選舉研究
第一期（83/5），pp.171-196

Modeling and Interpreting Interactions in Logit Analysis*

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In political science, and social science more generally, it is not unusual to encounter arguments that several factors jointly affect the phenomenon to be explained. For example, the effect of partisan support on presidential success in Congress is said to be conditional on how well the president is received by the general public (e.g. Edwards 1989). Similarly, the effect of the president's party strength in Congress on his veto use may well be conditioned by his public approval rate (Rhode and Simon 1985, 402-403). In the field of international relations, it is argued that whether power transition causes war between the dominant power and the rising challenger depends on how much the latter is satisfied with the status quo (e.g. Kim 1991, 838). In comparative politics, it is hypothesized that whether income inequality causes political violence depends on the regime type of the nation (Muller and Seligson 1987, 438). All these are examples of interactions, i.e., the effect of one variable on the outcome variable depends on the value or level of the other variable(s). Empirical tests of this type of theories have to go beyond simple linear additive regression equations.

Since Cohen's (1968) seminal work, interactions in linear multiple regression models have been studied intensively (see, for example, Friedrich 1982; Jaccard, Turrisi and Wan 1990; Aiken & West 1991). However, the method is still not fully utilized and sometimes misunderstood by applied researchers. In empirical political studies, we often find scholars arguing theoretically about interesting interaction between variables but failing to incorporate their ideas into their statistical models. Also, though less frequently, researchers include product terms in their equations without explicit theoretical justification of precisely how the variables involved interact with each other to affect the outcome. If this is the case for familiar standard linear regression models, it is not surprising

* An earlier version of this paper was delivered at the 1993 Annual Meeting of the American Political Science Association, The Washington Hilton, September 2-5, 1993. The authors would like to thank two anonymous referees for their invaluable comments and suggestions.

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that modeling and testing interactions when the dependent variable is dichotomous are even rarer, and when used, often cause more confusion rather than clarifying complex relationships among variables.

The purpose of this paper is to extend the existing literature on interactions into binary response models. We first examine the situations under which political scientists are most likely to include interaction terms in their regression equations in the context of familiar linear regression. Then we suggest a varying-coefficient approach to incorporate substantive hypotheses of interactions into the regression equation. The appropriate interpretation of such interactive terms in the context of logit analysis are then discussed and illustrated by an example on residential mobility and voting. Some technical details aside, the key argument here is quite straightforward: the best way of avoiding misinterpretation is to formulate explicitly the theoretical hypotheses about interactive effects before including higher-order terms in the equation.

Interactions in Standard Linear Regression Models

In this paper, interaction is defined as the situation where the effect of an independent variable on the dependent variable is a function of the value or categories of the other variable(s). In other words, the independent variable in question no longer exerts a constant effect on the outcome throughout the range of its values. Instead, its effect varies according to the other variable(s). The most familiar model occurs when the conditioning variable is a dummy with only two values: 0 and 1. For example, an (oversimplified) model may assume that quarterly average presidential approval rates fluctuate with economic conditions. This relationship is represented by the following simple regression:

(1) $y_i = \alpha_{0i} + \alpha_{1i} X_i + e_i$

where y_i is presidential popularity at quarter i and X is, say, unemployment rate. Suppose that we want to take into account the "rally around the flag" effect. We may argue that both the intercept and the negative effect of unemployment rate varies systematically according to whether the U.S. is involved in international conflicts. By creating a dummy variable D_i for U.S. involvement in conflicts, we formalize the rally effect into the following two equations:

(2) $\alpha_{0i} = \beta_0 + \beta_1 D_i;$
$\alpha_{1i} = \beta_2 + \beta_3 D_i.$

By substituting these two equations into the first equation, we get a familiar equation with an interaction between a dummy variable and unemployment:

(3) $y_i = \beta_0 + \beta_1 D_i + \beta_2 X_i + \beta_3 (X_i \cdot D_i) + \varepsilon_i$.

It is, of course, unnecessarily cumbersome to build a simple model this way. However, the example is only meant to illustrate the process of systematic (or non-stochastic) coefficient variation approach of modeling interactions (see, for example, Judge et al. 1985, 798-800). The advantage of this approach lies in linking substantive hypotheses with parameters and model specification in an explicit way. The parameter, β_3, attached to the interactive term (in multiplicative form) in equation (3) clearly represents the change in the effect of unemployment rate on presidential popularity when the U.S. is involved in a conflict, as formalized in the second expression of (2). And if the rally effect does occur, $\beta_3 > 0$. On the other hand, β_2 is the conditional effect of unemployment rate -- conditional on no U.S. involvement in international conflict, or $D_i = 0$. It should be noted that there is no compelling reason that lower-order effects must appear in the final equation. For example, if U.S. involvement in a conflict is assumed to have no effect on the intercept in equation (1) (not a very convincing scenario in this case), then $\beta_1 = 0$ and thus the dummy variable alone is not included in the final equation (3). When it is uncertain if the lower-order variable should be part of the model, it can be included for a statistical test.

The same approach can be extended to the situation where the conditioning variable is continuous. For example, if it is argued that presidential popularity takes a nose dive when the economy is stagnant, i.e., high unemployment cum high inflation rates, then the dummy variable in equations (2) and (3) are replaced by the variable of continuous inflation rate X_{2i}, and $\beta_1, \beta_3 < 0$. That is, equation (2) becomes:

(4) $\alpha_{0i} = \beta_0 + \beta_1 X_{2i}$;
$\alpha_{1i} = \beta_2 + \beta_3 X_{2i}$.

and, with X_{1i} standing for unemployment rate, the final equation is:

(5) $y_i = \beta_0 + \beta_1 X_{2i} + (\beta_2 + \beta_3 X_{2i}) X_{1i} + e_i$
$= \beta_0 + \beta_1 X_{2i} + \beta_2 X_{1i} + \beta_3 (X_{2i} \cdot X_{1i}) + e_i$.

Again, β_3 captures the change of the effect of unemployment rate on presidential popularity for each percentage increase in inflation rate, as formalized in the second expression of (4). Since the impact of unemployment rate depends on the level of inflation in this model, we can no longer interpret its coefficient β_2 as the constant effect, as we usually do in a standard linear additive model. Instead, it represents the conditional effect of unemployment rate -- conditional on a zero inflation rate. Since inflation is not very likely to be zero in reality, the overall effect of one percentage increase in unemployment rate is $(\beta_2 + \beta_3 X_{2i})$, whose value is a function of inflation rate at that quarter. Again, if inflation rate is assumed to have no effect on the level (or intercept) of presidential approval rate in equation (1), then it alone does not appear in the final equation (5).

So far, the variables interacting with each other are measured at the same level, that is, the U.S. as a whole. We call this same-level interaction. The other situation that interaction can occur is when the variables involved are measured at different levels, one at a disaggregate and the other at an aggregate level. We call this situation cross-level interaction. Typically, the data set in this situation is hierarchical in nature with disaggregate-level objects as primary units, which in turn can be grouped into well-defined aggregate level(s) whose relevant features are also recorded. In sociology and education research, this is often called contextual analysis, multilevel models, or hierarchical lienar models (see, for example, Iversen 1991; Bryk and Raudenbush 1992). In political science, this can happen when comparativists are comparing nations with data collected at subnational levels. Scholars of American politics also frequently use data collected by interviewing individual respondents but supplemented with, say, state-level characteristics such as types of political culture or restrictiveness of voter registration laws, etc...

The specification of multilevel models can start from the primary-unit level, and then go upward by bringing in relevant aggregate-level variables. For example, to explain individual i's contribution y_i to a political party during a certain period before a presidential election, one may speculate that the individual's income X_i is the most important determinant and, thus, specify the following individual-level model:

$$(6) \quad y_i = \alpha_{0i} + \alpha_{1i} X_i + e_i$$

However, whether the two parties are competitive at the state j, D_j, where the individual i resides may well condition the effect of his/her income on the amount of contribution. In other words, rich people may contribute even more if the party system is competitive in the state. To formalize this hypothesis, we first add the subscript j to the variables y_i and X_i in (6) to denote this additional source of state-level variation, and then replace the subscript i attached to the parameters with j to indicate that they now vary from state to state. Finally, we specify how the aggregate variable Dj affects the two parameters in (6):

$$(7) \quad \begin{aligned} \alpha_{0j} &= \beta_0 + \beta_1 D_j; \\ \alpha_{1j} &= \beta_2 + \beta_3 D_j. \end{aligned}$$

By substituting (7) into (6), we have a final model with cross-level interaction:

$$(8) \quad \begin{aligned} y_{ij} &= \beta_0 + \beta_1 D_j + (\beta_2 + \beta_3 D_j) X_{ij} + \varepsilon_{ij} \\ &= \beta_0 + \beta_1 D_j + \beta_2 X_{ij} + \beta_3 (X_{ij} \cdot D_j) + \varepsilon_{ij}. \end{aligned}$$

Equation (8) actually looks quite similar to equation (3) except the slight differences in notation. Again, β_3 depicts the change of the effect of individual income on political contributions given that the two major parties are competitive in that state. β_2, on the other hand, is the effect of income conditional on a non-competitive party system in the state. However, if theories specify that party competitiveness affects only the intercept but not the slope in equation (6) (i.e., people respond to party competition the same way regardless of their income), then $\beta_3 = 0$ in (7) and the cross-level interaction term does not enter the final model. The extension of this (oversimplified) two-level model to a continuous state-level variable should be straightforward.

Interactions in Logistic Regression of Binary Dependent Variable

Many phenomena that attract political scientists' attention are either binary in nature or coded as binary in practice. Typical dichotomous dependent variables include voting, war initiation, fate of top state leaders (staying in power vs. being overthrown), to name only a few. Although often considered a "simple" model, the popular logit analysis of binary dependent variables often causes much confusion about interactions due to its nonlinear functional form.

The systematic coefficient variation approach delineated above in the context of standard linear regression also applies to logistic regression. However, as indicated above, logit analysis models the probability of event occurrence, and the relationship between probability and the independent variable is inherently nonlinear in an S-shaped curve. Therefore, the interpretation of its coefficients, typically estimated by the maximum likelihood algorithm, are more complicated than their counterparts in standard linear models. Fortunately, logistic regression can be transformed in such a way that the dependent variable becomes the natural logarithm of odds (i.e., the probability of event occurring divided by that of non-event, given a particular value of the independent variable) and the right hand side of the equation looks just like the standard linear regression. In the case that there are no interactive terms included in the model, interpretation of logit coefficients follows directly from the linear regression. The only difference is that coefficients now do not represent effects on the value of the dependent variable, which is either 0 or 1, nor on the probability of event occurrence, which can be any real value between 0 and 1. Instead, each slope coefficient is the effect of a one-unit change in the explanatory variable on the log of odds (or logit). Logit ranges between $-\infty$ and $+\infty$ (since odds is always positive), and is not so easily understood. An easy way out of this difficulty is to take the antilog transformation (i.e. e to the power, where $e = 2.71828...$, or $\exp(\cdot)$)

of the coefficient β_k of the kth independent variable and interpret it as the ratio of odds. Odds ratio indicates how much more (or less) likely it is for the event to occur among those with an independent variable $X_k = a+1$ and among those with $X_k = a$. Since $e^0 = 1$, an odds ratio of 1 means no effect on the occurrence of the event. The stronger the relationship between the independent and dependent variables, the farther the odds ratio deviates from 1 in either direction. If the independent variable happens to be a dummy, then interpretation of its coefficient is particularly convenient since "one-unit increase" in a dummy simply means shifting from the absence to the presence of the characteristic. In the case where X_k is continuous and we are concerned with its effect when it grows from a to b and (b-a) ≠ 1, then the odds ratio is simply $\exp[\beta_k \times (b-a)]$. (See DeMaris 1991; 1992; Hosmer and Lemeshow 1989, chapter 3; and Huang 1993)

With this understanding in mind, we can now proceed to extend the systematic coefficient variation approach of modeling interactions into logistic regression. For convenience, I shall use lnO to stand for the "true" log of odds (i.e., logit) and $O(X=a)$ to denote the odds when variable X takes the value of a, and thus suppress the error term.

For the purpose of illustration, suppose that we are curious about how residential mobility affects voting. (We will examine this subject in greater detail later to demonstrate the substantive importance of our methodological arguments.) The dependent variable is coded as a dummy with 1=voting and 0=nonvoting. If we (arbitrarily) start from assuming that the number of years living in the same community X_i is a significant factor that affects voting, the equation is

$$(9)\quad \ln O_i = \alpha_{0i} + \alpha_{1i} X_i, \quad \alpha_{1i} > 0.$$

However, there is evidence indicating that recent residential mobility suppresses voting, although the adverse effects of such change seem to erode as time elapses. To take into account this interactive effect, a dummy variable D_i is created to code recent movers (who live at the current address for, say, two years or less) as 1 and others 0. The hypothesis is then formalized as follows:

$$(10)\quad \begin{aligned} \alpha_{0i} &= \beta_0 + \beta_1 D_i, \quad \beta_1 < 0; \\ \alpha_{1i} &= \beta_2 + \beta_3 D_i, \quad \beta_2, \beta_3 > 0. \end{aligned}$$

By substituting (10) into (9), we have a logit model with a same-level interaction:

$$(11)\quad \ln O_i = \beta_0 + \beta_1 D_i + \beta_2 X_i + \beta_3 (X_i \cdot D_i).$$

As explained earlier, interpretation in odds ratio makes better intuitive sense than in the log of odds. To remain consistent in this framework of odds ratio, we take antilog transformation of (11) and obtain:

$$(12)\quad O_i = e^{\beta_0} \cdot e^{\beta_1 D_i} \cdot e^{\beta_2 X_i} \cdot e^{\beta_3 (X_i \cdot D_i)}.$$

So the ratio for the odds of voting for new movers compared with others is:

$$(13)\quad \frac{O_i(D_i=1)}{O_i(D_i=0)} = e^{\beta_1} \cdot e^{\beta_3 X_i}.$$

Similarly, for non-new movers (Di=0), the ratio for the odds of voting for those who live in the same community for b years compared with those stay put for a years, b>a>2, is:

$$(14)\quad \frac{O_i(X_i=b)}{O_i(X_i=a)} = e^{\beta_2 (b-a)}.$$

Interpretation of coefficients in a logit model with interactions should now be clear. For the coefficient attached to a component variable of the product term, we can exponentiate it and then interpret the result as the conditional effect, very similar to the case of standard linear model. For example, $\exp(\beta_2)$ is the odds ratio of a one-year increase (when b-a=1) in living in the same community given that the individual is not a new mover (i.e., conditional on $D_i=0$). Suppose that $\beta_2=.20$, $\exp(.2)=1.22$ means that one more year of living in the same community makes a person (who did not move recently) 1.22 times more likely to vote. Or put it differently, for the non-new movers, each additional year of living in the same community brings about a 22% increase in the ratio for the odds of voting. Similarly, $\exp(\beta_1)$ is the odds ratio of new migrants who just moved into their current houses/apartments (i.e., conditional on $X_i=0$).

The interpretation of β_3, the coefficient attached to the interactive term, follows the same principle but demands additional caution. We know from equation (10) that β_3 depicts the assumed "compensation" (hence positive) effect of time on how recent moving "suppresses", by β_1, the logit of voting. This interpretation, though technically correct, is not very intuitively appealing. So again we interpret $\exp(\beta_3)$ as change to odds ratio of new movers (i.e., $D_i=1$) for each additional year living in the same community. This "change," however, does not add to (or subtract from) but multiply the odds ratio, as shown in (13). This is because the antilog transformation in (12) is no longer in the familiar additive form, as is the case in a standard linear regression model.

Since voting in the United States is a two-stage decision, we need to take into account the registration requirements imposed by states. Many argue that the number of days before an election that voter registration is closed is perhaps the single most important legal deterrent to voting (see, for example, Wolfinger and Rosenstone 1978; 1980; Nagler 1991). In general, the earlier the closing date, the greater the barrier. However, the requirement of re-registration after moving may hit the new movers hardest (Squire, Rosenstone and Glass 1987). To take into account this possibility, we start from equation (11), which is an individual-level equation, to bring in the state-level variable of closing date, X_{2j}. By adding subscript j to denote this additional source of variation, we formalize the hypothesis into the following coefficient variation equations:

$$\begin{aligned} &\beta_{0j}=\gamma_0+\gamma_1 X_{2j}, \quad \gamma_1<0, \\ (15)\quad &\beta_{1j}=\gamma_2+\gamma_3 X_{2j}, \quad \gamma_2,\gamma_3<0; \\ &\beta_{2j}=\gamma_4; \\ &\beta_{3j}=\gamma_5. \end{aligned}$$

Substituting (15) into (11) and denoting years of living in community by X_{1ij} yield:

$$(16)\quad \ln O_{ij}=\gamma_0+\gamma_1 X_{2j}+\gamma_2 D_{ij}+\gamma_3(X_{2j}\cdot D_{ij})+\gamma_4 X_{1ij}+\gamma_5(X_{1ij}\cdot D_{ij}).$$

The antilog transformation of (16) is:

$$(17)\quad O_{ij}=e^{\gamma_0}\cdot e^{\gamma_1 X_{2j}}\cdot e^{\gamma_2 D_{ij}}\cdot e^{\gamma_3(X_{2j}\cdot D_{ij})}\cdot e^{\gamma_4 X_{1ij}}\cdot e^{\gamma_5(X_{1ij}\cdot D_{ij})}.$$

The ratio for the odds of voting for the new movers compared with others becomes:

$$(18)\quad \frac{O_{ij}(D_{ij}=1)}{O_{ij}(D_{ij}=0)}=e^{\gamma_2}\cdot e^{\gamma_3 X_{2j}}\cdot e^{\gamma_5 X_{1ij}}.$$

A comparison of (18) with (13) reveals that they are quite similar except that (18) has an extra term in the middle, which captures the assumed additional negative effect of closing date on new movers as specified in the second expression of (15). Since $\gamma_3<0$ and $0\leqq X_{2j}\leqq 50$, $\exp(\gamma_3 X_{2j})\leqq 1$. This means that each earlier closing date of voter registration brings about a $[1\text{-}\exp(\gamma_3)]\times 100\%$ reduction in the odds ratio. If $\gamma_3=0$, however, earlier closing date poses no additional barrier to new movers compared to other citizens.

The coefficient γ_1 is attached to the first-order variable X_{2j} and thus is interpreted as conditional effect, as explained earlier. That is, $\exp(\gamma_1)$ is the effect on the odds ratio of each earlier closing date for non-new movers (i.e., conditional on $D_{ij}=0$). Since $\gamma_1<0$, $\exp(\gamma_1)<1$, which means a negative relationship with voting.

An Application: Residential Mobility and Voter Turnout

Studies of voter turnout provide an optimal setting for demonstrating the substantive importance of our previous methodological discussion. We have chosen this sub-field, and more specifically an article by Squire, Wolfinger, and Glass (1987), for several reasons. Studies of voter turnout are politically important as the low rate of electoral participation by American citizens may represent a foreboding trend in American democracy. Methodologically, studies of electoral activity typically utilize individual level data with dichotomous dependent variables -- rendering the use of logit and probit analyses extremely common. Further, many studies of voter turnout have failed to model and test the hypothesized interaction effects. Such omissions, as we will demonstrate, mislead conclusions as well as the policy recommendations based on such analyses.

Why study mobility? As Squire et al. (1987, 50) point out, the mobile segment of society is the "lightest voting group in the country, but the least studied." Indeed, despite the conclusion reached by Campbell et al. (1960, 90) over thirty years ago that "many people are kept from voting by legal barriers -- most commonly, in a nation of movers,...by political obstacles that they could not reasonably overcome," only a paucity of scholarly inquiry has been given to the relationship between residential mobility and political behavior. Nevertheless, the American populous has grown (and continues to grow) increasingly mobile. In fact, over forty million Americans moved during 1990-91, of which 86% were over the age of 18. In addition, forecasts predict that this rate will grow to forty seven million by the year 2000 (Crispell 1993).

Why Don't Recent Migrants Vote?

The few existing studies of voter turnout that investigate the effects of mobility "all agree that mobility strongly depresses turnout" (Squire et al. 1987, 49; see also Cassel and Hill 1981; Verba and Nie 1972, 139-146; Wolfinger and Rosenstone 1980, 50-54; and Rosenstone and Hansen 1993, 157-159). The puzzling question, however, is why are the recently mobile less likely to vote?

Most scholars have explained these findings through a Downsian cost-benefit analysis, nothing that migrants face considerable psychological and physical burdens during their attempts to adjust to new social and political communities. In other words, the immense demands that confront recent migrants are significant enough that most political interests and behaviors are given lower priority. For example, Squire et al. (1987) contend that the recently mobile have lower turnout rates largely because of the burden imposed by registration requirements (see also, Wolfinger and Rosenstone 1980, 52; Cassel and Hill 1981; Verba and Nie 1972, 139-172). In fact, Squire et al. (1987, 59) assert that if the costs of registration were decreased for recent migrants, voter turnout for presidential elections would increase by nine percentage points. More recently, Rosenstone and Hansen (1993) have made similar arguments.

Nevertheless, many scholars are not convinced of the efficacy of easing registration burdens as a remedy for the lack of citizen participation. In fact, several analysts have presented compelling evidence that registration laws are not significant impediments to voter turnout and efforts to reduce such costs have no always resulted in increased electoral involvement (see, for example Phillips and Blackman 1975; Erikson 1981; Rhine 1993).

Are recent migrants always less likely to vote?

In addition to questions concerning the effects of registration laws, political scientists have recently demonstrated that mobility itself may not always impede voter turnout. For example, Thad Brown (1988) has conducted an extensive analysis of the importance of migration upon individuals' political characteristics. Surprisingly, Brown (1988, 34) finds that the lower turnout rates for recent migrants in the 1980 presidential election can be accounted for by the socio-economic factors associated with those who move. Brown, however, does not believe that migration is politically irrelevant. Rather, he argues that migration is very important if the migration involves moving to a new political environment (Brown 1988, 104). Consequently, Brown's arguments only partially support the conventional wisdom that migrants don't vote. According to his analysis, the effects of migration will only decrease turnout when the move consists of changing political environments.

More recently, Denver and Halfacree (1992) confirm that recent migrants in Great Britain are also light voters. Drawing similiar conclusions to Brown's analysis, however, they illustrate that not all migration results in decreased electoral participation. According to these scholars (1992, 254), intra-constituency migration appears to have no independent effect on turnout.

In short, while the majority of extant evidence appears to confirm the importance of registration laws as a deterrent to voter turnout, many inquiries fail to fully support such conclusions. In addition, while conventional wisdom claims that a change in residence makes people less likely to participate in the electoral process, recent arguments presented by Brown (1988) and Denver and Halfacree (1992), however, question the generalizability of such claims. Given that the literature remains divided about the importance of registration laws and the generalizability of the effects of mobility, a reassessment of the relationship between mobility and registration is critical.

Does Mobility Interact with Other Variables?

Before re-specifying the relationship between mobility and registration, it is necessary to disentangle the many interactions between mobility and electoral participation. We agree with Squire et al. (1987) that the effects of mobility are likely to vary across "three dimensions" (Squire et al. 1987, 53). First, movers differ on individual-level attitudinal and demographic attributes. For example, citizens who are older, more educated, and have a great deal of political interest should be more capable of paying the additional costs associated with moving than are those movers who are young, poorly educated, and not very interested in politics. Secondly, also at the individual-level, the life situations of migrants are diverse. Those movers who are married are likely to have decreased information costs compared to migrants who are single. Also, those movers who own their own homes are likely to feel a greater stake in their community compared to those movers who rent or who are in some form of temporary shelter. Finally, on the state-level, movers vary according to the legal environments to which they are moving. For example, according to Squire et al. (1987, 55), those migrants who move to states with no registration requirements should be more likely to participate than are those migrants who move to states with more costly registration requirements. Consequently, the effects of mobility are likely to interact with a host of individual-level and contextual variables -- mandating the use of contextual or multi-level analysis.

Other Important Variables Influencing Voter Turnout

In order to isolate the effects of mobility on turnout, and the interaction effects across these "three-dimensions," we must control for other factors that influence the propensity for electoral participation. First among such catalysts is education. The literature provides enormous support for the effects of education on political participation (Rosenstone and Hansen 1993; Wolfinger and Rosenstone 1980; Milbrath and Goel 1977 ; Campbell et al. 1960). Education, it is argued, not only increases citizens' capacity for understanding the complex political arena, but also increases peoples' sense of citizen duty as well as experience with a variety of bureaucratic relationships -- all of which decrease the mental and physical costs of voting.

Also, income level and age have been well documented as having a positive relationship with political participation. As with education, those people who are older and have higher incomes are likely to have much more experience with the political world and are, therefore, more able to cope with the psychological and physical costs associated with electoral involvement (Rosenstone and Hansen, 1993; Wolfinger and Rosenstone 1980, 22; Milbrath and Goel, 1977).

In addition to these 'personal resource' variables, research has demonstrated the importance of social circumstances at the time of an election. For example, marriage has been shown to increase the propensity of turning out to vote (Wolfinger and Rosenstone, 1980). Marriage provides for an important source of interpersonal influence, encouragement, and the sharing of the psychological and physical costs of voting. Furthermore, peoples' interest in politics generally has a positive relationship with turnout. Intuitively, one would expect that those people who are the most interested will not only have a large amount of prior political knowledge but will also be more willing to pay the costs associated with political participation. Similarly, past research has demonstrated that those citizens with high levels of political efficacy are more likely to vote (Campbell et al. 1960; Almond and Verba 1963; Verba and Nie 1972; Milbrath and Goel 1977; Rosenstone and Hansen 1993, 141-142).

Squire, Wolfinger, and Glass's Model

Despite Squire et al.'s (1987) extensive theoretical discussion concerning the interactions between mobility and the "three-dimensions," they do not explicitly model and test these relationships in their empirical analyses. (The model that they test, using probit analysis, and our replication of their model, using logit analysis, is presented in Table 1.) The authors provide two types of empirical evidence to support their arguments of interactions. The first is the positive and significant effect of mobility, as measured by the length of time a person lives in the current house or apartment, on voting. It is correct to interpret this finding as: other things being equal, the longer a person lives in the same address, the more likely he or she will vote. However, this positive relationship is general to the entire population who live in the same place for less than six months all the way up to more than seventy years. The finding is stretched too thin to infer that new movers, defined as those who lived in the current address two years or less, are particularly penalized by the requirement of re-registration. It certainly provides no support to the hypotheses that the married, better educated, and politically interested new movers are less adversely affected by being mobile.

The second source of evidence used by Squire et al. to verify the assumed interactions between mobility and the "three dimensions" is simulation based on the entire sample. However, this strategy of citing aggregate simulation results to infer individual propensity to vote is also questionable. The better alternative is, as we have argued, to formalize the hypotheses in order to incorporate them into the model, and then test them explicitly.

A Re-specified Model of Mobility and Voter Turnout

In addition to explicitly testing the interaction effects of mobility and the "three-dimensions," we also include other important variables that were omitted from the original Squire et al. (1987) model. These variables are included in order to isolate the effects of mobility and to avoid the problems associated with model misspecification.

Table 1. The Original model of Squire et al.

Variable[a]	Squire et al.'s Probit estimates	Our Logit estimates
Closing date	-.032	-.0515
	(.007)	(.0122)
Age	.030	.0480
	(.016)	(.0266)
Age squared	-.00016	-.0003
	(.00017)	(.0003)
Income	.018	.0301
	(.010)	(.0158)
Rent/Own	.137	.2049
	(.114)	(.1862)
Education squared	.005	.0091
	(.0008)	(.0014)
Mobility	.057	.0946
	(.013)	(.0219)
Single/married	.223	.3984
	(.104)	(.1728)
Political Interest	.210	.3494
	(.046)	(.0768)
Local elections important	-.572	-.9733
	(.136)	(.2265)
Public Officials care/don't	-.226	-.3970
care what respondent thinks	(.092)	(.1549)
Constant	-1.700	-2.9132
N	1,005	1,024
% Correctly predicted	72.3%	72.2%

[a] The coding for each variable is given in the Appendix.

Note: 1. The numbers in parentheses are the standard errors.

2. As Amemiya (1981, 1488) points out, logit estimates are "typically" 1.6 times greater than that of probit. However, our duplication fails to obtain the identical sample size as reported by Squire et al. (1987, 52).

Recent analyses by Rosenstone and Hansen (1993) demonstrate the importance of campaign related variables on voting. These scholars argue that models of voter turnout that do not consider the importance of political actors are only looking at half of the picture. In other words, mobilization by political elites, such as being contacted by a political party, election campaign, or candidate decrease the costs of voting. Consequently, we include in our model indicators of strength of party affiliation, political contact and perceived closeness of the race. In terms of this last variable, however, we further hypothesize that the effect of perceived closeness of the election race on voting varies according to whether the person cared which party candidate would win the race. Specifically, those who perceived a close election race and cared which candidate would win are even more likely to vote than those who perceived a close race but did not care who would win. Therefore, unlike Rosenstone and Hansen's model, we add in an interaction between the perceived closeness of the race and whether the person cared about who would win the race.

In addition, we include a variable indicating the extent to which the respondent is a regular church attendant. As Rosenstone and Hansen (1993, 158) argue, people who attend church every week have more extensive social networks than do people who are less involved in their communities. Consequently, they are both more likely to receive "free" political information from their social interactions as well as more likely to be mobilized by strategic elites recruiting likely participants.

Based on the previous discussions, we come up with the following more comprehensive individual-level model of voting:

$$
\begin{aligned}
\ln O_i = {} & \alpha_{0i} + \alpha_1(\text{LiveHouse})_i + \alpha_2(\text{Income})_i + \alpha_3(\text{Edu})_i + \alpha_4(\text{Edu}^2)_i \\
& + \alpha_5(\text{Age})_i + \alpha_6(\text{Married})_i + \alpha_7(\text{OwnHome})_i + \alpha_8(\text{GoChurch})_i \\
& + \alpha_9(\text{Efficacy})_i + \alpha_{10}(\text{Party})_i + \alpha_{11}(\text{Interest})_i + \alpha_{12}(\text{Contact})_i \\
& + \alpha_{13}(\text{CloseRace})_i + \alpha_{14}(\text{CloseRace} \cdot \text{CareWin})_i + e_i
\end{aligned} \tag{19}
$$

However, state-level contextual variables should not be ignored. Besides the legal deterrent effect of the closing dates of voter registration, as reviewed earlier, existing literature also indicates that southern states in general have lower voter turnout than the rest of the nation, and that states with concurrent gubernatorial elections tend to stimulate higher voter turnout (Rosenstone and Hansen 1993; Wolfinger and Rosenstone 1980). Since many scholars argue that the better educated are less deterred by early closing dates (e.g., Rosenstone and Hansen 1993; Wolfinger and Rosenstone 1980; but see Nagler 1991 for a different view), we take into account this cross-level interaction by assuming that the closing date depresses the acceleration effect of a person's education on voting. These hypotheses are formalized as follows:

$\alpha_{0j} = \beta_0 + \beta_{15}(\text{Closing})_j + \beta_{16}(\text{South})_j + \beta_{17}(\text{GubElect})_j$;
$\alpha_{4j} = \beta_4(\text{Closing})_j$; and
$\alpha_k = \beta_k$, for $k \neq 0,4$.

Substituting these coefficient variation equations into (19) yields the following basic model:

$$\begin{aligned} \ln O_{ij} = {} & \beta_0 + \beta_1(\text{LiveHouse})_{ij} + \beta_2(\text{Income})_{ij} + \beta_3(\text{Edu})_{ij} + \beta_4[(\text{Edu}^2)_i \cdot (\text{Closing})_j] \\ & + \beta_5(\text{Age})_{ij} + \beta_6(\text{Married})_{ij} + \beta_7(\text{OwnHome})_{ij} + \beta_8(\text{GoChurch})_{ij} \\ & + \beta_9(\text{Efficacy})_{ij} + \beta_{10}(\text{Party})_{ij} + \beta_{11}(\text{Interest})_{ij} + \beta_{12}(\text{Contact})_{ij} \\ & + \beta_{13}(\text{CloseRace})_{ij} + \beta_{14}(\text{CloseRace} \cdot \text{CareWin})_{ij} \\ & + \beta_{15}(\text{Closing})_j + \beta_{16}(\text{South})_j + \beta_{17}(\text{GubElect})_j + \varepsilon_{ij} \end{aligned} \tag{20}$$

Logit estimates of this basic model are presented in Table 2. The Pearson χ^2 goodness-of-fit statistic (See Hosmer and Lemeshow 1989, 138) equals 893.269 with 867 degrees of freedom. Since the observed significance level is .261, we do not reject the null hypothesis that the basic model fits.

The basic model, comprehensive as it may seem, does not isolate the effect of recent migration, let alone its interactions with other variables. To specifically test what Squire et al. (1987, 53) call "variations in the effect of mobility," we follow the steps similar to those expressed in equations (10) to (11). We first create a dummy variable NewMove to identify new movers (who account for 32.8% of the 1980 NES sample) as defined by the three authors, and then hypothesize, following Squire et al.'s substantive arguments, that NewMove not only lowers the level (i.e., the intercept β_0) of the log of odds but intervenes into the effects on voting of all the variables related to the "three dimensions" as well as the factors of political mobilization. More specifically, NewMove interacts with demographic and attitudinal attributes (i.e., Income, Edu, Age, Efficacy, Party, Interest), life situations (i.e., Married, ownHome, GoChurch), the legal environment (i.e., Closing), and political mobilization and campaign (i.e., Contact, CloseRace). To detect if new movers indeed differ from the rest of the sample in the relationship between the length of time staying in the same place and voter turnout, we also allow NewMove to interact with the variable LiveHosue. Twelve out of these 13 interaction terms presumably have "compensation effects" (hence positive in sign) on voting. Only the coefficient attached to the interaction between NewMove and Closing is assumed to be negative, meaning that earlier closing dates of voter registration impose additional legal barrier to new movers for voting. The logit estimates of this more fully specified model is presented in Table 3.

A glance at Table 3 indicates that none of the 13 interaction terms involving NewMove reaches the conventional .05 level of statistical significance. To test jointly the variable NewMove and all the interaction terms it involves in, we conduct a likelihood

Table 2. Parsimonious Model

Variable[a]	Parameter estimates		Standard errors
LiveHouse	.2260	***	.0733
Income	.0118	*	.0071
Education	.0156		.0915
$Education^2 \cdot Closing$	.0003	**	.0001
Age	.0147	**	.0062
Married	.3679	**	.1821
OwnHome	.3051		.2003
GoChurch	1.3049	***	.2341
Efficacy	-.3729	**	.1661
Party	.8424	***	.2729
Interest	.8594	***	.2517
Contact	.0955		.1995
CloseRace	-.0763		.2502
CloseRace · CareWin	.5007	***	.1853
Closing	-.0573	**	.0247
South	-.3491	*	.1802
GubElect	.3537		.2607
Constant	-2.4426		1.2553
N	885		
% correctly predicted	72.88%		
log likelihood	-465.806		
Pearson chi-square (df=867)	893.269		

[a] The coding for each variable is given in the Appendix.
* significant at .10 level
** significant at .05 level
*** significant at .01 level

Table 3. Fully Specified Model

Variable[a]	Parameter estimates		Standard errors
NewMove	-1.0537		1.5659
LiveHouse	.2823	**	.1416
LiveHouse · NewMove	-.1344		.2662
Income	.0056		.0086
Income · NewMove	.0182		.0161
Education	.0226		.0943
Education · NewMove	.0296		.0822
Education^2 · Closing	.0003	*	.0001
Age	.0097		.0076
Age · NewMove	.0168		.0143
Married	.6001	***	.2260
Married · NewMove	-.5394		.4049
OwnHome	.3589		.2586
OwnHome · NewMove	-.2103		.4280
GoChurch	1.4977	***	.2829
GoChurch · NewMove	-.6120		.5297
Efficacy	-.4995	**	.2089
Efficacy · NewMove	.2479		.3622
Party	.7230	**	.3316
Party · NewMove	.1878		.5689
Interest	.7523	**	.3040
Interest · NewMove	.5996		.5637
Contact	-.1199		.2348
Contact · NewMove	.8337	*	.4678
CloseRace	-.2482		.3001
CloseRace · NewMove	.5831		.5188
CloseRace · CareWin	.4990	***	.1875
Closing	-.0453	*	.0266
Closing · NewMove	-.0297		.0239
South	-.3688	**	.1839
GubElect	.3330		.2655
Constant	-2.4171		1.3490
N	885		
% correctly predicted	73.67%		
log likelihood	-458.021		
Pearson chi-square (df=853)	907.550		

[a] The coding for both independent and dependent variables is given in the Appendix.
* significant at .10 level
** significant at .05 level
*** significant at .01 level

ratio (LR) test (see Judge et al. 1985, 184) by restricting the values of their coefficients and the coefficient of the dummy NewMove to zero. The LR test of -2 $\times$ (-465.806-(-458.021))=15.570 with 14 degrees of freedom in χ^2 distribution is not statistically significant at any conventional significance level. We therefore conclude that the basic model of equation (20) can be accepted as a more parsimonious model. This also means that, after controlling for relevant variables of various dimensions, our findings show neither additioinal penalty of closing dates on new movers above that experienced by all citizens, nor compensation effects of other variables on the mobile segment of society. Since the logit estimate of the coefficient of LiveHouse is still positive and significant, we confirm Squire et al.'s empirical finding in their original model. However, no matter what mechanism (e.g., sense of community, neighborhood support, or familiarity with local bureaucratic procedures, etc.) is responsible for this positive relationship between the length of time living in the same address and the likeliness of voting, it applies to the general public, including new movers and those who stay put. If this mechanism is not particularly disturbed by the closing dates of voter registration, then any policy change in this legal environment may have little effect on new movers' voter turnout. Of course, it is dangerous to draw such conclusion based on an analysis of only the 1980 NES data. It does, we hope, point out that some conventional wisdom about new movers, registration laws, and voting deserve further studies.

In the more parsimonious model of (20), only two interaction terms are included. The interaction between perceived closeness of election race and care about which candidate wins is positive and significant at .05 level. Since both variables are dummy, their product is also a dummy: 1 for those who perceived close race and care who wins, and 0 for others. Based on our hypothesis, this coefficient captures the effect on voting in addition to the effect of just perceiving a close race. However, the first-order variable of perception is insignificantly different from zero, so we can simply interpret the result as: those who perceived a close race and cared who would win are exp(.5007)$\approx$1.65 times more likely to vote than people who did not feel the same way about the closeness of the election or with who would win.

The other (cross-level) interaction between education-squared and closing date has a sign different from what we expected and is statistically significant at .05 level. Obviously, whether the better educated are less deterred by early closing dates and exactly how the mechanism works require much more careful analyses. Nevertheless, for the sole purpose of exercise, let us find the odds ratio of voting for a person who moves from a state that allows election-day registration to a state that closes voter registration 30 days before the election. Based on the same method used in equation (14), we obtain:

$$\frac{O_{ij}(\text{Closing}_j = 30)}{O_{ij}(\text{Closing}_j = 0)} = e^{\hat{\beta}_4(\text{Edu}^2)(30\text{-}0)} \cdot e^{\hat{\beta}_{15}(30\text{-}0)} \quad)$$
$$= (1.0090)^{\text{Edu}^2} \cdot (.1792).$$

If this person is exposed to no formal eduction at all (i.e., Edu = 0), this move leads to almost an 82% reduction in the odds ratio of voting. If this person is a high school graduate (i.e., Edu = 12), however, the move leads to approximately 35% reduction in odds ratio of voting. (These results may seem reasonable. However, if the person has post-college education, i.e., Edu = 17, then the move makes him or her more than twice as likely to vote.)

Conclusion

In this paper, we present a rather straightforward approach of systematic coefficient variation to help model and interpret interactions in both standard linear and logistic regressions. This approach starts from a simpler model without interactions, and then specifically models the (nonconstant) coefficient of the variable whose effect on the dependent variable is hypothesized to be a function of the other variable(s). The same "bottom-up" strategy also applies to multilevel models. With some appropriate transformation of the logit model, which is inherently nonlinear, we can extend the coefficient variation approach to this popular model of binary dependent variable. Basically, we interpret the antilog transformation of the coefficient attached to the product term between two variables as additional effect, and interpret the antilog transformation of the coefficient attached to the individual component of the interactive term as conditional effect. Since this approach treats modeling, testing and interpreting parameters and their estimates as an integrated procedure, we believe that it facilitates clear thinking in empirical investigation. As demonstrated in our example of residential mobility and voter turnout, specific modeling of interactions between being a new mover and other demographic, attitudinal, mobilizational, and legal variables casts some doubt on conventional wisdom on this subject.

Appendix:

Coding of the Variables

I. Models reported in Table 1

Dependent Variable:

Vote: for the case of replication, the dependent variable in table 1 is based on the classification scheme used by Squire, Wolfinger, and Glass (1987). As they state on page 61 in their Appendix, categories 0,4,5,6,7,8, and 9 on variable 1207, of the voter validation study of the 1980 American National Election Study, were deleted. See the relevant codebook: University of Michigan Center for Political Studies (1982, 712-713). While we constructed our dependent variable in the same manner, we still have 19 cases more than are reported by Squire, Wolfinger, and Glass (1987, 52).

Independent Variables:

Closing Date: 0 = living in state with election day registration; coded value for other states was the number of days from close of registration to election day (Council of State Governments 1980).

Age (v1197): respondent's age in single years, 18 to 97.

Income (v686): coded in 22 categories as done by NES with 1 = less than $2,000 and 22 = $ 50,000 and over.

Homeownership status (v719): 0 = rent or other financial arrangement, 1 = own.

Education squared: the square of the value coded for education (v429), which ranged in single years from 0 to 17.

Mobility (v718): less that 6 months = .25; 6 to 12 months = .75; 1 to 2 years = 1.5; 2 to 3 years = 2.5; 3 to 4 years = 3.5; 4 to 5 years = 4.5; 5 to 6 years = 5.5; 6 to 7 years = 6.5; 7 to 8 years = 7.5; 8 to 9 years = 8.5; 9 to 10 years = 9.5; more than 10 years = 11. (same coding as Squire et al. 1987)

Marital status (v409): 0 = never married, divorced, separated, widowed, common law, other: 1 = married.

Political interest (v974): 1 = hardly at all; 2 = only now and then; 3 = some of the time; 4 = most of the time.

Importance of Local Elections (v146): 0 = disagree (respondent does think that local elections are important); 1 = agree.

II. Full and Parsimonious Models

Dependent variable:

Vote: All subsequent models use a classification system that we believe is more theoretically justifiable than that used by Squire et al. (1987). Based upon the series of articles by Paul Abramson and William Claggett (1984, 1986, 1989), we also use the validated vote variable (v1207) as a summary measure. However, respondents classified as a 1 by the NES validation were coded as voters, while respondents classified as a 2, 3, or 4 were coded as non-voters. Respondents coded 5 were registered to vote, but they lived in two Alabama counties and one in Louisiana parish where officials would not allow the SRC field staff to verify voting records. We classify these people as voters based upon their self-report. All other classifications were coded as not ascertained.

Independent Variables:

NewMove (v718): coded one if the respondent had moved less than or equal to two years ago.

Income (v686): none or less than $2,000 = .5, $2,000-$2,999 = 2.5, $3,000-$3,999 = 3.5, $4,000-4,999 = 4.5, $5,000-$5,999 = 5.5, $6,000-$6,999 = 6.5, $7,000-$7,999 = 7.5, $8,000-$8,999 = 8.5, $9,000-$9,555 = 9.5, $10,000-$10,999 = 10.5, $11,000-$11,999 = 11.5, $12,000-$12,999 = 12.5, $13,000-$13,999 = 13.5, $14,000-$14,999 = 14.5, $15,000-$16,999 = 15.5, $17,000-$19,999 = 18.5, $20,000-$22,999 = 21.5, $23,000-$24,999 = 24, $25,000-$29,999 = 27.5, $30,000-$34,999 = 32.5, $35,000-$49,999 = 42.5, $50,000 and over = 60.

Education (v429): The number of years the respondent completed; variable ranges from 0 to 17.

Age: same as previous coding.

Married (v409): same as previous coding.

Efficacy (v1033): 1 = not efficacious; 0 = efficacious.

Party id (v775): apolitical or straight independent = 0; strong partisan = 1; weak partisan = .67; independent leaner = .33;

Interest in politics (v974): most of the time = 1, some of the time = .67, only now and then = .33, hardly at all = 0.

Closrace (v55): close race = 1, win by quite a bit = 0, not sure/don't know = .5. Carewin (v61): care very much = 1, don't care very much = 0.

Closrace · Carewin: coded as one for those people who perceived that the presidential race was going to be close and cared about which party would win the election.

Ownhome (v719): own = 1, rent = 0, occupancy part of financial arrangement with employer/owner = 0, other = 0.

GoChurch (v694): Every week = 1, Almost every week = .75, Once or twice a month = .67, a few times a years = .33, never = 0.

LiveHouse (v718) The log of the number of years that the respondent has lived in this house/apartment. If the person had lined in the present house all of his or her life, then this variable is coded to the respondent's reported age.

Closing: same as previous coding.

South: coded one for those states in the South: Virginia, Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Texas, and Tennessee.

GubElect: coded one for those states having a concurrent gubernatorial election: Arkansas, Delaware, Indiana, Missouri, Montana, new Hampshire, North Carolina, North Dakota, Rhode Island, Utah, Vermont, Washington, and West Virginia (Council of State Governments 1980).

Efficacy (v1033): 0 = disagree (efficacious); 1 = agree (not efficacious).

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