An empirical analysis of valence in electoral competition*

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October 8, 2008

Abstract

The spatial analysis of electoral competition, starting with Downs (1959), relies on the hypothesis that electors vote on the basis of their utility functions, and that these functions depend only on the distance between the voter preferred policy and the candidate proposed platform, i.e., candidates or platforms are evaluated without reference to other factors. Under the name of valence, more sophisticated models have been explored. The starting point is to enrich utility functions so as to take into account the fact that some candidates have non-spatial characteristics, i.e., non linked to the platform proposed by the candidate, e.g. incumbent effect.

The aim of this paper is thus to use data from a large survey, ran prior the 2007 French presidential election, to evaluate and compare several spatial voting models with valence. Existing models perform poorly in fitting the data. However, strong empirical regularities emerge. This leads us to a new model of valence that we call the partisan valence model. This new model makes sense theoretically and is sound empirically.

JEL Classification: C81,

Keywords: valence, voter's utility functions, spatial competition

PRELIMINARY VERSION

*We thank seminar participants in La Baule and the university of Paris 1 for their helpful remarks.

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1 Introduction

The spatial analysis of electoral competition, following Downs (1957), relies on the hypothesis that electors vote on the basis of their utility functions which is assumed to depend only on the distance between their preferred platform and the proposed ones. Candidates are then evaluated without reference to other factors than proposed platforms. This results in a simple and tractable model that has been widely used to analyze electoral competition. Its main prediction is that in a two-candidate election proposed platforms will converge to the preferred platform of the median voter, whence the median voter theorem. This simple model has been widely used in political economy models that seek to endogenize public decision making.

A first empirical test of this prediction has been provided by Poole and Rosenthal (1984). They support the view that some divergence in proposed platforms is likely to occur. To account for party divergence a lot of efforts have been made to propose models predicting such a differentiation. A common feature to the various attempts to explain differentiation is to introduce some new features in the downsian framework (see Osborne 1995 for a survey). There are roughly two lines of research that propose to explain differentiation; one relies on the idea that some of the basic elements used in the spatial model are only known with some uncertainty, e.g. the position of the median is not perfectly known. But introducing uncertainty implies additional assumption about risk aversion that can hardly be tested. The other approach, which we will focus on, introduce "valence" issues into the model, following an early suggestion by Stokes (1963). Its starting point is to enrich voters' utility functions so as to take into account "non policy" characteristics of the candidates, i.e., characteristics which are independent of the platforms they propose. For example, some candidates possess a valence advantage in electoral competitions, e.g. incumbent effect, better charisma, good reputation, etc. In such models, voters face a trade-off between policy factors and non-policy characteristics. In the last decade, a succession of papers has been devoted to the theoretical analysis of these valence models. It appears that simply by introducing an additional parameter into the voters utility function, to account for valence advantages, the convergence to the median is not granted anymore. This thus sounds like a simple and powerful way to explain party differentiation. Furthermore, as least some specifications of these models can be easily tested using survey data [1].

Surprisingly enough, very little empirical work has been devoted to the analysis of valence models (Grose and Husser 2008 being an exception). The aim of the present paper is thus to use data from a large survey, ran prior the 2007 French presidential election, to evaluate and compare several models of valence. For each individual we elicit three elements: his own political position, his utility if a given candidate is elected, and the position of each candidate on the left/right axis according to this individual. This allows us to estimate the shape of voters' utility function. We find that existing valence models are doing only slightly better that the downsian model, despite the addition of free parameters. However, a strong empirical regularity emerges. This leads us to propose and analyze a new model of valence, the partisan valence model. This new valence model fits particulary well the data and clearly outperforms existing models. Adopting the partisan valence model, we are able to provide precise estimates of the valence index for each candidate.

Let us briefly describe the main properties of the partisan valence model. Existing models suppose that a valence advantage enhance the utility of *all* voters simultaneously, e.g. everyone is better off if a candidate is less corrupted. The partisan valence however

[1]This study has some clear limitations. In particular it is not possible to estimate on the basis of our data whether parties adopt optimal positions. There are two reasons for that. The considered election is too complicated, a two round election, to get simple theoretical predictions. Second, we have only elicited the required data for some candidates, while there were eleven of them. Another interesting issue concerns the origin of valence. Again, the data we have used are not appropriate for such an investigation

suppose that a raise in a candidate valence may be a good news for his supporters, but a bad one for his opponents. Think of the ability of a candidate to implement his platform. Every voter may recognize that a candidate is good at transforming his campaign promises into public policy. But this may affect utility functions in a different way, given the opinion of the considered voter.

The paper is organized as follows. Section 2 recalls the existing models of valence and introduces the partisan valence model. We explain some econometrics in Section 3. This is followed by a description of the data and the estimation results in Section 4, and concluding remarks in Section 5.

2 Modeling valence

In existing models, the term "valence" usually defines a characteristic of candidates that is universally appreciated. A greater valence thus implies that all voters are better off. This is the reason why, valence is often described as a valence *advantage*. The literature on valence advantage has grown significantly in the last decade offering a better understanding of the strategic consequences of the introduction of a valence advantage (Groseclose(2001), Schofield (2003), Aragones and Palfrey(2002), Ansolabehere and Snyder(2000), Dix and Santore (2002) among others). Recent contributions propose more sophisticated models, that help understanding the origins of valence. A valence advantage could arise from a greater capacity to commit to a precise platform (Egan 2007), party support (Wiseman 2005) or campaign spending (Herrera et al. 2007, Ashworth and Bueno de Mesquita 2007). Explicitly modeling the process of valence formation allows one to take into account an endogenous determination of valence advantages. Candidates can choose a level of effort that (stochastically) increase their valence (Carrilo and Castanheira, 2002 and 2006 and

Meirowitz 2005) or a level of campaign spending (Erikson and Palfrey 2000, Sahuget and Persico 2006, Zakharov 2005). Our primary goal in this paper is to estimate the added value of valence models in terms of empirical estimation. We will thus not try to explain the origin of valence.

2.1 Existing models

We assume that M candidates compete for an election. A candidate j proposes a policy platform x_j that belongs to the policy space $X = \mathbb{R}^n$. A voter i can be identified with his preferred platform, or bliss point $a_i \in \mathbb{R}^n$. If candidate j is elected, the utility function of voter i is a decreasing function of the distance between x_j and a_i.

- The simplest model is the downsian model, where the utility of voter i if candidate j is elected can be written as:

$$u(a_i, x_j) = -\|x_j - a_i\| \tag{1}$$

- The additive model is the most popular model of valence advantage. It consists in adding a constant b_j to the utility function that depends on the considered candidate j.

$$u(a_i, x_j, b_j) = -\|x_j - a_i\| + b_j \tag{2}$$

$b_1 > b_2$ means that candidate 1 has a non policy-dependent advantage over candidate 2, for example because he has more charisma, or is more good-looking at TV.

- The multiplicative model was recently developed in Hollard and Rossignol (2008). Valence now takes the form of a multiplicative constant θ_j that depends on the considered candidate

$j.$:

$$u(a_i, x_j, \theta_j) = -\frac{1}{\theta_j} \|x_j - a_i\| \tag{3}$$

$\theta_1 > \theta_2$ means that candidate 1 has a policy-dependent advantage over candidate 2, for example because he is seen as more competent in economy or in foreign affair. Note that the effect of the valence advantage now interacts with the distance.

- In this paper we introduce the partisan valence model, described in the next section. The utility depends to a valence parameter, λ_j, and on a constant K.

$$u(a_i, x_j, \lambda_j, K) = \lambda_j (K - \|x_j - a_i\|) \tag{4}$$

Note that according to the sign of $(K - \|x_j - a_i\|)$, a variation of the valence index λ_j can either increase or decrease the utility.

The effects of a variation of the valence index are displayed in Figures 1, 2 and 3.

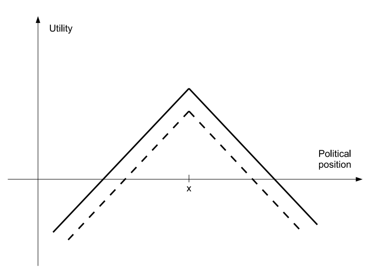

Figure 1: additive valence

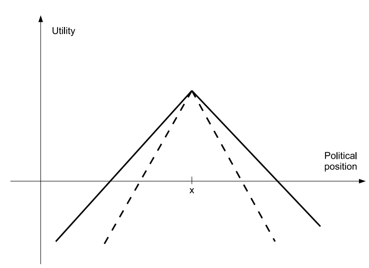

Figure 2: multiplicative valence

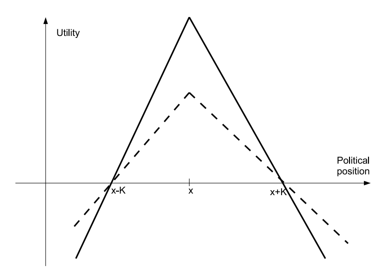

Figure 3: partisan valence

2.2 The partisan valence model

A possible weakness of existing valence models (additive or multiplicative) is that a candidate with a high valence gets a positive advantage for *every* voter. Indeed, if we consider both the multiplicative and the additive valence models, when the valence parameter increases, so does the utility of each voter (i.e. utility functions are increasing in θ_j and b_j respectively). But it could also be the case that voters agree on a candidate characteristics, but are affected in different ways. It is typically true for efficiency or intensity. If the valence index represents the capacity or the will of a candidate to implement its proposed platform, i.e. to turn campaign promises into policy. All voters can indeed agree that some candidate shows more potential in that respect than others. However, this can affect them in different ways. The supporters of a very promising candidate will be better off if their candidate is able to implement a lot of his campaign promises, while others might consider that it will decrease even more their utility if he is elected. Whence the name of partisan valence or intensity valence. Under a symmetry assumption, a platform x_j increases the utility of voters whose preferred platform a_i lies in an open ball $B(x_j, K)$ of center x_j and radius K and decreases the utility of others. Let us now introduce a valence index λ_j. Inside the ball $B(x_j, K)$, a more efficient candidate, i.e. with a greater λ_j , provides a higher utility, while voters outside that ball prefer a less efficient candidate. We are thus looking for a function $u(a_i, x_j, \lambda_j, K)$ that is increasing (resp. decreasing) in λ_j when $K - \|x_j - a_i\| > 0$ (resp. λ when $K - \|x_j - a_i\| < 0$). Assuming that utility functions are linear functions of $\|x_j - a\|$, with maximum in x_j, we get:

$$u(a_i, x_j, \lambda_j, K) = \lambda_j(K - \|x_j - a_i\|) \tag{5}$$

The partisan valence can be seen as a balancing the additive and the multiplicative forms. To make this clear, let us consider the following general model that combines additive and multiplicative valence $u(a, x_j, \theta_j, b_j) = -\frac{1}{\theta_j} \|x_j - a\| + b_j$ Now assume that for some reason the following constraint $b_j = \frac{K}{\theta_j}$ holds. Thus, setting $\lambda_j = \frac{1}{\theta_j}$, we obtain model

(5). In that model candidate can't get both a better additive and a better multiplicative valence. A better multiplicative valence leads to a smaller additive valence.

3 Econometric models

This section presents our empirical strategy to test if the Downsian or one of the valence utility types is empirically valid, i.e. if one of them fits well with the data. Our approach to test the hypotheses of these different theoretical utilities is to formulate a seemingly unrelated regressions (SUR) model that contains the hypotheses as restrictions on its parameters.

Let's assume that we have N voters, $i = 1, ..., N$, and M candidates, $j = 1, ..., M$, that compete at a mass election. Given the data at our disposal (described in the following section), we know U_{ij}, that is voter i's subjective utility if candidate j wins the election, as well as his ideal point, a_i, and the policy position of candidate j, x_j, for every i and j.

We want to evaluate the different models of valences as submodels of the more general model combining multiplicative and additive valences:

$$u(a_i, x_j, \theta_j, b_j) = -\frac{1}{\theta_j} \|x_j - a_i\| + b_j \tag{6}$$

Stacking all M utilities for the ith voter, we get the following system of equations:

$$\begin{pmatrix} U_{i1} \\ U_{i2} \\ \vdots \\ U_{iM} \end{pmatrix} = \begin{pmatrix} b_1 \\ b_2 \\ \vdots \\ b_M \end{pmatrix} - \begin{pmatrix} d_{i1} & 0 & \dots & 0 \\ 0 & d_{i2} & \dots & 0 \\ & & \vdots & \\ 0 & 0 & \dots & d_{iM} \end{pmatrix} \begin{pmatrix} \theta_1^{-1} \\ \theta_2^{-1} \\ \vdots \\ \theta_M^{-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{i1} \\ \varepsilon_{i2} \\ \vdots \\ \varepsilon_{iM} \end{pmatrix} \tag{7}$$

where $d_{ij} = ||a_i - x_j||$ and ε_{ij} are disturbances. The M couples of parameters $\{(b_1, \theta_1^{-1}),$ (b_2, θ_2^{-1}) $, \dots, (b_M, \theta_M^{-1})\}$ could be estimated separetely by ordinary least squares (OLS) using the N observations. However, our empirical strategy is to estimate these M equations jointly, i.e. via a SUR model, for two reasons. First, and as it will be clear below, the four theoretical utility types that we will test impose some cross-equation parameters restrictions on the system of equations (7). Thus, estimating the M equations separately will waste the information that some identical parameters appear in the M equations. Secondly, the disturbances can be correlated across the M levels of utility. For instance, the knowledge that individual i prefers leftist politicians gives some information about his preference for rightist politicians. If this is the case, an OLS system will be consistent but not efficient, because it will not consider the correlation between errors associated with the M equations.

In our SUR model, the errors associated with the dependent variables may be correlated. More precisely, we assume that disturbances are uncorrelated across observations but correlated across equations. To put this in a familiar context, the disturbance formulation is:

$$E[\varepsilon\varepsilon'|\mathbf{d_1}, \mathbf{d_2}, \cdots, \mathbf{d_M}] = \mathbf{\Sigma} \otimes \mathbf{I_N} = \begin{pmatrix} \sigma_{11}\mathbf{I_N} & \sigma_{12}\mathbf{I_N} & \cdots & \sigma_{1M}\mathbf{I_N} \\ \sigma_{21}\mathbf{I_N} & \sigma_{22}\mathbf{I_N} & \cdots & \sigma_{2M}\mathbf{I_N} \\ & \vdots & & \\ \sigma_{M1}\mathbf{I_N} & \sigma_{M2}\mathbf{I_N} & \cdots & \sigma_{MM}\mathbf{I_N} \\ & & & \end{pmatrix} \tag{8}$$

where $\mathbf{I_N}$ is a $N \times N$ identity matrix, $\mathbf{\Sigma}$ the $M \times M$ covariance matrix of the disturbances of the M equations, and σ_{js} is the covariance between equation j and equation s; here ε is a vector with MN coordinates. We estimate the SUR model via the asymptotic efficient iterated feasible generalized least squares (FGLS) procedure that gives maximum likelihood estimates. This procedure necessitates the use of a consistently estimated disturbance covariance matrix $\hat{\mathbf{\Sigma}}$ at each iteration.[2]

[2]Two remarks are in order. First, one might ask why we do not consider a direct maximization by simply inserting $\mathbf{\Sigma}$ in a log-likelihood function. The advantage of direct likelihood estimation is lost when the SUR is nonlinear, as Greene (2003, p.371) highlights. And one of the constrained model that we will estimate imposes nonlinear constraints on the unconstrained model 7. Second, one might note that

As we already said, the four theoretical models that we will test impose some cross-equation restrictions on the SUR model (7). The first theoretical utility type, the Downsian one, implies the following testable restrictions on the unconstrained model (7):

$$H_0 : \theta_j = \theta \ , \forall j, \text{ and } b_j = b \ , \forall j \tag{9}$$

The additive valence utility type imposes the following hypothesis:

$$H_0 : \theta_j = \theta \ , \forall j \tag{10}$$

The theoretical multiplicative valence utility type corresponds to the null hypothesis:

$$H_0 : b_j = b \ , \forall j \tag{11}$$

Lastly, the partisan valence utility type implies the following testable restriction on the unconstrained model (7):

$$H_0 : b_j = \frac{K}{\theta_j} + C \ , \forall j \tag{12}$$

Remark that the partisan valence utility type hypothesis imposes nonlinear restrictions on the linear model (7). As a consequence, the model (7) becomes nonlinear.

Note that these restrictions (9), (10), (11), (12) are equivalent to the theoretical models (1), (2), (3), (4) described in Section 2, since they are obtained via an increasing linear transformation of them. This is innocuous as long as we consider these utility functions as ordinal ones. In particular, the set of voters who support a given candidate is not affected by such transformation of the utility functions. The values of these parameters depend on

efficient estimation in a multivariate regression model only requires a consistent estimator of $\mathbf{\Sigma}$. The least square residuals are used to estimate consistently $\mathbf{\Sigma}$, so $\hat{\sigma}_{js} = \frac{1}{N}\sum_{i=1}^{N} \hat{\varepsilon}_{ij}\hat{\varepsilon}_{is}$. Iterated FGLS is maximum likelihood that uses $\hat{\sigma}_{js}$ to obtain an estimator of Σ at each iteration (for more details, see Greene, 2003, pp.211-212 and pp.344-350).

the specifications of the survey, e.g. we use a 0 to 10 scale.

4 Application

4.1 The data

The data come from a large survey that was ran in April 2007, prior to the first round of the French presidential election.We will focus our attention on the three main candidates, i.e. those who where expected to run for the second round of the French presidential election [3], that is Bayrou, Royal and Sarkozy. These three candidates indeed cumulated more than 75% of the votes.

In what follows, we will use data from three questions included in this survey:

1. The first question asks respondents to choose among 9 options regarding their position on the political spectrum: Extreme left, left, center left, center, center right, right, extreme right, Anarchist, no political opinion.

2. In the second question, respondents have then to assign marks from 0 to 10 to a set of five candidates. Precisely, they were asked for their feeling whether a given candidate was elected. "0" means "this is really bad news", while 10 means "this is really good news". In what follows, we will consider provided answers as a reasonable proxy for the utility level.

3. The third question asks respondents to estimate the position of each candidate on the left/right axis. "0" stands for extreme left, while "10" stands for extreme right. This

[3]The French presidential election has two rounds, the two candidates who got the more votes run for the second round. The 2007 election had eleven candidates running for the first round that took place on the 22th of April 2007.The two candidates that got the best score, namely Sarkozy and Royal, were selected to run into the second round that took place on the 6th of May. Sarkozy won with 53% of the votes. The complete results can be found at: http://www.presidentielle-2007.net/resultats-premier-tour.php.

leads to subjective position since two respondents may attribute different positions to the same candidate.

The total number of respondents was 3827, and 2698 of them, about 70%, reveal an explicit position. The rest declare that they have no political opinion (and a small minority recognized itself as anarchist). 2460 of these respondents answered the two other questions. All in all, to estimate the following models we will use the data of that subsample only.

To estimate these models some transformation of the data are to be made. The most critical one arise from the fact that the self position is reported on a 1 to 7 scale, while the candidates are located using a 0 to 10 scale. As we need to compute the distance between the voter's bliss point and the candidate location, some transformations are required. There are several ways to deal with this problem. In what follows, we chose to simply expand the 1 to 7 scale into a 0 to 10 one. Thus, new voters locations are $a_i = 10 \times (a'_i - 1)/(6))$, where a'_i are the initial position using the 1 to 7 scale.

The following figure displays, for each candidate, the mean utility according the self-reported position on the left/right axis. On average the utility functions are unimodal, symmetric around the mode and almost linear. Thus, the assumptions common to each models are reasonably satisfied.

4.2 Estimation results

Table 1 presents maximum likelihood estimates of the 5 SUR models described in the preceding sections. U_r, U_b, U_s are the utilities if Royal, Bayrou or Sarkozy is elected. The constants b_j for these three candidates are denoted by b_r, b_b, b_s respectively. Similarly we define θ_r, θ_b, θ_s. Column [1] presents the maximum likelihood estimators of the unconstrained system composed of the three equations. As we already said, there is no efficiency

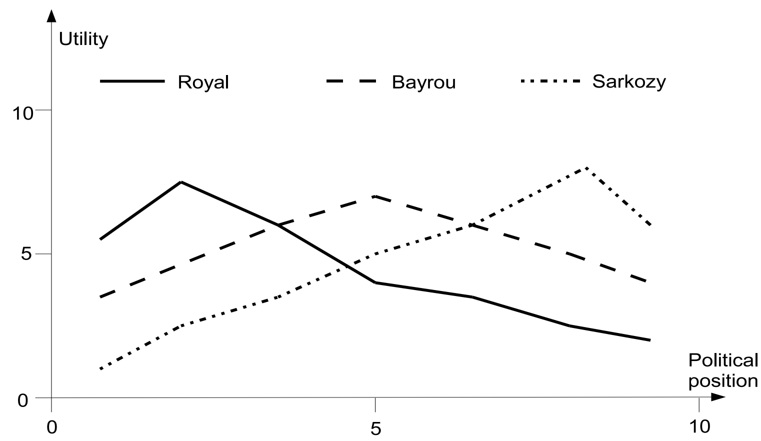

Figure 4: mean utility as a function of political position

payoff to jointly estimate these equations if they are actually unrelated. The Breusch and Pagan (1980) statistic is 177.987, with 3 degrees of freedom.[4] The 1 percent critical value is 11.34, so the hypothesis that the disturbances of the three equations are uncorrelated is rejected.

Columns [2]-[5] give the 4 constrained models discussed in the previous section. If restrictions on the utility functions of Column [1] are valid, then imposing them should not lead to a large reduction in the log-likelihood function. With the exception of the model which estimates the Partisan valence utility function type (Model [5]), this is not the case.

Model [2] imposes the Downsian hypothesis, $Ho : \theta_j = \theta$ and $b_j = b$, $\forall j$. So, in our application, estimating the Downsian utility type imposes 4 restrictions ($\theta_r = \theta_b$, $\theta_r = \theta_s$, $b_r = b_b$, $b_r = b_s$). This model does not fit the data as well as the unconstrained model of Column [1]. Indeed, the likelihood ratio test statistic is 97.434.[5] The 1 percent critical value

[4]The Breusch-Pagan statistic is distributed as χ^2 with $M(M-1)/2$ degrees of freedom. In our application, $M = 3$, so this statistic has 3 degrees of freedom.

[5]A likelihood ratio test is twice the difference between the log-likelihood functions of the unconstrained

Table 1: Maximum Likelihood Estimates of the 5 Seemingly Unrelated Regressions Models

		[1] N.C.	[2] Downs $b_r = b_b = b_s$ & $\theta_r = \theta_b = \theta_s$	[3] Additive valence $\theta_r = \theta_b = \theta_s$	[4] Multiplicative valence $b_r = b_b = b_s$	[5] Partisan valence $b_r = \frac{K}{\theta_r} + C$ & $b_b = \frac{K}{\theta_b} + C$ & $b_s = \frac{K}{\theta_s} + C$
$\mathbf{U_r}$						
	b_r	6.336***	7.206***	6.893***	7.203***	
		(0.106)	(0.053)	(0.074)	(0.053)	
	$\frac{1}{\theta_r}$	-0.475***	-0.652***	-0.656***	-0.658***	-0.480***
		(0.028)	(0.0143)	(0.014)	(0.020)	(0.028)
$\mathbf{U_b}$						
	b_b	7.347***		7.269***		
		(0.085)		(0.061)		
	$\frac{1}{\theta_b}$	-0.683***			-0.640***	-0.669***
		(0.025)			(0.018)	(0.018)
$\mathbf{U_s}$						
	b_s	7.684***		7.420***		
		(0.084)		(0.071)		
	$\frac{1}{\theta_s}$	-0.734***			-0.654***	-0.740***
		(0.019)			(0.016)	(0.019)
	K					5.154***
						(0.417)
	C					3.873***
						(0.275)
Log-likelihood		-17392.452	-17441.169	-17421.392	-17440.656	-17392.764

Notes: i.*, ** and *** represent 10, 5 and 1% significance, respectively.
ii. Standard errors are in parentheses.
iii. N.C. stands for no constraints, i.e. it provides the maximum likelihood estimator of the SUR model at unconstrained values of the parameters.

from the chi-squared distribution with 4 degrees of freedom is 13.28, so the hypothesis that the parameters in all three equations are equal is rejected. As a consequence, the Downsian utility type is not well supported by the empirical evidence.

Model [3] is the SUR model where agents have additive valence utility type ($Ho : \theta_j = \theta$, $\forall j$). So there are 2 restrictions on Model [1] in our application ($\theta_r = \theta_b$, $\theta_r = \theta_s$). First, we reject the null hypothesis that the additive valence utility type is valid: the likelihood ratio

and constrained models ($2 \times (-17392.452 - (-17441.169)) = 97.434$). It is asymptotically distributed as chi-squared with degrees of freedom equal the reduction in the number of parameters that results from imposing the restrictions.

statistic, 57.88, is higher than 9.21, the 1 percent critical value from the chi-squared table with 2 restrictions. So, similarly to the Downsian utility type, the additive valence utility type does not fit the data as well as the unrestricted model. Second, remark that Models [2] and [3] are nested. In other words, Model [2] is not only a subset of the unrestricted model [1]: it is also obtained as a restriction on Model [3]. As a consequence, one might ask: Do the additional parameters in the additive valence utility type model (compared to the Downsian) permit to fit the dataset significantly better? The answer is yes. The likelihood ratio test is 39.55 and much higher than the 1 percent critical value from the chi-squared distribution with 2 degrees of freedom (9.21 as already said). So the relatively more complex additive valence utility type model is empirically more relevant than the simpler Downsian utility type model.

The SUR model where agents have multiplicative valence utility type is presented in Column [4]. This model performs very poorly. On the one hand, the model with multiplicative valence utility type does not fit the data as well as the unconstrained model [1]: we reject the null hypothesis $b_r = b_b = b_s$ from a likelihood ratio test ($LRT = 96.41$ and $p < 0.000$). On the other hand, the simpler Downsian utility type model fits the data as well as the multiplicative valence utility type model. Model [2] is a specification that is a subset of Model [4]. The maximized value of the log-likelihood of the multiplicative valence utility type model is larger than the one of the Downsian, but the difference is very small (-17440 and -17441, respectively).[6] The doubt cast on the empirical pertinence of the additional parameters in the multiplicative valence utility type (compared to the Downsian) is confirmed from a likelihood ratio test ($LRT = 1.025$ and $p = 0.598$).

Last but not least, Column [5] presents the maximum likelihood estimates of the partisan valence utility type model. This model is the unique constrained model that fits the data

[6] Remark that it is logical that the log-likelihood of Model [4] is larger than the one of Model [2]: an unrestricted optimum must be superior to a restricted one.

as well as the unconstrained model of Column [1] ($LRT = 0.62$ and $p = 0.42$). In other words, the partisan valence utility type is the only one that is supported by the empirical evidence.

A clear cut result has emerged from the econometric analysis. A particular model, namely the partisan valence model, performs well in fitting our data. This fact calls for several comments. First, it supports the view that valence *does* matter to account for voters' utility function since the Downsian model performs poorly. The multiplicative model performs really poorly since the addition of a free parameter provides almost no efficiency gain. The picture is a bit better when we turn to the additive model, some efficient gains are there. But this is not enough to conclude that it worth complicating the model by adding new parameters. The partisan model outperforms these models, at the price of additional degrees of freedom however.

Using the partisan valence model allows one to accurately estimate a valence index for each candidate. Note that these valence indices are estimated with a very good precision. Since this valence index differs across candidates, ranging from 0.48 to 0.74, the predictions of the partisan valence model are in sharp contrast with those of the Downsian model. In particular, such a difference in the valence indices predicts the victory of a candidate that is far away from the median. The winner of the election studied is located around 8 on a 0 to 10 scale measuring political position. According to the Downsian model such a candidate will loose against any candidate who is closer to the median position.

5 Conclusion

So far, very few empirical papers were devoted to valence issues, i.e., to non-policy factors. The present paper is a first step toward an empirical account of valence issues in elections.

This paper has shown that traditional ways for introducing valence indices in utility functions, i.e. additively or multiplicatively, are too simple and perhaps misleading. Indeed, we have not find empirical evidence for these utility functions. In contrast, we have proposed a theoretically derived utility function with partisan valence that has a strong empirical support. This strong empirical support is probably due to the fact that, contrary to the valence in additive and multiplicative models, the valence in the partisan valence utility function has a voter-specific dimension. All voters can indeed agree that some candidate has some objective characteristics (e.g. show great charisma, is a very promising one and so on). However, this can affect voters in different ways. Thus, an objective characteristic does not necessarily results in a valence *advantage*, whereas existing models assume that an better valence index results in a greater utility for *all* voters. In the partisan model, a change along the valence dimension increases the utility of some voters but at the same time decreases the utility of some other ones.

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