https://doi.org/10.20378/irbo-52894

Normal Vote Analysis: A Methodological Note

HANS RATTINGER

University of Bamberg, Federal Republic of Germany

JÜRGEN W. FALTER

Free University of Berlin, Federal Republic of Germany

ABSTRACT

By juxtaposing observed voting behaviour and voting expected due to partisan affiliations, normal vote analysis attempts to classify elections at the aggregate level and to estimate the impact of short-term variables on the vote. Apart from graphical illustrations, this latter task is performed by the effect coefficients proposed by Boyd. This contribution demonstrates that these coefficients under certain circumstances can exaggerate the effect of short-term influences on the vote, proposes a modified formula, and shows how normal vote analysis can be adapted to comprise the notion of statistically controlling for third short-term forces. Finally, an attempt is made formally to relate the effect coefficients of normal vote analysis to the decomposition of variance in multiple regression analysis. It is demonstrated that such a formal relationship cannot be established, so that in terms of variance decomposition normal vote analysis is incapable of precisely and numerically comparing short-term *vs.* long-term influences on the vote, or of comparing short-term effects across different variables or even across different samples.

Since the publication of Converse's (1966) article, 'The Concept of a Normal Vote', normal vote analysis has become an established instrument of electoral research in the United States. Applications of this method attempt to answer two fundamental questions. On the one hand, actual voting outcomes are contrasted to the 'normal', expected results of an election or of a series of elections, i.e. to hypothetical outcomes exclusively due to distributions of partisan affiliations. On the other hand, this comparison of actual and 'normal' voting behaviour is disaggregated for subsamples which are defined along theoretically relevant variables in order to shed light on their relative impact on the vote, after controlling for partisanship. While in the former version normal vote analysis contributes to the historical description and empirical classification of elections, in its latter form it sets out to separate long-term from short-term influences on individual voting.

So far there have been – at least to our knowledge – no attempts to adapt the method for the analysis of political systems outside the United States. In a research effort summarized recently (Falter and Rattinger, 1983), the present authors have tried to overcome this deficiency for the Federal Republic of Germany. This attempt was based on the assumption that the notion of long-standing partisan affiliation could usefully be applied to the German type of party system, possibly even to true multiparty systems. This crucial assumption and its implications have been extensively dealt with in another recent article (Falter and Rattinger, 1982), so there is no need to be redundant here. Instead, this contribution will focus on some fundamental methodological problems of normal vote analysis that have to be confronted, no matter what type of party system the technique is applied to.

First, we take a critical look at the effect coefficients introduced into normal vote analysis by Boyd (1972). Then we turn to juxtaposing normal vote analysis and regression analysis and seek to show why normal vote analysis does not and cannot perform the type of quantitative decomposition of variance that regression analysis provides. We will present our argument in as general a form as possible, drawing on our own empirical research for the Federal Republic only occasionally for illustrative purposes.

1. QUANTIFYING LONG-TERM AND SHORT-TERM EFFECTS IN NORMAL VOTE ANALYSIS

The primary goal of normal vote analysis is to find out what makes actual vote shares depart from expected ones. Frequently, this comparison of expected and observed voting is performed graphically, which gives high intuitive plausibility. While normal vote diagrams excellently serve illustrative purposes, they cannot quantitatively distinguish between long-term and short-term influences on voting.

Boyd (1972) therefore proposed two measures, L and S, to capture long-term and short-term factors respectively. We present his formulae with a slight modification. Generally in the United States, fewer respondents intend to vote than offer a party identification. Therefore, for each category of a given analytic variable, Boyd proceeded with two numbers of cases as weights: the number of respondents registering a voting intention, and the number of respondents which can be assigned a party identification. This retains a higher number of cases but has two disadvantages. The formulae for L and S become complicated, and long-term and short-term effects on the vote are computed for different subsamples. To avoid this, we propose to compute L and S only for those respondents who report *both* a party identification *and* a voting intention. If we have a variable with K classes of n_i such respondents respectively, and if we denote the sum of all n_i by N, the expected percentage of the vote in the i-th class as E_i, and the observed percentage of the vote in the i-th class as O_i, then L and S are defined as follows:

$$L = \frac{\sum_{i=1}^{K} n_i \left| E_i - \frac{\sum_{i=1}^{K} n_i E_i}{N} \right|}{N} = \frac{\sum_{i=1}^{K} n_i \left| E_i - \bar{E} \right|}{N}$$

$$S = \frac{\sum_{i=1}^{K} n_i \left| O_i - E_i - \frac{\sum_{i=1}^{K} n_i (O_i - E_i)}{N} \right|}{N} = \frac{\sum_{i=1}^{K} n_i \left| O_i - E_i - (\bar{O} - \bar{E}) \right|}{N}$$

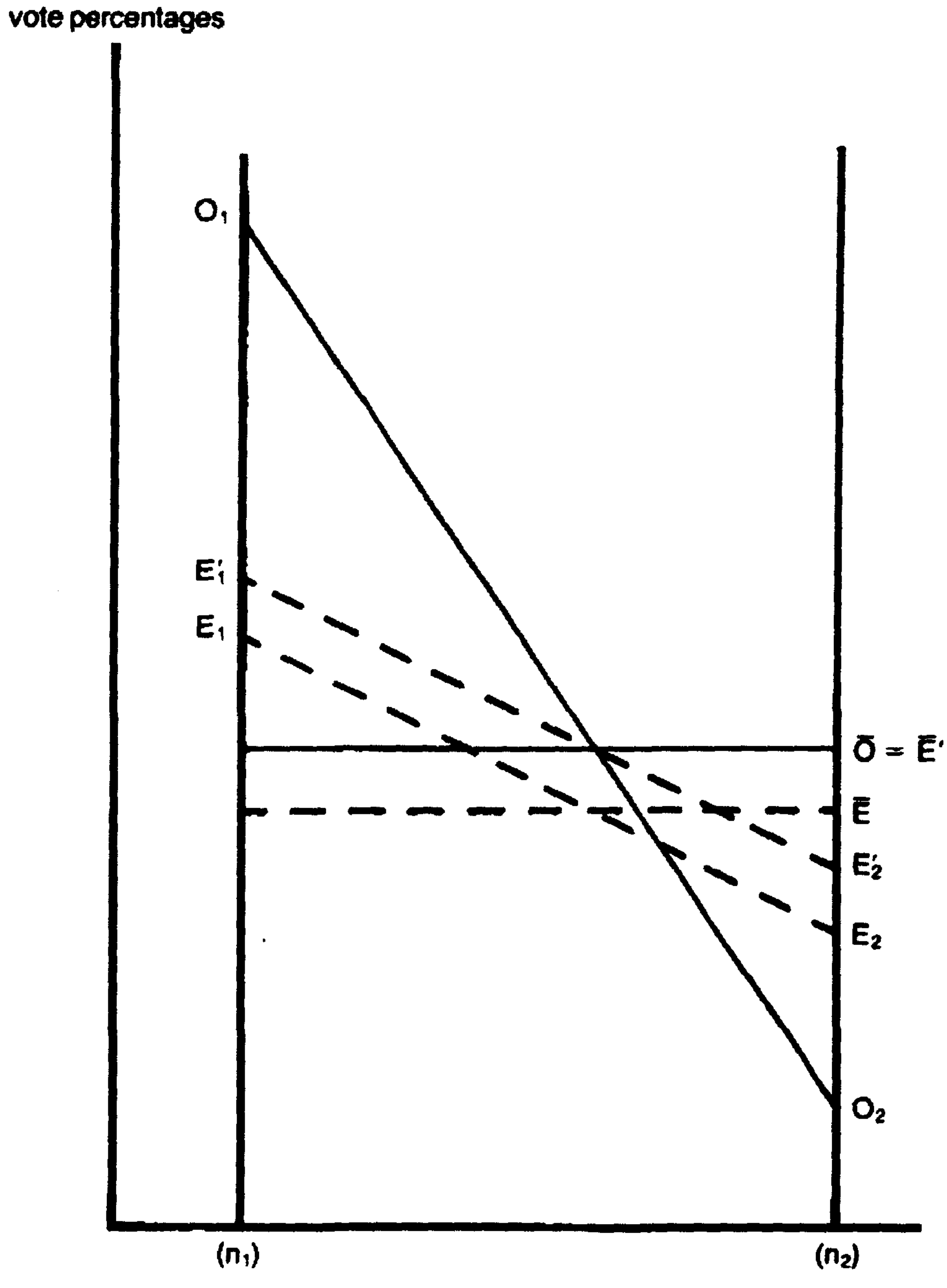


Fig. 1. Graphical illustration of normal vote coefficients.

L and S can be illustrated in Figure 1 as representing a division of a sample into two categories. L is the weighted mean of the distances between E_1 and $\bar{E}$, and between E_2 and $\bar{E}$. If we did not have the classification along the analytic variable, we would expect $\bar{E}$ for all N respondents. Due to different partisan affiliations within these two classes, however, we expect E_1 and E_2 respectively, so the deviations of E_1 and E_2 from $\bar{E}$ measure the contribution of party identification to the divergence of observed vote shares.

S can be explained as follows. As $\bar{E}$ and the weighted mean of observed vote shares, $\bar{O}$, are usually not identical, expected values are so transformed by the last expression in the numerator of S that $\bar{O}$ and the weighted mean of transformed expected values E_1' and E_2', which we denote by $\bar{E}'$, are identical. In other words, expected values are displaced into E_1' and E_2' by adding $(\bar{O}-\bar{E})$ to E_1 and E_2. The formula for S, then, represents the weighted mean of the distances between O_1 and E_1', and between O_2 and E_2'. These latter deviations are interpreted as effects of the analytic variable which underlies the classification of the sample. Note that L and S exactly split the deviations of O_1 and O_2 from $\bar{O}$ into two components.

Compared to their wide application, criticism of Boyd's coefficients has been sparse.[1] RePass (1976) complained only marginally that S lacks a 'standard base' for comparing the effects of different short-term factors on the vote within one sample. However, Page and Jones recently (1979) launched a full-scale attack on normal vote analysis which is mainly directed against L and S. Their critique seems to consist of two challenges. They assert, first, that there are no well-defined upper and lower boundaries for L and S. Second, they describe Boyd's decomposition of deviations of voting observed in the categories of a variable from the overall sample mean into a long-term and short-term component as arbitrary as well as imprecise.

While we will elaborate later on the second accusation, we believe that the first one can be refuted. Minima of L and S are obvious. If voting expected due to party identification is equal across all categories of a variable, L is zero. If observed equals expected voting across all categories, S is zero.

Theoretical maxima for L and S can also be given. If our analytic variable is a dichotomy with n_1 and n_2 equal, the upper boundary of L is 50, if $E_1 = 0$ and $E_2 = 100$, or vice versa. S, then, reaches its maximum of 100 if simultaneously $O_1 = 100$ and $O_2 = 0$, or vice versa. If n_1 and n_2 are *not* identical, the theoretical maximum of L is defined by $200n_1n_2/N^2$, and the upper limit for S, as before, is double that for L. The factor 200 is due to the habit in normal vote analysis not to write percentages as decimals. If one would, e.g., write 40% as .4, this factor should be two, and L and S would range from 0 to .5, and from zero to one, respectively.

If a variable has more than two categories, maxima of L and S are reached if one lumps all categories together into two groups with N_1 and N_2 respondents respectively, so that the absolute difference between N_1 and N_2 is minimized. In the most extreme case, all categories in one group would have expected values of zero and observed values of 100, while in the second group the reverse would be the case. After such an aggregation of categories, the above boundaries for L and S hold again, if you replace n_1 and n_2 by N_1 and N_2.

As the second point of Page and Jones' critique is not explicit enough for a formal clarification, we restate it to represent our own considerations. First, L and S can give the impression that *all* variations of voting between response categories are accounted for by partisan affiliation and by the variable which underlies the classification. Second, the measurement of short-term influences on voting by S can be inaccurate.

As to the first issue, we have seen in Figure 1 that L and S arithmetically split the distance between O and $\bar{O}$ into a first deviation between E' and $\bar{O}$ and a second between O and E'. This is mathematically correct, but can lead to the erroneous notion that observed voting has been fully accounted for. The fundamental logic of normal vote analysis, however, is not to explain deviations of observed vote shares from *their* overall mean, but from the mean *expected* vote. Due to party identification we would, had we no further information, expect the overall normal vote $\bar{E}$, and not $\bar{O}$! If we know the distribution of partisanship within the response categories of a variable, we no longer expect $\bar{E}$, but E_i – the normal vote specific to the i-th category. In total, one thus has to explain a weighted mean sum of the deviations of O from E *and* of the deviations of E from $\bar{E}$. This total we denote by T:

$$T = \frac{\sum_{i=1}^{K} n_i(|O_i - E_i| + |E_i - \bar{E}|)}{N}$$

This definition of T underscores the two steps of normal vote analysis. First, we explain by party identification that expected voting should vary between categories; then we have to explain why observed and expected values fall apart. If, instead, one strives only to explain the deviations of observed voting from *its* overall mean, one neglects the discrepancy between mean expected and mean observed voting that might be called the 'election wind', and that is arithmetically eliminated in the formula for S. The sum of L and S is equal to the weighted absolute mean distance between O and $\bar{O}$, but if $\bar{O} \neq \bar{E}$, it is *smaller* than T. The notion that all variation of observed voting is captured by L and S rests upon the choice of the wrong baseline. If mean expected behaviour is accepted as the proper base, the difference between $\bar{O}$ and $\bar{E}$, the 'election wind', clearly remains as unexplained by either partisanship or any short-term variable. Only in the exceptional case with $\bar{O}$ equal to $\bar{E}$ do L and S exhaust the total variation T.

So far we have assumed that L and S *accurately* measure long-term and short-term effects. We now proceed to show that this is *not* necessarily so for S. There are two logically possible configurations of data. In the first case, observed vote shares in *all* categories are either above or below expected vote shares. If this is so, shifting E into E′ by $\bar{O} - \bar{E}$ always takes place towards observed vote shares, and there is no problem with computing S from the above formula.

The second logically possible case is that observed vote shares across response categories sometimes are above and sometimes below expected voting. As an example, we have presented in Figure 2 FDP vote shares in the German 1980 election[2] for the item, 'Would you prefer someone else to run for Chancellor for the CDU/CSU?'. For 'yes' respondents, observed FDP voting is above expected; in the 'no' category expected is above observed. This pattern is more typical of normal vote diagrams than the first one. The overall mean deviation of observed from mean expected voting is T = 3.4. L and S, according to the above formulae, are .5 and 3.2 respectively, i.e. the sum of L and S exceeds T, defying all logic.

The reason is not difficult to detect. In order to have $\bar{E} = \bar{O}$, expected values are shifted upwards by $\bar{O} - \bar{E}$ = 1.8 into E′. In the 'no' category E'_2 thus is shifted *away* from O_2. In this category the distance between E'_2 and O_2 is now entered into the computation of S. Out of this distance, the section $E'_2\bar{E}$ does not have to be accounted for at all, since it is not a component of T. The section $\bar{E}E_2$ has already been explained by party identification and has entered into the computation of L. Therefore, S is obviously inflated if the data follow this kind of pattern. Under such circumstances S alone can exceed T!

If we want to correct this, we have to remember that, on the one hand, expected values should be transformed so that $\bar{E} = \bar{O}$, but that on the other hand, a transformation *away* from O leads to the undesirable consequences just described. One

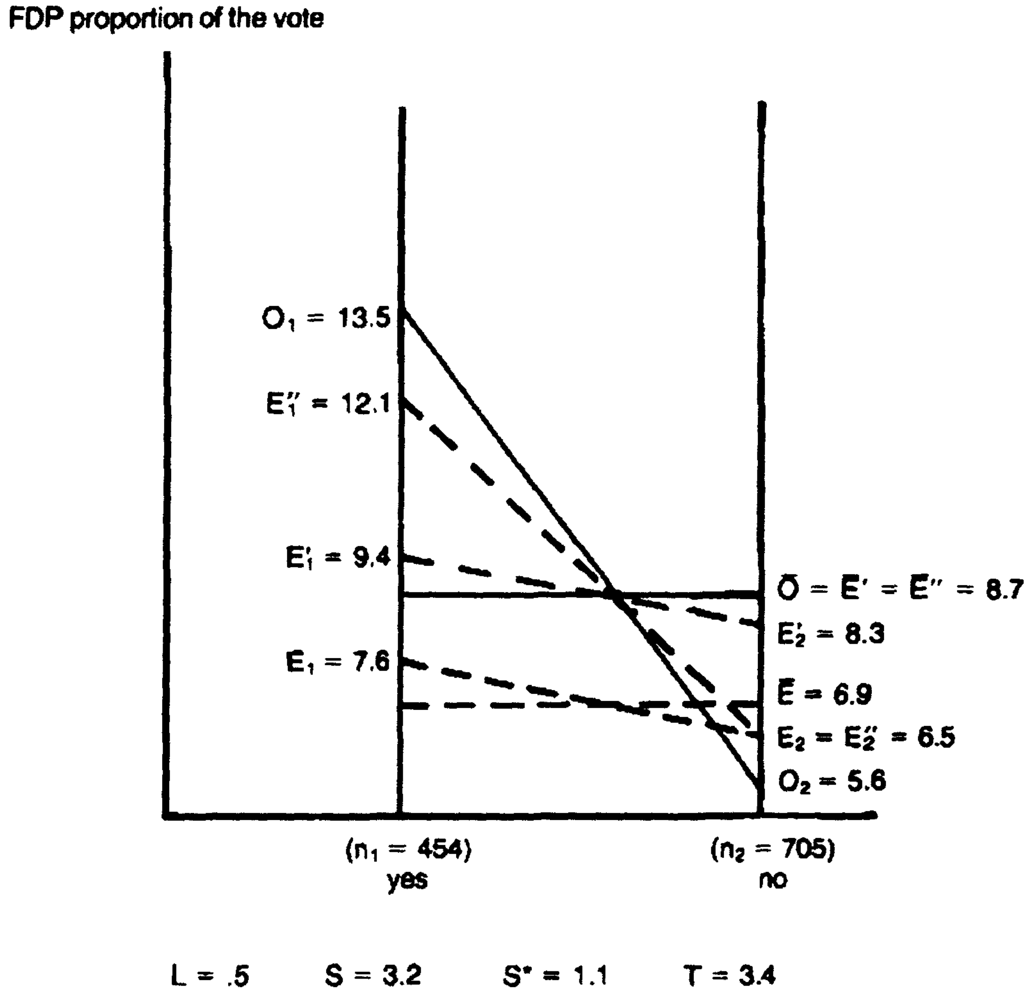


Fig. 2. Normal vote analysis – second configuration of data: Would you prefer someone else to run for Chancellor for the CDU/CSU?

solution to this dilemma would be to retain E_2 as E_2'' in the 'no' category, and to shift E_1 only in the 'yes' category, appropriately stronger by the amount $(\bar{O}-\bar{E})N/n_1$, into E_1'', so that $\bar{E}'' = \bar{E}' = \bar{O}$. As the above formula for S contains the standard shift of E into E′ in its numerator, we propose a modified S* with E″ defined as just described:

$$S^* = \frac{\sum_{i=1}^{K} n_i |O_i - E_i''|}{N}$$

In our example, S = 3.2 is replaced by S* = 1.1. Our modification of Boyd's S can easily be generalized for more than two categories. Whenever adding $(\bar{O}-\bar{E})$ to E_i would shift E_i' away from O_i in at least one category, S* has to be computed instead of S. In all those categories E_i'' equals E_i; in all other categories their joint number of cases is denoted by N_1, and E_i'' is defined as $E_i + (\bar{O}-\bar{E})N/N_1$. We do not claim that our S* is the *only* conceivable modification to correct S. We do maintain, however, that short-term influences are exaggerated whenever the data exhibit the pattern we just have analysed and conventional values of S are reported.

Before comparing normal vote analysis to regression analysis, we want to mention two more deficiencies of L and S. First, there are no significance criteria available. Second, the idea of statistically controlling for third (short-term) variables has never been applied to the effect coefficients of normal vote analysis.

While because of space constraints we cannot go into deriving significance bounds, we can fairly quickly demonstrate how S can be adapted to allow statistical controls for a second short-term variable. Let O_{Ai} and E_{Ai} (O_{Bj} and E_{Bj}) be observed and expected vote shares in the K (L) categories of a short-term variable A (B), and let subscripts ij denote numbers of cases and observed and expected voting in the KL categories of the cross-classification of A and B. Then, a partial S, $S_{A.B}$, controlling the effect of B, can be defined as follows (with E either E′ or E″, according to whether S or S* is to be computed):

$$S_{A.B} = \frac{\sum_{j=1}^{L} \sum_{i=1}^{K} n_{ij}|(O_{ij} - E_{ij}) - (O_{Bj} - E_{Bj})|}{N}$$

In Table I this procedure is illustrated by CDU/CSU vote shares and the two short-term variables, 'competence to fight inflation' and 'preferred Chancellor', from the German 1980 election survey. For the former variable alone, we get S* of 4.5, for the latter variable S* of 6.7, and for their cross-classification S* is 6.8 – which strongly suggests collinearity. This impression is supported by the partial effect

TABLE I. Controlling a short-term variable in normal vote analysis (CDU/CSU vote percentages)

Short-term variable A	Perceived competence to fight inflation				
	SPD		CDU/CSU		
O_{Ai}	4.1		87.4		S* = 4.5
E''_{Ai}	8.1		82.2		
n_i	499		381		
Short-term variable B	**Preferred Chancellor**				
	Schmidt		Strauss		
O_{Bj}	8.0		98.2		S* = 6.7
E''_{Bj}	13.1		88.8		
n_j	566		314		
Combined index AB	Schmidt + SPD	Schmidt + CDU/CSU	Strauss + SPD	Strauss + CDU/CSU	
O_{ij}	2.1	41.9	91.3	98.4	S* = 6.8
E''_{ij}	7.3	48.0	63.6	89.5	
n_{ij}	489	77	10	304	
Controlling for B $\lvert(O_{ij} - E''_{ij}) - (O_{Bj} - E''_{Bj})\rvert$	.1	1.0	18.3	.4	$S^*_{A.B}$ = .5
Controlling for A $\lvert(O_{ij} - E''_{ij}) - (O_{Ai} - E''_{Ai})\rvert$	1.2	11.3	31.7	3.8	$S^*_{B.A}$ = 3.3

coefficients. If we hold perceived competence to fight inflation constant, the partial S for Chancellor preference is 3.3, but if Chancellor preference is held constant, the partial S for competence to fight inflation drops to .5. Thus, while it obviously made a difference for voting in the German 1980 election whom voters wanted to see as Chancellor, the effects of attributions of competence to fight inflation are largely spurious. This finding is not at all new or surprising; what is new is that the effect coefficient of normal vote analysis can be adjusted to produce such a finding. As this contribution is concerned with method rather than with substance, we will not elaborate on these results, but will proceed to a comparison between normal vote and regression analysis.

2. NORMAL VOTE ANALYSIS AND REGRESSION ANALYSIS

There now remains a very fundamental question to be dealt with. Is it possible, by means of L and S, to compare long-term and short-term effects for one analytic variable, to compare those effects across different variables from one sample, or even from different samples? Normal vote analysis is a 'conservative' method in proceeding from the assumption that party identification is causally prior to most other determinants of voting behaviour. A similarly 'conservative' research strategy can be pursued by means of regression analysis – an extremely important difference being that, in normal vote analysis, the relationship between party identification and voting is controlled as it became visible over a longer period, whereas regression analysis can only control this relationship for one point in time.

In a normal vote analysis of the German 1980 election we have performed the standard computations for many potential short-term influences on the vote. We have entered the same (over 100) variables in a second step into ordinary least squares regression models (using 1980 voting intention as the dependent variable) into which party identification had been entered in the first step. While R^2 from the first step measures the percentage of the total variance in voting accounted for by party identification, the increment of R^2 in each second step measures the reduction of unexplained voting variance due to each of the short-term variables.

Without going into any substantive detail, we can say that the results from both techniques are similar in that both identify the same short-term variables as most important and that the direction of their relation with voting behaviour is the same. But, in comparing both methods, we face the problem that there is no obvious monotonous relationship between normal vote coefficients and the multiple coefficient of determination or its increments. Frequently we find that short-term variables, which in regression analysis lead to a strong increase in explained total variance, are associated with a lower S than other variables which are less potent as predictors in regression models. The well-known quantification of explanatory power in regression analysis has no manifest equivalent in normal vote analysis.

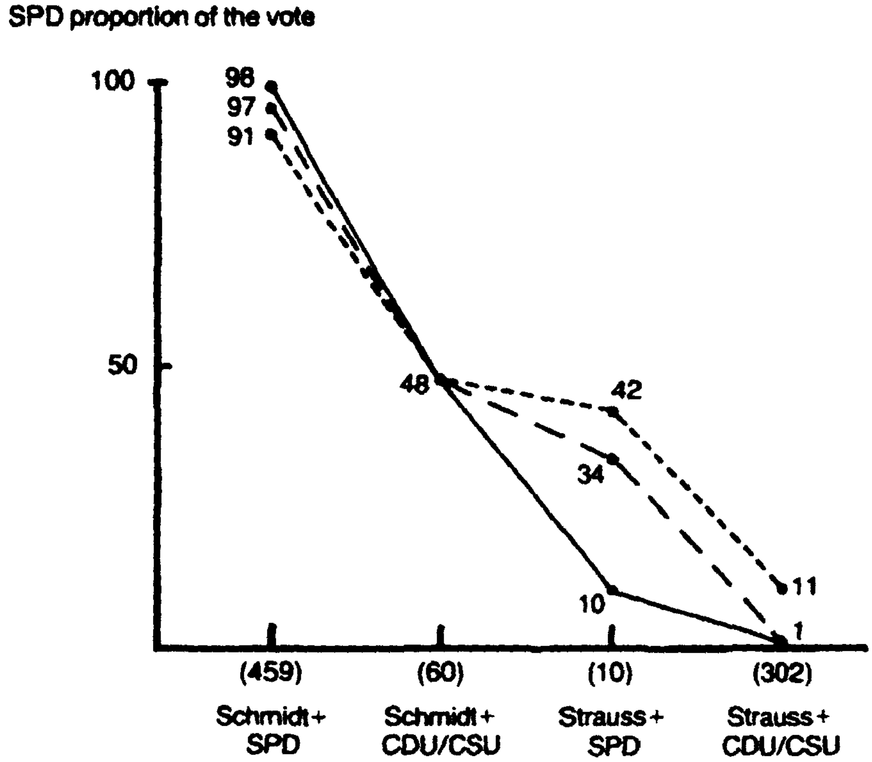
The reason for this can be demonstrated by performing a modified normal vote analysis based upon regression results, again using as an example the cross-classification of preferred Chancellor against perceived competence to fight inflation. Regressing voting intention on party identification leads to a first prediction equation for E_L, voting behaviour expected on account of party attachments alone. Regressing voting intention on party identification *and* on the cross-classification of both short-term variables gives us a second prediction equation for E_{LS}, i.e. voting behaviour expected on account of party attachments, perceived competence to fight inflation, and preference for a Chancellor. Since for each of the four categories of the combined index we know mean voting intention and mean party identification, from these two equations we can derive two predictions of vote shares for each category, which can, together with observed behaviour, be entered into Figure 3, which looks very similar to a standard normal vote diagram. Although party identification here is only controlled for the one September 1980 survey, Figure 3 is almost identical to the corresponding 'genuine' normal vote diagram.

For Figure 3, we now contrast a slightly modified normal vote analysis to a regression-type decomposition of variance. In Figure 3 we have, apart from observed voting, *two* sets of expected values. In normal vote analysis, we can generally compute *only* expected voting due to party identification, which is one of the reasons why it yields results which cannot be directly translated into regression findings. Accordingly, we have to redefine the normal vote coefficients somewhat. T and L can be computed as before, with L again being the weighted mean of absolute differences between voting expected on account of party identification and overall mean expected voting. But since in regression analysis the global predicted and observed means are identical, there is no need to correct for their difference, so a modified S can simply be defined as the weighted mean of absolute differences between E_{L} and E_{LS}. The coefficients in Figure 3 have been computed accordingly.

Regression analysis splits the total sum of squared deviations of observations from their mean into explained and unexplained proportions. For the respondents in Figure 3, the sum of squared deviations of voting intentions from mean voting is 2022672. Out of this total variation around the grand mean, a sum of squares of 1744275 occurs *between* the four categories; the remainder reflects variation of voting intentions *within* groups around category means. We now further decompose the variation *between* categories, which we denote as SST: let SSL be the sum of squares explained by party identification, and let SSS be the variation explained by party identification *and* by the combined index.

These different sums of squares receive a straightforward interpretation within a regression model where all voting intentions have been set equal to their respective category means, so that there is no within-category variation, and SST measures the total variation to be explained. Then, obviously, SSL/SST measures the percentage of total variation explained by party identification, and is identical to conventional R^2. The proportion of variation accounted for by party affiliation and the combined index is, of course, SSS/SST, so that (SSS − SSL)/SST is the increment of R^2 due to the introduction of the index into a stepwise regression – after first entering party identification – with voting intentions recoded as group means as the dependent variable.

What is the use of running regressions and decomposing the variation for this variable, which is not the one we initially deal with in regression, i.e. individual voting? The answer is that only for this redefined variable and only after modifying the normal vote coefficient S as above is it possible to construct *some* kind of formal relationship between the two methods. The same distances that go into the computation of T (L) also enter into the calculation of SST (SSL), and the deviations entered in computing SSS for each case are a sum of the deviations from which L and S are calculated. But since SST, SSL, and SSS are computed as sums of squares,



L = 35.9 S* = 7.8 T = 44.1

SST = 1744275 SSL = 1157520 SSS = 1707037

——: O – observed.
----: E_L – expected on account of party identification.
– – –: E_{LS} – expected on account of party identification, preference for a Chancellor, and perceived competence to fight inflation.

Fig. 3. Normal vote diagram from regression analysis: Index combined from 'preferred Chancellor' and 'perceived competence to fight inflation'.

whereas T, L, and S are defined as weighted mean absolute differences, it is *impossible* to derive *exact* equations linking the two sets of coefficients. Only in exceptional cases is a sum of squares equal to the square of the sum. But since here the same error similarly occurs both in numerators and denominators, it can be shown analytically that the following approximate equations hold:

$$\frac{SSL}{SST} \approx \frac{L^2}{T^2}$$

$$\frac{SSS}{SST} \approx \frac{(L+S)^2}{T^2}$$

$$\frac{SSS-SSL}{SST} \approx \frac{S^2+2LS}{T^2}$$

With these expressions it is possible, from the kind of normal vote analysis presented in Figure 3, to approximate values of R^2 for a *hypothetical* stepwise regression of *recoded* voting intention on, first, party identification, and, second, any short-term variable, without actually running that regression.

This clarifies the formal connection between normal vote analysis and regression analysis, but also confronts us with a dilemma. As soon as we return to 'classical' normal vote analysis in order to control the effects of partisanship as exhibited over a *longer* period of time, we have only *one* set of expected values, and the approximate quantitative decomposition of variation by means of normal vote coefficients is no longer feasible. If one, therefore, decides to forsake the longitudinal control of partisan effects in favour of controlling within only one survey, the approximate interpretation of L and S in variance decomposition terms is available again, *but* – as has been done for Figure 3 – this same decomposition can be performed *exactly* by sums of squares alone, without ever thinking of normal vote analysis, or, for that matter, of actually running a regression with the *recoded* dependent variable. The decomposition of SST that *could* be approximated by the modified normal vote coefficients, moreover, has nothing to do with decomposing the variation of individual voting intentions, but refers only to variation *between* response categories. Variation *within* groups is neglected. The only method for decomposing individual voting variation is (stepwise) regression analysis. As we cannot conceive of any modification of normal vote analysis that would take voting variation within response categories into account, we have to conclude that this technique cannot produce a quantitative separation of long-term and short-term influences on individual voting that could be formally related to the established method of multiple regression.

3. CONCLUSION

'In reality, voting decisions involve a blend of (short-term and long-term) components, and it is illuminating to be able to split them analytically. The normal vote concept enjoys a theoretical rationale and a sound operational base for this task. And, as is perhaps the true proof of the pudding, when put to use it leads to empirical findings of clear theoretical intelligibility' (Converse, 1966, 33). Quite a few authors have tasted from the normal vote pudding – and most have liked it. Our own conclusions are a little bit more skeptical. There can be no doubt that the normal vote technique graphically and analytically somehow manages to split short-term from long-term influences on the vote, and that it elegantly controls the relationship between voting and partisanship that has held over an extended period of time. We have also shown several objections to the normal vote coefficients to be unfounded.

On the other hand, no statistical significance criteria are available for normal vote analysis. Conventionally computed effect coefficients can exaggerate the impact of short-term variables on voting behaviour. Also, RePass's (1976) complaint about the lack of a 'standard base' for comparison could not be contradicted by efforts to establish a correspondence between normal vote analysis and familiar procedures for the decomposition of variance. This latter failure does not distract from the illustrative power of the normal vote technique. Its diagrams involve a lot of analytical and computational effort, yet their message is immediately apparent and intuitively plausible. If this is all one desires, why not put normal vote pudding on the menu?

However, if the 'analytic split' referred to by Converse is to be quantitatively accurate in variance decomposition terms, and also is to be comparable across different variables and different surveys, the appetite will hardly be satisfied. We have shown that – with appropriate modifications – a formal approximation between normal vote analysis and decomposition of variance can be established. But this relationship holds only for the 'wrong' dependent variable; and even if one decides that one might take interest in this 'wrong' dependent variable, its variation is more easily and precisely split into its components by procedures other than a modified normal vote technique, which, ironically, can also only be applied *after* regressions for the original unrecoded voting intentions have been run. Why, then, still insist on pudding for dessert? 'Normal vote analysis ought to be abandoned for most purposes. The appropriate cross-tabulation or regression techniques are superior' (Achen 1979, 354). For reasons very different from those expounded by Achen, we cannot but support this judgment.

NOTES

1 Achen's (1979) thorough critique of normal vote analysis is not directed against Boyd's coefficients, but against the estimation of normal vote parameters by means of regression analysis proposed by Converse (1966). Normal vote parameters can also be estimated, however, by averaging turnout and defection rates across a series of prior elections. This has been done by Miller (1979), and we have adopted this idea for our own normal vote analysis of the German 1980 election (Falter and Rattinger, 1983). To this type of estimates Achen's challenges do not apply.

2 Data come from the September wave of the 'Wahlstudie 1980' and have been made available by the Central Archive for Empirical Social Research in Cologne (Study no. 1053).

REFERENCES

Achen, C. H. (1979). 'The Bias in Normal Vote Estimates', *Political Methodology* 6, 343–56.

Boyd, R. W. (1972). 'Popular Control of Public Policy: A Normal Vote Analysis of the 1968 Election', *American Political Science Review* 66, 429–49.

Converse, P. E. (1966). 'The Concept of a Normal Vote', pp. 9–39 in Campbell, A., Converse, P. E., Miller, W. E. and Stokes, D., *Elections and the Political Order*. New York: Wiley.

Falter, J. W. and Rattinger, H. (1982). 'Parties, Candidates and Issues in the German Federal Election of 1980: An Application of Normal Vote Analysis', *Electoral Studies* 1, 65–94.

Falter, J. W. and Rattinger, H. (1983). 'Parteien, Kandidaten und politische Streitfragen bei der Bundestagswahl 1980: Möglichkeiten und Grenzen der Normal-Vote-Analyse', in Kaase, M. and Klingemann, H.-D. (eds), *Wahlen und politisches System: Analysen aus Anlass der Bundestagswahl 1980*. Opladen: Westdeutscher Verlag.

Miller, A. H. (1979). 'Normal Vote Analysis: Sensitivity to Change over Time', *American Journal of Political Science* 23, 406–25.

Page, B. I. and Jones, C. C. (1979). 'Reciprocal Effects of Policy Preferences, Party Loyalties and the Vote', *American Political Science Review* 73, 1071–89.

RePass, D. (1976). 'Comment: Political Methodologies in Disarray: Issues and American Voters, 1956–1968', *American Political Science Review* 70, 814–31.