
BIC	-137930.645	-137829.606	-137769.982	-137805.217	-137905.700	-136752.342
DIC	-138536.104	-138820.728	-138762.831	-138658.545	-138906.520	-139681.493
N	36573	36573	36573	36573	36573	36573
Groups	96	96	96	96	96	96

Table 17: Multilevel models for the Le Pen vote at the first round of the 2007 presidential election.

	$M_1$	$M_2$	$M_3$	$M_4$	$M_5$	$M_6$
CS1	0.098***	0.103***	0.098***	0.098***	0.107***	0.117***
CS <sub>2</sub>	$(0.006) \\ 0.065***$	$(0.006) \\ 0.072^{***}$	$(0.006) \\ 0.066***$	$(0.006) \\ 0.065***$	$(0.006) \\ 0.078***$	(0.006) 0.091***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)
CS <sub>3</sub>	$-0.043^{***}$ $(0.008)$	-0.043*** $(0.008)$	-0.046*** $(0.008)$	-0.043*** $(0.008)$	-0.024** (0.008)	-0.015 $(0.008)$
CS <sub>4</sub>	0.135***	,	0.132***	0.136***	0.139***	, ,
CS <sub>5</sub>	$(0.005) \\ 0.187***$	0.181***	(0.005)	$(0.005) \\ 0.188***$	$(0.005) \\ 0.183***$	
	(0.005)	(0.005)	0.250***	(0.005)	(0.005)	
CS6	0.350*** (0.004)	0.344*** (0.004)	0.350*** (0.004)		0.338*** (0.004)	
CS <sub>7</sub>	0.090***	0.093***	0.091***	0.090***		
S8	$(0.002)$ $0.249^{***}$	$(0.002) \\ 0.249***$	(0.002) $0.249***$	(0.002) $0.249***$	0.247***	0.228***
244	(0.004)	$(0.003) \\ 0.037***$	(0.004)	(0.004)	(0.004)	(0.003) $0.037***$
S41		(0.009)				(0.008)
CS46		$0.164^{***}$ $(0.012)$				0.168*** (0.011)
CS <sub>47</sub>		0.238***				0.235***
CS48		$(0.015) \\ 0.330***$				(0.014) $0.324***$
		(0.021)				(0.020)
CS51			0.189*** (0.008)			0.187*** (0.008)
CS <sub>54</sub>			0.228***			0.193***
CS <sub>55</sub>			$(0.012) \\ 0.200***$			(0.012) 0.190***
			(0.015)			(0.015)
CS <sub>5</sub> 6			0.141*** (0.011)			0.131*** (0.011)
CS61			, ,	0.340***		0.353***
CS66				$(0.007) \\ 0.362^{***}$		$(0.007) \\ 0.371***$
CS69				$(0.008) \\ 0.350***$		(0.008) $0.297***$
C309				(0.014)		(0.013)
CS71					0.081*** (0.005)	0.119*** (0.005)
CS72					0.065***	0.087***
CS <sub>73</sub>					(0.011) $-0.013$	$(0.010) \\ -0.005$
					(0.007)	(0.007)
CS <sub>7</sub> 6					0.145*** $(0.004)$	0.150*** (0.004)
$CS_1 \times RFUCGI_{11}$						$-0.054^{***}$ $(0.014)$
CS2 × RFUCGI11						0.014)
CS <sub>3</sub> × RFUCGI <sub>11</sub>						(0.020) $-0.154***$
						(0.014)
CS <sub>41</sub> × RFUCGI <sub>11</sub>						0.075*** (0.018)
CS46 × RFUCGI11						0.101***

	$M_1$	$M_2$	$M_3$	$M_4$	$M_5$	$M_6$
						(0.025)
$CS_{47} \times RFUCGI_{11}$						0.059
CS48 × RFUCGI11						(0.031) $0.161**$
C348 X RFUCGITI						(0.046)
CS51 × RFUCGI11						0.063***
J						(0.018)
CS <sub>54</sub> × RFUCGI <sub>11</sub>						0.038
OG PERIODI						(0.027)
$CS_{55} \times RFUCGI_{11}$						0.157** (0.033)
CS56 × RFUCGI11						-0.016
						(0.025)
CS61 × RFUCGI11						0.171**
						(0.015)
CS66 × RFUCGI11						0.046**
OCC PELICOI						(0.018) 0.319**
CS69 × RFUCGI11						(0.032)
CS71 × RFUCGI11						0.109**
,						(0.011)
CS72 × RFUCGI11						0.099**
						(0.022)
CS <sub>73</sub> × RFUCGI <sub>11</sub>						-0.022
CS76 × RFUCGI11						(0.013) $0.006$
C5/0 × KrocGIII						(0.008)
CS8 × RFUCGI11						-0.038**
						(0.007)
$R^2$	0.912	0.913	0.912	0.912	0.913	0.918
adj. $\mathbb{R}^2$	0.912	0.913	0.912	0.912	0.913	0.918
sigma	0.055	0.055	0.055	0.055	0.055	0.053
F	47335.313	34693.482	34451.513	37870.491	34781.692	10829.810
p	0.000	0.000	0.000	0.000	0.000	0.000
Log-likelihood Deviance	53908.530 $112.120$	54039.118 $111.322$	$53922.402 \\ 112.035$	53910.428 $112.109$	54081.483 $111.064$	$55314.068 \\ 103.822$
AIC	-107799.060	-108054.237	-107820.804	-107798.857	-108138.966	-110550.135
BIC	-107722.500	-107952.157	-107620.304 $-107718.724$	-107795.337 $-107705.284$	-108036.886	-110330.133 $-110218.376$
DIC		,,				
N	36558	36558	36558	36558	36558	36558

Table 18: textscols models for the Le Pen vote at the first round of the 2012 presidential election.

CS <sub>1</sub>						
	0.172***	0.175***	0.179***	0.172***	0.153***	0.158***
	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)	(0.013)
CS2	0.173***	0.178***	0.176***	0.173***	0.176***	0.187***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
CS <sub>3</sub>	-0.024	-0.024	-0.025	-0.026	-0.007	-0.005
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)
CS <sub>4</sub>	0.130***		0.130***	0.130***	0.134***	
	(0.009)		(0.009)	(0.008)	(0.009)	
CS <sub>5</sub>	0.195***	0.191***		0.195***	0.194***	
	(0.008)	(0.008)		(0.008)	(0.008)	
CS6	0.310***	0.306***	0.310***		0.301***	
00	(0.010)	(0.010)	(0.010)	0.100***	(0.009)	
CS <sub>7</sub>	0.123***	0.124***	0.123***	0.122***		
	(0.005)	(0.005)	(0.005)	(0.005)	0.404**	0.400***
CS8	0.193***	0.193***	0.193***	0.192***	0.194***	0.193***
2 00	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
$\sigma_{Dpt}^2$ CS1	0.016	0.015	0.016	0.015	0.014	0.011
0	(0.127)	(0.124)	(0.126)	(0.123)	(0.117)	(0.104)
$\sigma_{Dpt}^2$ CS2	0.015	0.015	0.015	0.015	0.015	0.016
	(0.121)	(0.121)	(0.124)	(0.122)	(0.122)	(0.126)
$\sigma_{Dpt}^2$ CS3	0.014	0.013	0.013	0.013	0.012	0.010
$\sigma_{Dpt}^2$ CS4	(0.116)	(0.113)	(0.114)	(0.114)	(0.108)	(0.098)
	0.004		0.004	0.004	0.004	
	(0.065)		(0.065)	(0.061)	(0.066)	
$\sigma_{Dpt}^2$ CS5	0.003	0.004		0.003	0.003	
	(0.059)	(0.059)		(0.056)	(0.057)	
$\sigma_{Dpt}^2$ CS6	0.008	$0.007^{'}$	0.008	,	0.006	
	(0.087)	(0.084)	(0.087)		(0.080)	
$\sigma_{Dpt}^2$ CS7	0.001	0.001	0.001	0.001	()	
Dpt /	(0.038)	(0.037)	(0.038)	(0.038)		
$\sigma_{Dpt}^2$ CS8	0.004	0.003	0.004	0.003	0.004	0.004
Dpt coc	(0.059)	(0.059)	(0.060)	(0.059)	(0.060)	(0.064)
$\sigma^2_{Residual}$	0.002	0.002	0.002	0.002	0.002	0.002
Residual	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)	(0.045)
CS41	(0.040)	0.049***	(0.040)	(0.040)	(0.040)	0.060***
0041		(0.013)				(0.012)
CS46		0.173***				0.176***
C040		(0.016)				(0.015)
CS <sub>47</sub>		0.199***				0.199***
0047		(0.022)				(0.020)
CS <sub>4</sub> 8		0.277***				0.277***
C040		(0.030)				(0.027)
$\sigma_{Dpt}^2$ CS41		0.008				0.008
$\sigma_{Dpt}$ C541		(0.091)				(0.088)
$\sigma_{Dpt}^2$ CS46		0.014				0.009
$\sigma_{Dpt}$ C340						
-2 CC		(0.117)				(0.097)
$\sigma_{Dpt}^2$ CS <sub>47</sub>		0.023				0.018
2 00 0		(0.153)				(0.133)
$\sigma_{Dpt}^2$ CS48		0.044				0.033
		(0.209)				(0.183)
CS <sub>51</sub>			0.198***			0.197***
			(0.011)			(0.010)
CS <sub>54</sub>			0.181***			0.164***

	$H_1$	$H_2$	$H_3$	$H_4$	$H_5$	$H_6$
			(0.018)			(0.017)
CS <sub>55</sub>			$0.230^{***}$ $(0.025)$			0.219*** (0.023)
CS <sub>5</sub> 6			0.180***			0.170***
			(0.016)			(0.017)
$r_{Dpt}^2$ CS51			0.005			0.004
			(0.070)			(0.067)
$\sigma^2_{Dpt}$ CS <sub>54</sub>			0.016			0.014
2 00			(0.128)			(0.117)
$\sigma_{Dpt}^2$ CS55			0.037			0.028 $(0.168)$
$c_{Dpt}^2$ CS56			$(0.193) \\ 0.013$			0.015
Dpt C550			(0.115)			(0.121)
S61			(0.220)	0.310***		0.302***
				(0.013)		(0.011)
S66				0.315***		0.300***
P.C.				(0.013)		(0.012)
S69				0.313*** (0.024)		0.306*** (0.023)
$^2_{Dpt}$ CS61				0.012		0.007
				(0.109)		(0.084)
$^{2}_{Dpt}$ CS66				0.010		0.008
				(0.101)		(0.090)
C <sub>Dpt</sub> CS69				0.030		0.026
				(0.172)		(0.163)
71					0.159***	0.161***
72					$(0.008) \\ 0.128***$	(0.008) 0.128***
12					(0.014)	(0.013)
73					0.035***	0.043***
					(0.009)	(0.009)
6					0.145***	0.143***
CC					$(0.006) \\ 0.004$	(0.006)
pt CS71					(0.061)	0.004 $(0.063)$
$_{pt}$ CS72					0.001)	0.003
					(0.091)	(0.084)
opt CS73					0.003	0.003
					(0.057)	(0.054)
opt CS76					0.002	0.002
DELICCI					(0.049)	(0.048)
1 × RFUCGI11						-0.036 $(0.025)$
2 × RFUCGI11						0.029
						(0.031)
3 × RFUCGI11						-0.044*
nn						(0.021)
S <sub>41</sub> × RFUCGI <sub>11</sub>						(0.027
S46 × RFUCGI11						(0.025) $0.089**$
40 × 10 000111						(0.030)
17 × RFUCGI11						$0.097^{*}$
						(0.041)
48 × RFUCGI11						$0.135^*$

	$H_1$	$H_2$	$H_3$	$H_4$	$H_5$	$H_6$
						(0.057)
$CS_{51} \times RFUCGI_{11}$						0.023
CS <sub>54</sub> × RFUCGI <sub>11</sub>						(0.021) $0.056$
C354 × KFUCGIII						(0.035)
CS55 × RFUCGI11						0.108*
33						(0.045)
$CS_{56} \times RFUCGI_{11}$						-0.063
						(0.034)
CS61 × RFUCGI11						0.109** <sup>*</sup> (0.022)
CS66 × RFUCGI11						0.022) $0.020$
COOO X IG CCGIII						(0.026)
CS69 × RFUCGI11						0.085
						(0.049)
CS71 × RFUCGI11						0.020
CS72 × RFUCGI11						(0.017) $0.024$
C5/2 × KFUCGIII						(0.024)
CS73 × RFUCGI11						-0.028
						(0.016)
CS76 × RFUCGI11						0.016
OOO PERIODI						(0.012)
CS8 × RFUCGI11						-0.024 (0.013)
sigma	0.046	0.046	0.046	0.046	0.046	0.045
Log-likelihood	60135.119	60308.931	60228.497	60219.035	60323.349	60650.327
Deviance	-120270.239	-120617.862	-120456.994	-120438.069	-120646.699	-121300.655
AIC	-120180.239	-120461.862	-120300.994	-120306.069	-120490.699	-120842.655
BIC	-119797.439	-119798.343	-119637.475	-119744.630	-119827.180	-118894.631
DIC	-120392.520	-120775.611	-120615.673	-120584.861	-120814.256	-121778.977
N	36558	36558	36558	36558	36558	36558
Groups	96 o: Multilevel mod	96	96	96	96 2 presidential ele	96

Table 19: Multilevel models for the Le Pen vote at the first round of the 2012 presidential election.